Fluorescence spectroscopy as a monitoring technique for membrane bioreactor water reclamation systems

by

Jeffrey D. Scott

B.S., Kansas State University, 2013

B.S., Kansas State University, 2016

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Biological and Agricultural Engineering
College of Engineering

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2017

Approved by:

Major Professor
Dr. Stacy Hutchinson

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Abstract

The shortage of clean, usable water is a global problem (Millennium Ecosystem Assessment, 2005). As much as 80% of the world's population has been reported to be in areas of high water security risk due to a convergence of factors, such as watershed disturbance, pollution, water resource development and biotic factors (Voeroesmarty et al., 2010). Water reuse technologies are a potential solution to this problem. However, implementation of treatment technologies for improved water reuse require rapid, effective monitoring techniques capable of insuring treatment quality. Fluorescence spectroscopy has shown potential for wastewater treatment monitoring due to its sensitivity, selectivity, and capacity to be employed in-situ. Online fluorescence data and full fluorescence excitation-emission matrices coupled with parallel factor analysis (PARAFAC) were employed to evaluate the treatment performance of a membrane bioreactor (MBR) at Fort Riley, KS. Specific research goals were to evaluate the effectiveness of fluorescence for monitoring wastewater treatment of a full scale MBR and to determine the contamination detection limit of fluorescence techniques in a non-potable reuse scenario. Study results revealed a two-stage startup period, the first 60 days indicated membrane cake layer formation and the first 90 days showed signs of oxic tank maturation. Fluorescence was found to be effective at monitoring carbon concentration trends throughout the MBR system, and showed preferential removal of protein-like dissolved organic matter (DOM) throughout the study period, and an increase in biodegradation of DOM as the oxic tank matured. A ratio of the humic-like fluorescent components to the protein-like fluorescent components was found to correlate to TOC removal ($R^2 = .845$, $p < .001$). Also, fluorescence was able to detect contamination in the effluent at the 0.74-1.24mg C/L level using two wavelength pairs,

indicating that effective real-time monitoring for contamination can be accomplished with minimal instrumentation and post-processing of data.

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Acknowledgements

The author would like to thank Dr. Stacy Hutchinson, Dr. Natalie Mladenov, and Dr. David Steward for their guidance and patience throughout this work. Not to mention the comradery and aid of my fellow graduate students. I will remember this time of my life fondly. Thank you for your friendship, Kelsey. The project was funded by the EPA – Net Zero Initiative.

Dedication

This work is dedicated to my wife, Meagan, and my baby girl. Your love and support have proven invaluable.

Lord, bless you both.

The heavens declare the glory of God, and the sky above proclaims his handiwork.

Day to day pours out speech, and night to night reveals knowledge.

There is no speech, nor are there words, whose voice is not heard.

Their voice goes out through all the earth, and their words to the end of the world.

Chapter 1 - Introduction

Water reuse and reclamation technologies have tremendous potential to make a large supply of previously used water available for reuse, stretching our limited resources further and reducing our impact on fresh water supplies. While water reuse and reclamation are widely practiced across the globe, the current 9.8 million cubic meters per day of reused water in the United States makes up only a small percentage of the total effluent generated (Miller, 2006).

Despite the potential benefits of water reuse, reuse systems are not yet widely implemented in the US. This is due, in part, to the risk related to water reclamation technology failures and heightened perceived risk by reclaimed water consumers. In order to decrease infrastructure costs, water reclamation systems are often installed near the location of source water and the point of reuse. Failure in these reclamation systems poses an elevated threat due to the lack of travel time from treatment back to consumers (Hambly, Henderson, Baker, Stuetz, and Khan, 2012; Henderson et al., 2009). In addition to the actual risk involved, failure in these systems feed in to negative public perception of reused water and provide justification for opponents of water reuse systems. These issues present a need for acute, real-time water monitoring to increase public confidence as well as to defend the public from system failures. Acute, real-time monitoring of these systems can improve their safety by detecting lower levels of contamination and providing timely system failure information, allowing for appropriate action to protect the public.

Fluorescence based techniques are very sensitive and may be employed inline in water treatment systems and can therefore meet this need (Henderson et al., 2009), however more research needs to be done to determine their effectiveness and limitations in different water treatment contexts.

Research Objectives

In response to the need for improved water treatment monitoring, the goals of this study are to: evaluate the effectiveness of fluorescence based techniques to monitor wastewater treatment throughout a full scale membrane bioreactor (MBR), including correlation to carbon removal, and determine the contamination detection limit of fluorescence techniques in a non-potable reuse scenario.

Significance of Work

MBRs are a widely used for water reclamation, but are prone to membrane fouling (Le-Clech, Chen, and Fane, 2006). Fouling leads to increased operation costs as the membrane must be replaced or cleaned periodically. Current efforts to reduce fouling involve optimizing MBR operation and understanding the mechanism of fouling. Fluorescence techniques have an advantage over commonly used bulk carbon measurements for this application in that they provide information about the types of carbon compounds present in the wastewater, rather than only the amount of carbon. Therefore, fluorescence based techniques can be used to further understand MBR operation and fouling mechanisms in order to reduce membrane fouling and the related costs.

Fluorescence techniques have been used to detect contamination in clean water sources from wastewater (Hambly et al., 2010; Stedmon et al., 2011), and the sensitivity of monitoring techniques in drinking water systems has been reported (Hambly et al., 2010; Stedmon et al., 2011). However, no work has been done to determine detection limits between non-potable recycled water and wastewater, which has a much smaller difference between influent and effluent quality. This study offers detection limits of several fluorescence based measurements in a non-potable context. Since direct measurement of pathogens often involve plating and growing

the pathogens, immediate online detection of contamination allows for appropriate action to be taken to protect the public from harm much more quickly.

Fluorescence has also been shown to correlate with DOC removal by different common treatment processes and in different environments (Baghoth, Sharma, and Amy, 2011; Hur and Cho, 2012; Shutova, Baker, Bridgeman, and Henderson, 2014), and with biodegradability (Yang, Shin, and Hur, 2014). This study contributes to this body of knowledge by examining the relationship TOC removal and fluorescence parameters.

Chapter 2 - Literature Review

State of Water Resources

The world's water resources are in jeopardy, both in terms of quality and quantity. The National Academy of Engineers (NAE) identified providing access to clean water to be a grand challenge for engineers in the twenty first century (National Academy of Engineers, 2016). It is not only those in the arid regions that are facing challenges in sustaining a supply of potable water. As much as 80% of the world's population has been reported to be in areas of high water security risk (Voeroesmarty et al., 2010). Communities around the world are facing water related sustainability challenges due to increased demand, contamination of ground and surface water, and dependence on single sources of supply (Henderson et al., 2009; Miller, 2006). The Millennium Ecosystem Assessment reports that water withdrawal from rivers and lakes for irrigation, household, and industrial use has doubled over the last forty years (Millennium Ecosystem Assessment, 2005). In addition to the issues caused by water resource management and increasing population, the situation is exacerbated by the changing climate. Unpredictable rainfall patterns and periods of increased drought are moving communities to create sustainable water management plans while still meeting customer demand (Henderson et al., 2009; Miller, 2006).

Wealthy nations have largely been sheltered from the impacts of diminishing water resources through tremendous wealth and abundance of natural resources (Voeroesmarty et al., 2010). Wealthy nations have the ability to mitigate water security risk through investment in infrastructure that other nations cannot afford. For example, much of the U.S. and European population are in areas of high water security risk based on the convergence of watershed disturbance, pollution, water resource development, and biotic factors (Voeroesmarty et al.,

2010). This risk is highly mitigated by considerable water infrastructure investment, shifting the risk of wealthy areas of the globe from the 90th percentile down to the 5th.

This being said, there is an increasing trend in water shortages and water quality issues here in the U.S. For example, the drinking water supply of Wichita Falls, Texas fell from 90% to 20% capacity from 2010 to June, 2014 (City of Wichita Falls, TX, 2014). In response, the town of 150,000 has implemented a Direct Potable Reuse Program. The measure is temporary until a $35 million Indirect Potable Reuse project is completed within the next few years (City of Wichita Falls, TX, 2014).

More recently the city of Flint, Michigan experienced highly contaminated water entering their drinking water supply (CBS News, 2014). Corrosive water in the pipes dissolved lead into residents' drinking water. This was the result of an economic decision to shift the town's water supply from clean but expensive Lake Huron to the Flint River, an infamously contaminated tributary of the lake. Just seventy miles from the largest group of fresh water bodies on earth, the town of Flint has been unable to provide its citizens with fresh water due to industrial practices detrimental to environment. Reflecting on the state of American water infrastructure, the American Water Works Association's *Buried No Longer: Confronting America's Water Infrastructure Challenge* reports that restoring and expanding the existing drinking water infrastructure in the U.S. will cost at least 1 trillion USD over the next 25 years (Raucher, Cromwell, and Reynolds, 2012).

Water Reuse

Water reuse and reclamation technologies have potential to make a large supply of previously used water again available for use, stretching our limited resources much further than before and reducing our impact on fresh water supplies.

While water reuse and reclamation are practiced widely across the globe, the current 9.8 million cubic meters per day of reused water in the United States makes up only a small percentage of the total effluent generated (Miller, 2006). According to Shannon et al. (2008), agriculture returns 30-40% of its wastewater to the environment, while industrial uses return 80-90%, power generators return 95-98%, and public and municipal users return 75-85% **Table 1**. The majority of this water is returned to the environment after a single use. While **Table 1** neglects to account for the situation specific barriers that may arise, such as distance from treatment location to reuse or space limits for additional infrastructure, it is clear the tremendous impact widely implemented water reuse can have on freshwater resources.

Category	Freshwater withdrawals by use ($Mm^3\ day^{-1}$)[1]	% return by use[2]	Volume available for reuse ($Mm^3\ day^{-1}$)
Agricultural	478.5	35%	167
Industrial	80.3	85%	68
Power generation	609.5	96%	588
Public and municipal	172.6	80%	138
Total	1340.9	71%	961

Table 1 - Reusable percentage of freshwater withdrawals by water source

1 - (Maupin et al., 2014)

2 - (Shannon et al., 2008)

Consider freshwater withdrawal for power generation as an example. Since 2005, water withdrawals for power generation have decreased by 20%, yet thermoelectric water withdrawals still account for 45.5% of the total daily withdrawals for the U.S. (Kenny, Barber, Hutson,

Linsey, and Maupin, 2009; Maupin et al., 2014). This decrease reflects the shift in cooling technologies from open-loop systems to the much more efficient closed-loop recirculating systems and, as this trend continues, replacing the necessary coolant water with reclaimed water becomes more possible.

An obstacle to reuse is the additional infrastructure to transport reclaimed water to its location of use, but this can be overcome by locating power plants and wastewater treatment plants near each other. This is difficult because many municipal wastewater treatment plants are large centralized systems. These systems have been in place for long periods of time and the piping is buried under city blocks, making it very difficult to replace or improve upon. Building new thermoelectric power plants and wastewater treatment plants near one another reduces the need of much additional infrastructure. This practice has been increasingly common as freshwater resources are becoming scarcer and as restrictions are being placed on their use (Li, Chien, Hsieh, Dzombak, and Vidic, 2011). Li et al. (2011) estimate that if power plants switch to recirculating systems, ~50% by capacity of existing power plants in the U.S. could meet their cooling water demand with municipal wastewater from a treatment plant located within a 10 mi. radius. Increasing the radius to 25 mi would allow for 76% of existing power plants to meet their water cooling needs with treated wastewater.

If this practice were implemented, there would be a significant improvement in water security in the affected regions. The study by Li et al. (2011) only considered the impact of water recycling in regard to thermoelectric power plants, this practice could be implemented to provide recycled water for a variety of uses near appropriate sources of recyclable water.

Communities are implementing smaller, decentralized systems in new developments to stem the increasing wastewater load on their existing centralized system, or simply to reach rural

areas with no centralized water treatment system (Hambly, Henderson, Baker, Stuetz, and Khan, 2012; Massoud, Tarhini, and Nasr, 2009). With the installation of these small systems, it is possible to install piping back into residential or commercial areas to return the water for non-potable use, thus reducing the cost of installing the long distance piping to reach a centralized water treatment facility. In general, proximity between the source of reclaimed water and the location of its use is valuable and developing this precedent opens the door for more patterns of water reuse to emerge.

Membrane Bioreactors

An important treatment technology for water reuse is the membrane bioreactor (MBR). This technology was first reported in 1969, but has since remained in the spotlight for its potential for creating high quality effluent (Smith, Di Gregorio, and Talcott, 1969). This process combines the biological digestion of activated sludge methods with microfiltration or nanofiltration to replace sedimentation. These technologies have the capability to produce high quality effluent that is immediately ready for some reuse applications, such as irrigation, or as a pretreatment for RO systems to return the water to potable quality (Shannon et al., 2008).

The commonly cited advantages of MBR systems are reduced footprint compared to the traditional settling tank technology, reduction in excess sludge production, flexible design, automated operation, and improved final quality compared to traditional systems (Brindle and Stephenson, 1996; Howell, Chua, and Arnot, 2004; Le-Clech, Jefferson, and Judd, 2003; Shannon et al., 2008; Wang, Wu, and Tang, 2009a; W. Yang, Cicek, and Ilg, 2006). Due to these strengths, particularly automated operation and small footprint, MBRs may be ideal for decentralized water reuse.

Obstacles to Water Reuse

There are still significant challenges to decentralized water reuse that need to be overcome. When water reuse technologies are installed near to the point of reuse, the travel time from the system to consumer is short. This poses increased risk to the consumer in the event that the water reuse system fails or becomes contaminated (Hambly et al., 2012; Henderson et al., 2009). Large centralized systems can take advantage of the longer travel times from the plant to the consumer, which increases the time for reaction to system failure. Decentralized systems must be able to detect and respond to contamination events much more rapidly than a traditional water treatment system.

In addition to real risk experienced by consumers, there is an added perceived risk toward water reuse systems. Hambly et al. (2012) published a review of cross-connections related to dual reticulation systems, a common use for MBR systems. Included is a review of reported cross connection events between drinking water pipes and recycled water pipes, or cases of contamination of drinking water as a result of failing dual reticulation systems. As a result of these events and the inherent challenge of trusting the quality of recently treated wastewater, the Dutch government has discouraged the use of recycled water in domestic properties and surveys of communities and professionals in the US have shown skepticism toward the quality of reused water (Hambly et al., 2012; Hartley, 2006)

Lastly, in regard specifically to MBR systems, there is the problem of irreversible membrane fouling. It has been reported that this is the primary limitation to the widespread use of MBR systems (Le-Clech, Chen, and Fane, 2006). Membrane fouling contributes to increased pumping costs and decreased flux across membrane surfaces. This leads directly to the necessity of back-flushing and relaxation periods, periods of zero or negative treated effluent production,

as well as frequent cleanings. In response to these drawbacks, the research community has produced a large number of studies on the nature of foulants, and the processes which contribute to their formation (Hur et al., 2014; Kimura et al., 2005; Le-Clech et al., 2006; Maqbool et al., 2016). Currently, soluble microbial products (SMP), or a related organic fraction, extracellular polymeric substances (EPS) are attributed as the largest factor influencing fouling in an MBR. These organic fractions of wastewater bodies are mostly made up of proteins, lipids, and polysaccharides. While there is agreement that these substances are at least partly responsible for fouling, their concentration does not necessarily correlate to fouling rate (Drews, Vocks, Bracklow, Iversen, and Kraume, 2008). Current research is attempting to identify more precisely the foulants themselves and the circumstances that most affect fouling.

Each of these issues present a need for acute, real-time water quality monitoring. Acute, real-time monitoring would allow for more rapid contamination or treatment failure, thereby allowing appropriate action to be taken to protect the consumer. This may also increase public confidence in water reuse systems. Lastly, detailed monitoring throughout the system may increase understanding of how and why membrane fouling occurs and allow for improved MBR operation, thereby decreasing irreversible fouling and associated costs.

Water Treatment Monitoring

Before water reclamation technologies become standard in new developments and projects, public perception of treated water quality and safety, as well as the actual safety of these technologies, must increase. These hurdles can be overcome by rapid, acute, real-time monitoring technologies that reliably detect changes in water quality related to treatment failure or cross contamination.

Studies in this area have been collected in reviews and have covered a broad variety of monitoring techniques (Hambly et al., 2012; Henderson et al., 2009). The techniques evaluated include BOD, COD, TOC, metal ion concentrations pH, free chlorine, oxidation reduction potential, dissolved oxygen (DO), electric conductivity (EC), turbidity, chloride, ammonia, and nitrate. Of these, only EC and TOC have been shown to be able to differentiate between potable and recycled water, but only for extreme values (**Table 2**).

Water quality parameter	Potable water values	Recycled water values
TOC (mg/L)	0.4-6.4	0.1-6.7
EC (μS/cm)	13-570	65-1240

Table 2 - Range of reported water quality parameters from Henderson et al. (2009)

While TOC and EC do vary between potable sources and recycled water sources, there is significant overlap (**Table 2**). The detection limit of these two techniques in this context is around 5% intrusion, meaning 5% of the potable water flow is now recycled water. This is only if the conductivity difference is 700μS/cm or TOC difference is 3mg/L or more and it is clear that recycled water and potable water can have TOC and EC values that differ much less than this (**Table 2**, Henderson et al., 2009). A superior monitoring technique is desired. Fluorescence spectroscopy has shown much promise in this regard.

Principles of Fluorescence Spectroscopy

The phenomenon of fluorescence is the emission of light caused by an energetically excited molecule relaxing to a ground state (Lakowicz, 1999). Excitation takes place when a molecule's electrons absorb light at a wavelength that corresponds to the difference in energy between the electron's current (likely ground) state and a more excited state (S_1 or S_2, typically).

The reverse of this absorption process is fluorescence where the excited electron quickly falls back down to the ground state and emits light at the wavelength corresponding to the amount of energy lost by the electron. Between the two processes of absorption and fluorescence, internal conversions are likely to occur. Internal conversion describes the transfer of the excited electron from one energy state to another state at a nearly identical energy level. Generally, excited electrons fall to the lowest vibrational energy level (the lowest S_1 or S_2 level) before falling to the ground state and emitting fluorescence. Since the wavelengths of light both emitted and absorbed are defined by the energy levels of the fluorescing molecule, the fluorescing light offers information as to the chemical nature of the molecule (**Figure 1**, Lakowicz, 1999).

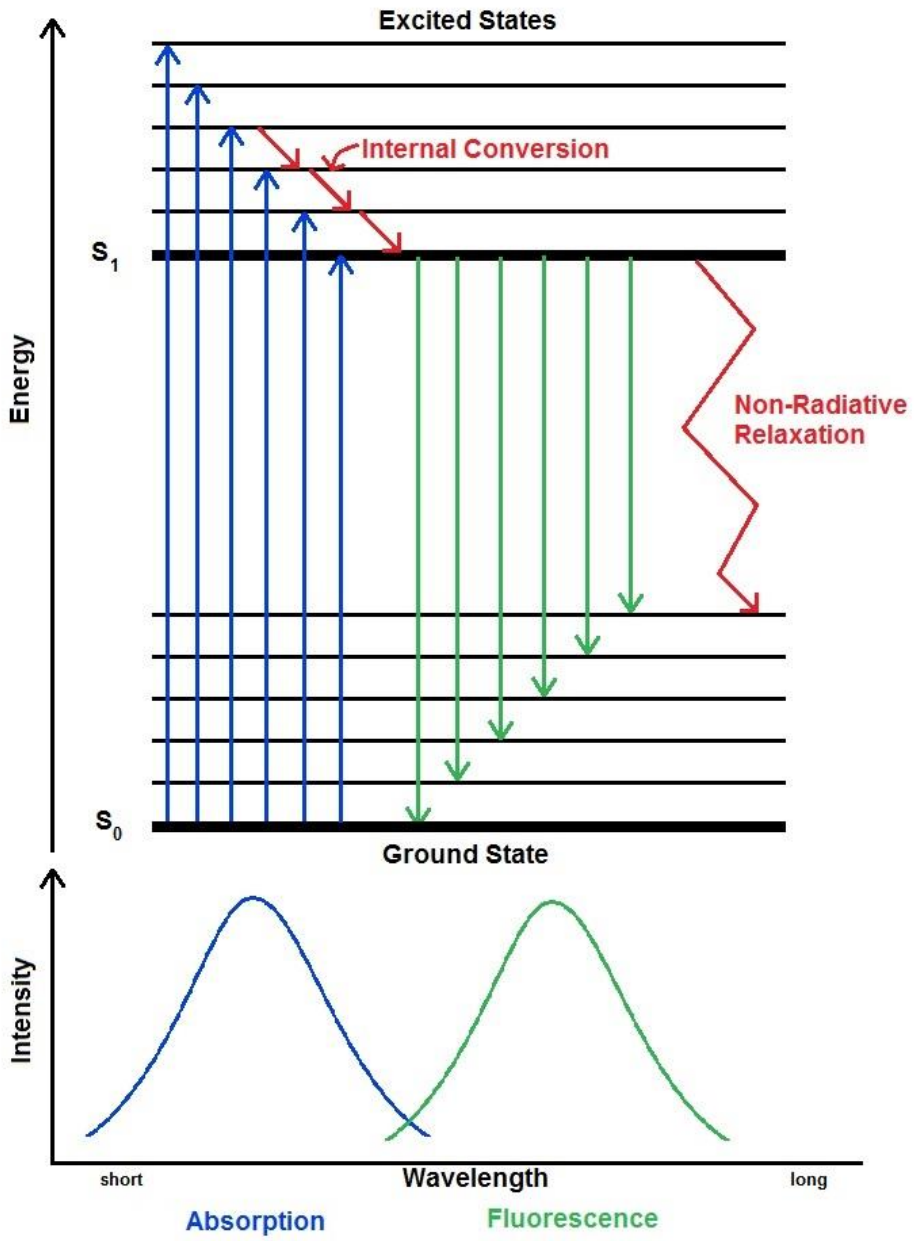

Figure 1 - Jablonski diagram of a fluorescing molecule. (Adapted from Hudson et al., 2007)

The upper portion of **Figure 1** is an illustration of the possible energy transformations initiated by the absorption of light. Once the light is absorbed and an electron is excited, the electron may undergo fluorescence or non-radiative relaxation. Non-radiative relaxation occurs when excess energy is lost due to vibrations.

Due to the rapid and repeatable nature of the energy transformations that result in the release of fluorescent light, the fluorescence technique is extremely sensitive, such that a single fluorescing molecule may be detected (Peck, Stryer, Glazer, and Mathies, 1989). In addition to high sensitivity, fluorescence techniques are highly selective and non-destructive. The selectivity stems from the influence that the structure and functional groups of a molecule have on the wavelengths emitted and absorbed.

Fluorescence Monitoring of WW

Over the past 20 years, fluorescence spectroscopy has been used to characterize aquatic organic matter in natural waterbodies and wastewater streams (Coble, Green, Blough, and Gagosian, 1990; Coble, 1996; Vasel and Praet, 2002). Methods have evolved from taking single peak fluorescence measurements to generating three dimensional matrices from sequential excitation-emission measurements (Stedmon et al., 2003). These three dimensional structures are called excitation emission matrices (EEMs). In addition to the improvement of fluorescence measurements, several analytical methods have been developed to extract more usable information from emission spectra.

A common use for fluorescence spectroscopy is in the analysis of dissolved organic matter (DOM). DOM is a complex mixture of carbon based compounds and are heavily present in wastewater and therefore relevant to the present study. The properties of DOM will be covered in a subsequent section (**Dissolved Organic Matter**).

In regards to DOM, several classes of molecules have been identified from their fluorescent properties or have been shown to have unique fluorescent properties. The fluorescence characteristics of DOM are typically taken by consecutive scans across a range of

emission wavelengths using iterating excitation wavelengths. These scans are collected and used to create an EEM. Based on the composition of the fluorophores present, fluorescence of DOM generally offers information about proteins and humic-like substances present (**Figure 2**)(**Table 3**).

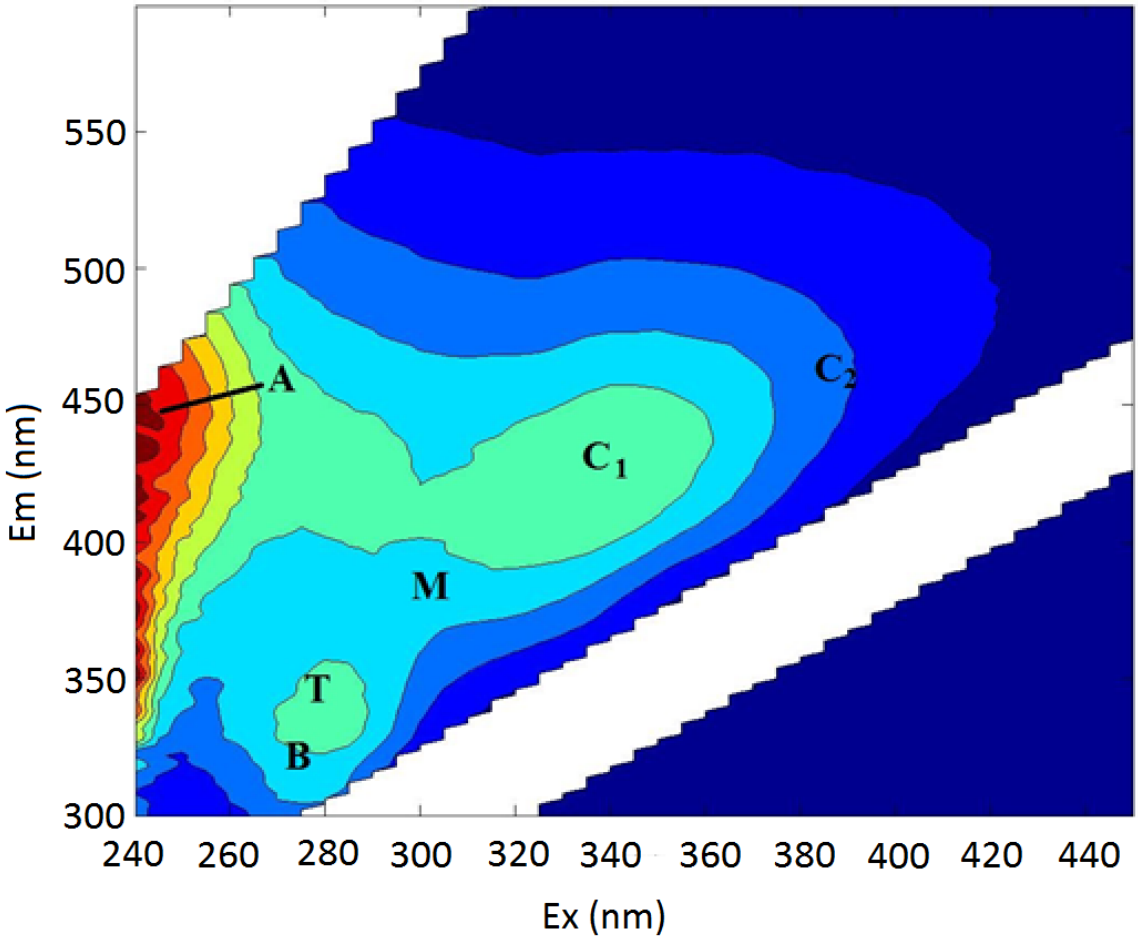

Figure 2 - EEM of MBR effluent from the present study with commonly observed peaks labeled. The scale of fluorescence intensities are in Raman units.

Parameter	Excitation / Emission Wavelengths	Description	Source
Peak B	270-275/304-312	Tyrosine	Coble 1998
Peak T_1	275/340	Tryptophan	Coble 1996
Peak T_2	225-237/340-381	Tryptophan	Coble 1996
Peak M	290-325/370-430	Marine/Algae	Coble 1998, Stedmon and Markager 2005
Peak C_1	320-340/410-430	Fulvic	Baker 2001
Peak C_2	370-390/460-480	Humic	Baker 2001
Peak A	237-260/400-500	Humic	Coble 1996

Table 3 - Commonly identified fluorescence peaks present in DOM

Studies using 3D fluorescence spectroscopy to analyze DOM initially arose in the field of oceanography (Baker, 2001; Coble et al., 1990; Coble, 1996). These studies largely focused on the character and identity of the fluorophores. Use of this technique then spread to the study of freshwater (Del Castillo et al., 1999; Galapate et al., 1998; McKnight et al., 2001; Spencer, Bolton, and Baker, 2007) and wastewater treatment (Ahmad and Reynolds, 1999; Hambly et al., 2012; Henderson et al., 2009; Hudson, Baker, and Reynolds, 2007; Reynolds and Ahmad, 1997).

From these EEMs, scientists are able to extract much information about the character of the OM in the source water. The presence of a given peak may reveal the presence of the corresponding type of organic matter. Peaks C_1 and C_2 are representative of fulvic and humic-like matter, respectively (Baker et al., 2001). Peak A also corresponds to humic substances (Coble et al., 1996). Peak M is a humic peak originally thought to be associated with marine waters, but has more recently been associated with algae (Coble et a., 1996; Stedmon and

Markager, 2005). Peaks T_1 and T_2 are caused by tryptophan-like substances and Peak B by tyrosine like compounds (Coble et al., 1996).

Correlations to Water Quality Parameters

In addition to each peak describing a group of compounds, peaks also correlate to water quality parameters. Measures of carbon are useful in water treatment systems. These include BOD, COD, and TOC, but each of these traditional parameters has drawbacks for online monitoring. BOD is very time consuming, taking several days, and is imprecise. COD is much quicker than BOD, but still takes hours to measure and uses harmful chemicals. TOC is a technique rapid enough for online monitoring, but, along with COD, cannot differentiate biologically available carbon from biologically inactive carbon (Carstea, Bridgeman, Baker, and Reynolds, 2016).

Some correlations between fluorescence EEMs of various water sources and water quality parameters have been collected in a review by Henderson et al. (2009) (**Table 4**). The strongest correlations have been shown by the protein related peaks T_1, T_2. In sewage works, T_1 has shown strong correlations with BOD ($r = .96$), COD ($r = .97$), and TOC ($r = .96$) (D. Reynolds, 2002). Peaks A and C have been shown to correlate with BOD with a high Pearson's r of 0.77 and 0.72 respectively (Hudson et al., 2008).

Source Water	Peak	Water Quality Paramater	Pearson's r	Reference
river water				Baker and Inverarity 2004
	T1	PO_4^{3-}	0.8	
		NO_3^-	0.87	
	T2	BOD	0.85	
		NH_3^-	0.7	
		DO	-0.65	
	C1	TOC	0.68	Baker, 2002
sewage/trade effluent and surface water	T1	BOD	0.91	Hudson et al. 2008
		TOC	0.8	
	T2	BOD	0.85	
		TOC	0.8	
	C2	BOD	0.77	
		TOC	0.87	
	A	BOD	0.72	
		TOC	0.81	
treated and untreated sewage	T1	BOD	0.96	Reynolds 2002
		COD	0.97	
		TOC	0.96	
filtered raw sewage	T1	COD	0.42	Vasel and Praet 2002
		TOC	0.41	
		N_k	0.69	
		NH_4-N	0.65	

Table 4 - Selected correlations between water quality parameters of interest and fluorescence peak intensity (adapted from Henderson et al. 2009)

Effect of Treatment on Fluorescence

From these correlations, it is possible to predict and study the ways in which a given wastewater treatment train will affect the fluorescence peaks of the water. Henderson et al. (2009) composed a table which describes a typical treatment train and the expected effect on DOM fluorescence. **Table 5** shows the treatment train used in a typical MBR and the corresponding effects. From this treatment train, T_1 and T_2 peaks would likely be the most

influenced by the treatment process and therefore hold promise for both monitoring treatment efficiency and breakthrough detection.

Stage	Process	Target constituent	Impact on fluorescence	Reference for correlation between constituent and fluorescence
Raw sewage				
Screening/grit removal	SaniTee filter	Solids, non-degradable matter		
Primary treatment	Settling tank	SS, BOD	T_1, T_2 intensity decrease	Hudson 2008
Secondary treatment	Activated sludge bioreactor	BOD[a], NH_3[-a], COD[b]	T_1[b], T_2[a] intensity decrease	Baker and Inverarity 2004[a], Reynolds 2002[b]
Tertiary treatment for nutrient removal	Oxic/anoxic cycling	NO_3^-, PO_4^{3-}	T_1, T_2 intensity decrease	Baker and Inverarity 2004
Filtration	Membrane microfiltration (0.2μm pore size)	SS, colloids, bacteria	Decrease in all fluorescence intensity	Z. Wang 2009
Disinfection	UV	Bacteria and virus	Decrease in T_1 intensity, increase in C_1 and C_2. Blue shift of peak locations	Choi and Choi 2010
Recycled water				

Table 5 - Impacts of treatment processes on fluorescence. (Adapted from Henderson et al. 2009)

Simply examining the peaks, however, makes minimal use of the wealth of information present in EEMs. A more detailed analysis can yield useful information and retains the rapid, real-time nature of peak picking methods. Several techniques have been developed to extract more information from EEMs. These methods involve considering the volume under the EEMs

at certain regions, the slopes of peaks, and statistical methods for breaking the large volume of data into its underlying components (**Table 6)**.

	Calculation	Description	Source
T_1 to C_1 ratio	(em intensity at ex 275 em 350)/(em maximum observed within ex 320-340nm em 410-430nm)	T1:C1 ratio of sewage impacted waters has been shown to be ~1.0, whereas natural waters have a higher ratio ~3.0	Baker 2001
fluorescence index	(em intensity at 450nm) / (em intensity at 500nm) taken at ex 370nm	Ratio has shown differences in microbial (1.9) and terrestrially (1.4) derived organic matters. Method requires isolation of fulvic acids	Mcknight 2001
freshness index	(em intensity at 380nm) / (em maximum observed between 420nm and 435nm) taken at 310nm	Numerator represents more recently derived DOM; denominator more decomposed DOM	Parlanti et al., 2000; Wilson and Xenopoulus 2009
humification index	(area under emission spectra from 435-480nm)/ [(area under emission spectra from 435-480nm) + (area under emission spectra from 300-345nm)] taken at ex 254nm	Used for determining the extent of humification (decomposition) of a DOM sample	Ohno 2002
specific UV	(UV absorbance at 254nm) / (DOC concentration in mg/L)	Surrogate parameter for % aromaticity	Weishaar et al. 2003
spectral slope ratio	(slope of 275-295nm region of UV absorbance spectrum) / (slope of 350-400nm region)	Related to DOM molecular weight, photobleaching, and source	Helms et al. 2008
fluorescence regional integration	Integrated volume of five EEM regions normalized for the area integrated and DOC concentration	Used to differentiate wastewater effluent DOM from drinking water DOM	Chen 2003
PCA	A mathematical reduction of the EEM into orthogonal vectors that describe the most variation in the matrix	PCA analysis produces a primarily mathematical description of the variation of the data. This creates difficulties in interpretation, however it has been used successfully in differentiating DOM sources and correlating fluorescence to COD.	Persson andWedborg, 2001; Stedmon et al. 2003; Galinha and Claudia, 2011

PARAFAC	PARAFAC is a multi-way analysis method that breaks the EEM into underlying fluorophores	PARAFAC is similar to PCA in that the data is broken into underlying components, however PARAFAC retains a clear relationship with the chemical components of the mixture	Stedmon et al. 2003
redox index	$(Q_{red})/(Q_{red} + Q_{ox})$	Q_{red} is the sum of all the reduced components identified by PARAFAC and Q_{ox} is the sum of all the oxidized components, giving the oxidation state of chromophoric DOM	Miller et al. 2006

Table 6 – Description of commonly used techniques for analysis of EEMs

Interferences

When properly handled, fluorescence spectroscopy provides a wealth of information, but there are many factors that can create artifacts in the EEMs that are not related to the nature of the DOM being studied. These artifacts include the drift of peak locations and changes in peak intensity and may vary at different excitation and emission wavelengths. Many potential effects have been reviewed by Henderson et al. (2009) and Hambly et al (2012).

The most ubiquitous features in fluorescence EEMs are referred to as Raman and Raleigh-Tyndall effects. The Raman effect appears as a thin line in the EEM across excitation 260-350 nm and emission 280-400 nm (Hudson et al., 2007). This feature is caused by the vibration of the O-H bonds in water molecules caused by incident light and is used as an internal standard to correct for instrument bias in the comparison of collected EEMs across instruments (Hudson et al., 2007). The Raman effect is easily removed from the spectra by subtracting a pure water EEM as a "blank" from the sample EEM. The Raleigh-Tyndall effect is the reflection of the incident light off of the sides of the cuvette (Hudson et al., 2007). These features are located where the excitation and emission wavelengths are equal or where emissions wavelengths are twice that of the excitation wavelengths. These appear as uniform bars cutting across the EEM.

These features are either removed from the spectra by entering null values in the regions where they are present or are simply left in place.

Inner filtering effects (IFE) occur when the excitation or emission light is absorbed by the sample rather than the emission detector, resulting in decreased fluorescence intensity or a distortion of the spectra (Henderson et al., 2009). This effect can take place in two different ways. First order inner filtering occurs when the excitation light is absorbed by the sample prior to the light reaching the interrogation zone; that is, before the light reaches the portion of the sample that the emission detector is reading. Second order inner filtering occurs when the light emitted as fluorescence is reabsorbed by the sample prior to the light leaving the sample and entering the emission detector (Ohno, 2002). This is possible because the light emitted and absorbed in the fluorescence process are often close in wavelength (see **Figure 1**). Both of these effects are prevalent when the samples are at high optical densities. In the case of wastewater treatment, this would mean that the chromophoric DOM are in high concentration. A study by Hudson et al. (2007) showed that treated wastewater samples with TOC values less than 25mg/L showed no IFE. In the case that IFE is present, Ohno (2002) has developed a mathematical correction factor IFE that is commonly used.

Temperature is another variable that is well known to influence fluorescence intensity. In general, as temperature increases 1^{o} C, fluorescence intensity decreases by about 1% (Henderson et al., 2009). This is a result of increased vibrational modes of relaxation compared to photon emitting modes (**Figure 1**). To avoid the effects of temperature on fluorescence measurements, samples need to all be analyzed at the same temperature or a correction factor for the group of samples in question needs to be created and applied. Temperature effects are linear which allows for a correction factor to be created easily, but this correction would have to be performed for

each peak of interest. For example, Baker and Inverarity (2004) show that temperature affects the T_1:C_1 ratio, indicating that different regions of the EEM may experience differing temperature effects. Additionally, the correction factor is only possible provided that all samples have a very similar composition. This is often not the case and since EEM variations between samples are often of interest, the best approach is to operate under uniform temperature when possible.

Extremes of pH have been shown to modify fluorescence, and unlike temperature, the effect is nonlinear. Generally the effect of pH on each peak is to increase fluorescence intensity from a pH of ~2 to some higher value and then decrease as pH continued to increase (Henderson et al., 2009), reflecting that each peak in fluorescence has its crest at different pH values. Due to the nonlinear effects of pH on fluorescence EEMs, in situations where pH is very high or very low and variable, samples should all be analyzed at a uniform pH. In the context of sewage treatment, pH effects are generally negligible due to the low variability within a treatment system (Hambly et al., 2012).

Fluorescence has been shown to be affected by metal ions in solution as well. The effects of the ions vary by species and by the character of the DOM. McIntyre and Guéguen (2013) analyzed a number of common metal ions via titration of the ions into algae derived DOM and stock DOM samples. While their experiment showed that metal ions have an impact on fluorescence EEMs, little work has been done investigating the presence and state of metals in the context of recycled water systems (Henderson et al., 2009). It is generally considered that metals in the environment are present in colloidal form or complexes. These types of metal species have not been shown to affect fluorescence, however some studies correct for metal ion effect by reducing pH to 2, in order to precipitate the metals out. This, then, introduces pH

effects and changes the fluorescence signal which must be taken into account when relating data collected in this way with data from other sources.

Chlorine and ozone are chemicals commonly used for disinfection purposes in wastewater treatment. These chemical species disinfect by breaking chemical bonds and inserting oxygen or chlorine species. This affects the chemical nature of DOM in a water sample (Swietlik and Sikorska, 2004), and, in turn, affects the fluorescence of that sample. Specifically, oxidation can shift peak locations to either higher or lower wavelengths as well as increase some peaks' intensity and decrease others' (Liu et al., 2011; Swietlik and Sikorska, 2004). Different types of oxidants can also induce different shifts in peaks. Swietlik and Sikorska observed that oxidation by ozone shifted EEM peak locations toward longer wavelengths (red-shift), while oxidation via chlorine dioxide shifted peaks toward shorter wavelengths (blue-shift) (Liu et al., 2011; Swietlik and Sikorska, 2004). Along with chemical methods of oxidation, UV light has been shown to oxidize compounds, and is often used in disinfection of treated sewage (Choi and Choi, 2010). Due to the complexity of these effects, in order to avoid them wastewater effluent samples may be collected prior to oxidation.

PARAFAC

Once interferences have been accounted for, there are a variety of powerful analytical methods available for extracting data from EEMs. One of the most widely used is PARAFAC, or parallel factor analysis. It is a multivariate analysis technique that, when applied to EEMs of DOM, is able to mathematically separate the underlying fluorophores that make up the dataset (Stedmon et al., 2003). These underlying fluorophores are called components. PARAFAC has the unique advantage over similar techniques in that the components identified in a validated

model relate to chemically identifiable fluorophores (Stedmon et al., 2003), such as humic-like or tryptophan-like material.

PARAFAC of a 3D dataset decomposes the data into a set of trilinear terms and a residual matrix (Murphy, Stedmon, Graeber, and Bro, 2013):

$$x_{ijk} = \sum_{f=1}^{F} a_{if} b_{jf} c_{kf} + e_{ijk}$$

where $i = 1, \ldots, I$; $j = 1, \ldots, J$: $k = 1, \ldots, K$. When applied to a set of EEMs, x_{ijk} is the point in the dataset corresponding to the i^{th} sample, j^{th} emission wavelength, and k^{th} excitation wavelength (**Figure 3**). There are I samples in the dataset, K excitation wavelengths, and J emission wavelengths.

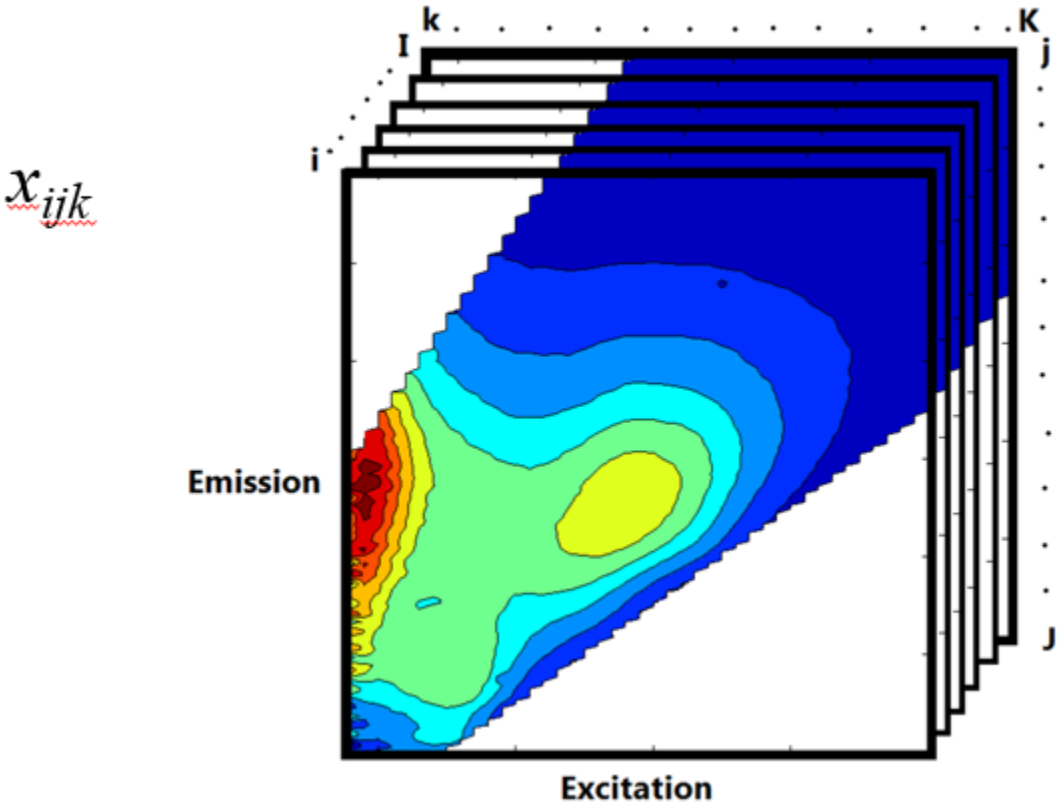

Figure 3 - Diagram of a dataset of EEMs arranged in a 3D structure. EEM shown is from the present study. (Adapted from Murphy et al., 2013)

Each *f* in the above equation corresponds to one of *F* PARAFAC components in the model. Each component has an estimated value for each location in the three dimensional dataset. That is, each component has *I a* values, one for each sample, *J b* values, one for each emission wavelength, and *K c* values, one for each excitation wavelength. The unique benefit of PARAFAC is that the created components reflect fluorescence spectra of an identifiable group of chemical compounds. As a result of this attribute of valid PARAFAC components, *a*, *b*, and *c* values correspond to real physical attributes of the fluorophores present. These parameters correspond to the concentration, emission spectrum, and molar absorptivity of the f^{th} fluorophore, respectively. The remaining e_{ijk} is a matrix containing the error between the sum of the estimated components and the point being estimated.

Limitations of PARAFAC

Studies have also been performed on the PARAFAC method itself, aiming to answer questions about the sensitivity, repeatability, or potential weaknesses of the method. A recent paper on this subject was published by Yu et al. (2015).

Yu et al. (2015) collected samples from diverse sources to investigate the sensitivity of PARAFAC to diverse sources of DOM. Samples were collected from an oligotrophic river (n=76), WWTP effluent (n=62), and extracellular organic matter from *Microcystis aeruginosa* (n=85). Yu et al. (2015) demonstrated that similar, but overlapping spectral components in samples can inhibit the ability of the PARAFAC model to differentiate between spectral components. Even if this occurs only at in a single component, the estimation of PARAFAC components happens simultaneously and the erroneous estimation of one peak can influence the

estimation of others as well. For this reason, Yu et al. (2015) stated that PARAFAC can only be effective in contamination warning and online monitoring when there is no overlap in components.

A potential solution to this problem is to use the peak-picking method instead. Murphy et al. (2011) has shown that PARAFAC components correlate strongly to selected peak wavelengths. This method avoids the noise created by shifts in peak / component locations and can therefore register the signal rather than noise.

Due to the data intensive and time consuming nature of PARAFAC, its strengths and limitations should be considered before using this method. However, if used in the proper context, this methods has the potential to provide detailed information about the underlying fluorophores present in a set of EEMs and thereby information on the types of carbon species present in a sample (Stedmon et al., 2003).

Dissolved Organic Matter

In the context of municipal wastewater reuse, dissolved organic matter (DOM) is of concern because it contains trace levels of personal care products and pharmaceuticals, and reacts with disinfectants to produce potentially carcinogenic byproducts. DOM has been the subject of much research for the past 100 years (Williamson, Morris, Pace, and Olson, 1999). These studies have investigated the composition, concentration, cycling, ecological role, role in water treatment processes, membrane fouling properties, and myriad other characteristics of DOM and in a variety of environments. The treatment of DOM in this research has often been either chemical or in regard to its ecological role.

In terms of chemical characteristics, DOM is composed of large heterogeneous hydrocarbon molecules ranging from 100-100,000 Da (Da being Daltons, a measure of atomic mass), which is in the colloidal size range (Leenheer and Croue, 2003). These compounds are formed, in part, from lower molecular weight compounds through humification, which takes place largely from microbial synthesis (Sparks, 1995). These molecules can have amide, carboxyl, hydroxyl, ketone, and other functional groups (Baker, Tipping, Thacker, and Gondar, 2008; Leenheer and Croue, 2003). In addition, DOM varies as it moves away from its source as predominately biological processes degrade the material for energy (Stedmon et al., 2003). Due to the breadth of this definition, it is not particularly descriptive, but due to the complexity of the mixture of constituents and of the variability of DOM in space and time, the breadth is necessary. The chemical makeup of DOM determines its optical properties. This optically active portion of DOM is referred to as chromophoric dissolved organic matter (CDOM) and is related to the large number of aromatic hydrocarbon rings found in DOM. Although less than 1% of DOM moieties are fluorescent, nearly all natural waters exhibit fluorescent character. Due to the ubiquity of CDOM, UV absorbance and fluorescence spectroscopy are often used to characterize DOM in water samples and can be correlated to other chemical properties such as TOC, COD, BOD, [PO_4^{3-}], [NO_3^-], [NH_3], [NH_4—N] (Henderson et al., 2009). Apart from correlations to other water quality parameters, fluorescence spectroscopy can reveal information about the types and source of organic matter present. This will be covered in detail later in this paper.

In a natural environment, allochthonous DOM is a result of the degradation of terrestrial plant material and soil humic substances from the associated watershed. Therefore, factors such as land use, canopy cover, and river order impact allochthonous DOM in terrestrial waters. This material consists of less reactive and more colored humic and fulvic acids (Wetzel, 1983). The

remaining fraction of DOM is autochthonous and is a result of the excretion of phytoplankton or macrophages (Wetzel, 1983). Ecologically, DOM fulfills a variety of roles including contributing to the transport of organic and inorganic contaminants, influencing transport of metal ions, providing carbon for biological processes, mediating photochemical processes, and attenuating light in natural waters (McIntyre and Guéguen, 2013; Mopper and Kieber, 2002; Tessier and Turner, 1996; Walsh et al., 2003). Due to the importance of these ecological roles, the character and concentration of DOM in a given environment has implications for that system's ecosystem services. While DOM has been shown to increase coagulation and sedimentation rates of heavy metal ions in lake and river ecosystems (Wilkinson, Joz-Roland, and Buffle, 1997), an increase in DOM is generally considered to have negative effects on an ecosystem. An experiment by Christensen et al. (1996) using a split-lake design has shown an increase in DOM can cause increasing water color, decreasing 1% attenuation depth of photosynthetically active radiation, decreasing maximum depth of oxygenation, and increasing the proportion of the phytoplankton community in the epilimnion as compared to the reference basin (Williamson et al., 1999). These negative effects are associated with the process of eutrophication and are symptoms of decreased water quality.

Anthropogenic DOM that enters the environment is mainly related to treated wastewater. This treated wastewater is characterized by large nutrient and pathogen loads. In many wastewater treatment schemes a combination of biological digestion and settling are used to remove organic matter. However, more recent technologies have also proven successful at DOM removal. The membrane bioreactor (MBR) is a semi recent technology that is currently the attention of much research (Brindle and Stephenson, 1996; Hur, Shin, Kang, and Cho, 2014; Judd and Judd, 2006; Kimura, Yamato, Yamamura, and Watanabe, 2005; Liu, Chen, Yu, and

You, 2011; Ma et al., 2013; Maqbool, Quang, Cho, and Hur, 2016; Meng et al., 2009; Zhang, Chua, Zhou, and Fane, 2006).

Treatment Monitoring

Fluorescence spectroscopy often correlates well with traditional water quality parameters and can therefore be used as a surrogate parameter for some time consuming tests such as BOD or COD (**Table 4**, Henderson et al., 2009). However, fluorescence is most valuable in its ability to provide insight into the types of carbon present throughout water treatment trains, where other carbon measurements cannot (Henderson et al., 2009). This benefit has been well researched and, recently, PARAFAC has been included in this type of study (Baker and Inverarity, 2004; Shutova et al., 2014; Stedmon et al., 2011). For example, it has been found that physical treatment processes and biological treatment processes preferentially remove humic substances and protein-like substances, respectively (Baghothet al., 2011; Cohen et al., 2014; Yang et al., 2014). This information has led to the effective monitoring of treatment via the tryptophan-like component (Baghoth et al., 2011; Cohen et al., 2014; Stedmon et al., 2011; Yang et al., 2014).

There have been limited attempts to use fluorescence to investigate changes in MBR water quality over time, all of which were at benchtop or pilot scale (Hur et al., 2014; Maqbool et al., 2016; Zhou et al., 2012). In each case, the fluorescence character of the effluent changed minimally over time, while changes from within the reactor were more obvious. These changes over time reflected a cake layer formation on the membrane surface, thus dividing the membrane system performance into two periods, cake layer formation and post formation (Hur et al., 2014; Maqbool et al., 2016).

While these studies offer guidance, additional research has shown that lab scale experiments mostly offer qualitative information in regards to operation of full scale MBR systems (Kraume et al., 2009). Research suggested this was due to differences in hydrodynamic conditions, sludge freshness and composition, ambient conditions, and energy input (Kraume et al., 2009). There is need for investigation of fluorescence based treatment monitoring of a full scale MBR system.

Fluorescence and treatability

As a type of treatment monitoring, fluorescence has been used shown to correlate to DOC removal by different common treatment processes and in different environments (Baghoth et al., 2011; Hur and Cho, 2012; Shutova et al., 2014), and to biodegradability (Yang et al., 2014). So far, this has been done effectively by creating regressions with ratios of, or combinations of humic and protein like PARAFAC components (Shutova et al., 2014; Yang et al., 2014).

The ability to determine treatment efficacy in terms of a bulk carbon measurement prior to installing new water treatment infrastructure is a valuable tool in cost assessment and in determining the treatment steps necessary to achieve the desired water quality. Organic matter poses several problems to efficient treatment of wastewater causing membrane fouling, oxidant demand, disinfection byproduct formation, and poor coagulation efficiency (Ishii and Boyer, 2012; Wang et al., 2009a; Yang et al., 2014).

These studies on treatability indicate that PARAFAC can elucidate the treatability of DOM in both DW and WW treatment plants. The present study aims to improve the correlations found between the influent DOM and effluent quality. As Yang (2014) supposed, the inclusion of more water quality parameters into these regressions may improve our ability to predict the

treatment methods best suited for DOM removal and predict effluent water quality. This study aims to determine a fluorescence based parameter that shows good correlation to TOC removal.

Contamination Detection

By the same principles that allow fluorescence to be effective at monitoring treatment efficacy, fluorescence spectroscopy also has the potential to be an effective monitoring technique for contamination detection. This is also an area of research yet to be well explored. Two studies have been done to determine the detection limit of wastewater contamination in drinking water.

Stedmon et al. (2011) simulated wastewater contamination of a groundwater supplied drinking water system by creating a series of dilutions from a single wastewater sample from a nearby wastewater treatment plant. The detection limit was determined by changes in a fluorescence ratio that corresponded to the tryptophan-like peak intensity over some low-noise background region. The detection limit corresponded to this ratio exceeding two standard deviations of the drinking water fluorescence ratio. (Hambly et al., 2010) performed a Monte Carlo Simulation to determine the contamination detection limit of non-potable recycled water in drinking water. This study used purely statistical methods to determine the detection limits of fluorescence monitoring. The detection limits determined were very different, as were the applied methods. Therefore is room to investigate the detection limits of fluorescence techniques using different source water and treatment levels, and of different water treatment systems. Additionally, both studies leave room for improvement in their methods. The present study aims to build upon this body of work by determining detection limits of a water reclamation system designed for non-potable reuse and by using multiple pairs of corresponding samples from the

oxic tank and effluent rather than one pair of samples to take into account the variability of wastewater and treated effluent of an MBR system.

Research Objectives

Research in wastewater treatment monitoring has largely focused on improving the monitoring of WW treatment in order to optimize the process. This has been done by correlating fluorescence to other wastewater quality parameters (Baker, 2002; Baker and Inverarity, 2004; Baker et al., 2008; D. M. Reynolds, 2002; Vasel and Praet, 2002) and more recently, using PARAFAC to inform the selection of wavelengths for online monitoring, followed often by correlations to water quality parameters (Baghoth et al., 2011; Cohen et al., 2014; Hur et al., 2012; Shutova et al., 2014; Stedmon et al., 2011; Yang et al., 2014). This was beneficial in order to capture the inexpensive and rapid nature of fluorescence spectroscopy as compared to other commonly used water quality monitoring techniques. These studies often focus on WW from a variety of sources and rarely include advanced treatment techniques. There is a need for studies using the PARAFAC method on MBR systems at larger scale, that treat non-synthetic WW to examine if the correlations found in the lab reflect what occurs in realistic treatment scenarios (Kraume, Wedi, Schaller, Iversen, and Drews, 2009).

In response to the need for improved water treatment monitoring, the goals of this study are to: evaluate the effectiveness of fluorescence based techniques to: monitor wastewater treatment throughout a full scale membrane bioreactor, and determine the contamination detection limit of fluorescence techniques in a non-potable reuse scenario.

Chapter 3 - Materials and Methods

Study Site Description

Research was conducted on a full scale membrane bioreactor located in Fort Riley, KS. The MBR was custom designed by Biomicrobics (Lenexa, KS) for the study as part of the Department of Defense Net Zero Water Research initiative (US Environmental Protection Agency, 2016). The MBR design flow was 15000 L/day with a retention time of 29 hrs.

The system contains three tanks: a 2300L settling tank, 7900L anoxic tank, and a 7900L oxic tank providing a total capacity of 18,100L. There were six 0.2μm membrane filter stacks submerged in the oxic tank. Each stack was comprised of two cassettes with $7m^2$ of filtration area per cassette, providing $84m^2$ total filtration area (**Figure 4**). The membranes are constructed from a combination of Polyvinylidene Fluoride (PVDF) and Polyethersulfone (PES) and have nominal pore size of 0.2μm (Bio-Microbics, 2016). Water was added to the system from a wastewater line servicing multiple military barracks and motor pools. After the diversion from this main line, a grinder pump was installed to reduce clogging in the MBR due to larger debris entering the system.

The effluent pump and blower pump were triggered by a system of float switches in the oxic tank and a timed control. The blower pump was always run when the effluent pump activated to reduce fouling on the membrane surface by maintaining crossflow while the system was operating, but the blower pump also ran for 30min after every 90min of rest time. When the total water level was sufficiently above the top of the stacks, the pumps turn on according to a schedule that provides the designed outflow of 1500L/day. As a safety, when the water level in the system is too high, activating the second float switch, the pumps run regardless of the

schedule until the water level dropped back to normal ranges. If the water level fell too low, the effluent pump would not activate. While the system is in filtration mode (effluent pump is on), the effluent pump ran in 30min cycles with 5 minutes of rest time. The rest time during filtration allowed for the blower pump to scour the surface of the membranes with pressurized surface air and remove particulates that decrease flow rate and increase transmembrane pressure.

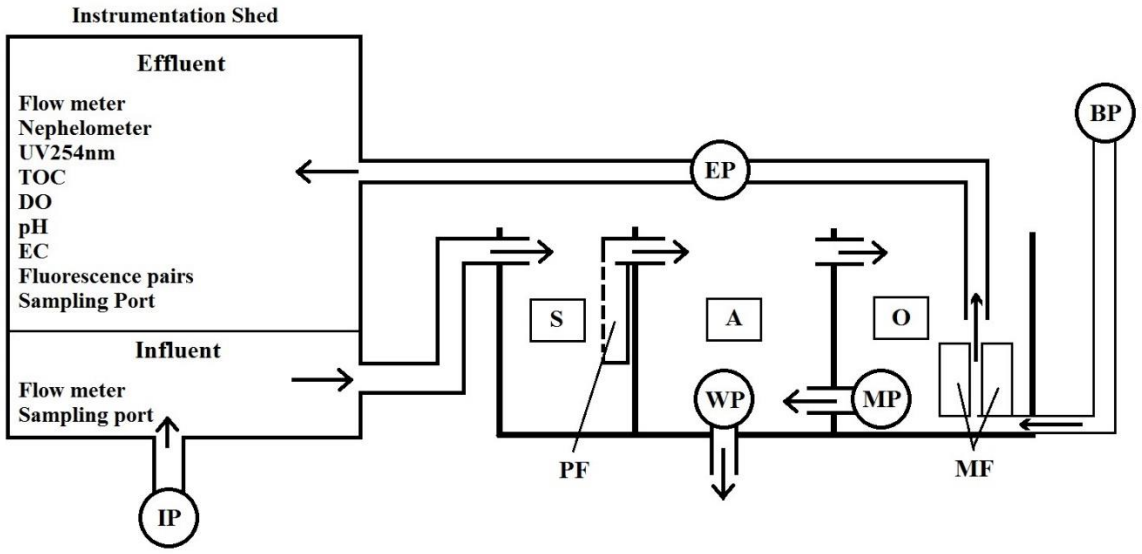

Figure 4 - Diagram of the MBR system. IP - influent pump, EP - effluent pump, WP - waste pump, MP - mixing pump, BP - blower pump supplying oxygen, S - settling tank, A - anoxic tank, O - oxic tank, PF - particulate filter, MF - membrane filter stacks

Instrumentation

The influent and effluent lines of the MBR system were piped through a shed where several continuous water quality monitoring instruments were installed. In the influent line, a 1720E Low Range Turbidimeter (Catalog #6010018, Hach, Loveland, CO), and a Toshiba LF654 Flowmeter (Houston, TX) was installed, which measured flowrate and cumulative flow. The effluent line contained the same flowmeter, a FT660 sc Laser Nephelometer (Catalog

#6016000, Hach, Loveland, CO), a Sievers 5310C Laboratory Total Organic Carbon Analyzer (GE Analytical Instruments, Boulder, CO), a Real UV254 M3000 (Real Tech Inc., Whitby, ON, Canada) which measured absorbance at 254nm, three Campbell Scientific probes including CS547A Conductivity and Temperature Probe, CS511-L Dissolved Oxygen Probe, CSIM11 pH Probe (Logan, UT), and a Turner Designs C6 Multi-Sensor Platform equipped with tryptophan and CDOM fluorescence probes (Part #998-2205, Sunnyvale, CA) which measured fluorescence at excitation/emission wavelengths of 325/470nm and 285/350nm respectively. Both the 1720E and FT660 turbidity instruments were connected to a sc200 Universal Controller Configurator (Catalog #LXV404.99.00552, Hach, Loveland, CO) to supply power and provide maintenance messages from the instruments. Data were collected from these instruments using a Campbell Scientific CR1000 Measurement and Control System with an attached AM16/32 Relay Multiplexer (Logan, UT).

Sample collection

Sampling trips to the MBR system were taken once or twice a week from May to August 2016. On each trip, three 300mL samples were collected from each of three sources: the influent line, the effluent line, and the oxic tank. Additionally, each week a 0.2μm Rexeed-25S ultrafilter (Asahi Kasei medical Group, Japan) was used to filter 50L of effluent and an additional 1L influent sample was collected. The ultrafilter and 1L influent sample were sent on ice overnight to the Environmental Protection Agency's National Environmental Research Labs in Cincinnati, OH, for bacteriological analysis. The grab samples were collected in 240mL glass bottles (Catalog # 02991346, Qorpack, Chicago, IL) and stored at 4^{o}C until analysis. Samples were generally analyzed within a week, depending on the test being performed (U. S. Environmental

Protection Agency, 1983). A portion of each grab sample was filtered using 0.45µm sterile filter (Catalog # HAWG047S3, Millipore, Billerica, MA) and separated into two 40mL subsamples. One subsample was acidified with 2% (v/v) 5M HCl (U. S. Environmental Protection Agency, 1983) to pause bacterial action on organic matter for TOC analysis and the other was left at the original pH to minimize the variation in fluorescence characteristics between sample collection and analysis. The remaining unfiltered portion of each grab sample was tested for COD and coliforms and sent to the KSU Soil Testing Labs for chemical analysis.

Chemical and Bacteriological Analysis

Grab samples were analyzed for chemical oxygen demand (COD) directly upon arrival at the laboratory to ensure reliability of the tests. COD testing was done according to the USEPA approved Reactor Digestion Method, Method 8000 described by (Jirka and Carter, 1975) using Hach Low-Range Digestion Solution for COD test kits (Product #2125815, Hach, Loveland, CO), DRB200 reaction block (#LTV082.53.40001, Hach, Loveland, CO), and DR/2400 portable spectrophotometer (#5940000, Hach, Loveland, CO). Effluent samples produced COD values in the detectable range (3-150mg/L COD) for the test kits without adjustment.

Initial influent samples were run at 1/10, 1/5, 1/2, and full concentration to determine the range of values produced for the given dilutions. It was determined that a 1/5 dilution routinely produced values within the detectable concentrations of the COD test kits, the other dilutions of influent were no longer run.

A filtered, acidified subsample was created from each grab sample. Upon analysis, each sample was transferred to clean glass TOC vial that had been acid washed and cooked in a muffle furnace at 550^{o}C for two hours. The samples were loaded into a TOC-L Total Organic

Carbon Analyzer (Shimadzu, Kyoto, Kyoto Prefecture, Japan) and analyzed in triplicate. The closest two samples were averaged for the final result (standard protocol for the instrument).

Nitrogen analysis was completed by the KSU Soils Testing Lab. Samples were collected and sent to them in bulk for chemical analysis. Nitrogen analysis included total, nitrate, and ammonia. Total N was found using a cadmium reduction method according to Hosomi and Sudu (Hosomi and Sudu, 1986). Ammonia and nitrate were found using an Aplkem autoanalyzer according to Alpkem Corp. RFA Methodology no. A303-S021 and RFA Methodology no. A303-170, respectively (Aplkem Corporation, 1986). Influent samples were analyzed for total N and effluent samples were analyzed for total N, nitrate, and ammonia.

Kansas State Soils Testing Lab completed all phosphorus analysis. Total P was measured according to Hosomi and Sudu (Hosomi and Sudu, 1986). Ortho-Phosphate was measured using an Alpkem RFA autoanalyzer according to RFA Methodology no. A303-S200-13 (Alpkem Corporation, 1979). This procedure is an ammonium molybdate blue colorimetric procedure. Influent was analyzed for total P and effluent for total P and ortho-phosphate.

Escherichia Coli and Total Coliforms were analyzed from grab samples on arrival to the laboratory using the Colilert – 18/Quanti-Tray2000 water analysis system. This analysis was done according to IDEXX's IDX 33/02 – 06/12 and IDX 33/01 – 11/09 WATER ANALYSIS METHODS (Dichter, 2011). One Hundred Twenty milliliter shrink-banded vessels with sodium thiosulfate (#98-09221-00, IDEXX, Westbrook, ME) were filled with 100mL sample. Colilert-18 digestion medium (#98-27164-00, IDEXX, Westbrook, ME) was added to the sample and was shaken vigorously until dissolved. The sample and digestion medium were added to Quanti-Tray / 2000 quantification trays (98-21675-00, IDEXX, Westbrook, ME) and sealed in a Quanti-Tray

sealer with rubber 97 well insert (98-9011779-00, IDEXX, Westbrook, ME). The trays were then incubated at 35^{o}C for 18-22hrs and the MPN was recorded from an IDEXX reference sheet.

Fluorescence

A C6 Multisensor platform (Part # 998-2205, Turner Designs, San Jose, CA) was equipped with two Cyclops 7 submersible fluorescence sensors (Part # 998-2100, Turner Designs, San Jose, CA). One fluorometer measured chromophoric dissolved organic matter (CDOM) using excitation/emission wavelengths of 325/470nm. The other fluorometer was used to monitor tryptophan at 285/350nm. The instruments recorded relative fluorescence units (RFU) every 15 seconds at the chosen wavelengths. These fluorescence units were relative values in that they were not compared to a standard, however they were blank subtracted by subtracting the relative fluorescence of deionized water.

Grab samples were stored at 4^{o} C in glass vials in the dark until analysis. Samples were filtered using 0.45μm filter disks. Excitation emission matrices (EEMs) were created using a Jobin Yvon Aqualog Fluorometer (Horiba, Japan) from ex 500nm-240nm with 3nm increments and em 621.49nm-211.76nm with 3.21nm increments (instrument default). Gain was set to high. It was determined that 0.5 seconds was a suitable integration time for most samples, with a few exceptions. The raw EEMs were corrected for inner filter effect (Ohno, 2002), first and second order Raleigh scattering bands removed (Stedmon and Bro, 2008), Raman normalized using 18.3MΩ ultra-pure water at 350nm, and blank subtracted. Additionally, a quinine sulfate standard was run. From the processed EEMs, several indices were calculated. These include: fluorescence index, freshness index, humification index, spectral slope, peak intensities, CDOM, and tryptophan as measured by the Cyclops 7 online fluorometers.

PARAFAC Modeling

PARAFAC is a multivariate analysis technique that is able to mathematically separate the underlying fluorophores present in a set of EEMs (Stedmon et al., 2003). PARAFAC modelling was primarily carried out using the DOMFluor toolbox for MATLAB (REF). The drEEM toolbox (REF) was also used to calculate core consistencies and to project finished models onto larger datasets. The tutorial by (Stedmon and Bro, 2008) was followed in order to create the models. Additional guidance for model selection was found in (Murphy et al., 2013).

Creation of the Total Model

There were n = 227 samples collected from the three locations along the MBR treatment train. After the removal of outliers, 198 samples were used for model generation. **Figure 5** is a typical EEM from this dataset with common peak locations labelled. Descriptions of these peaks have been covered previously and are summarized in **Table 3**.

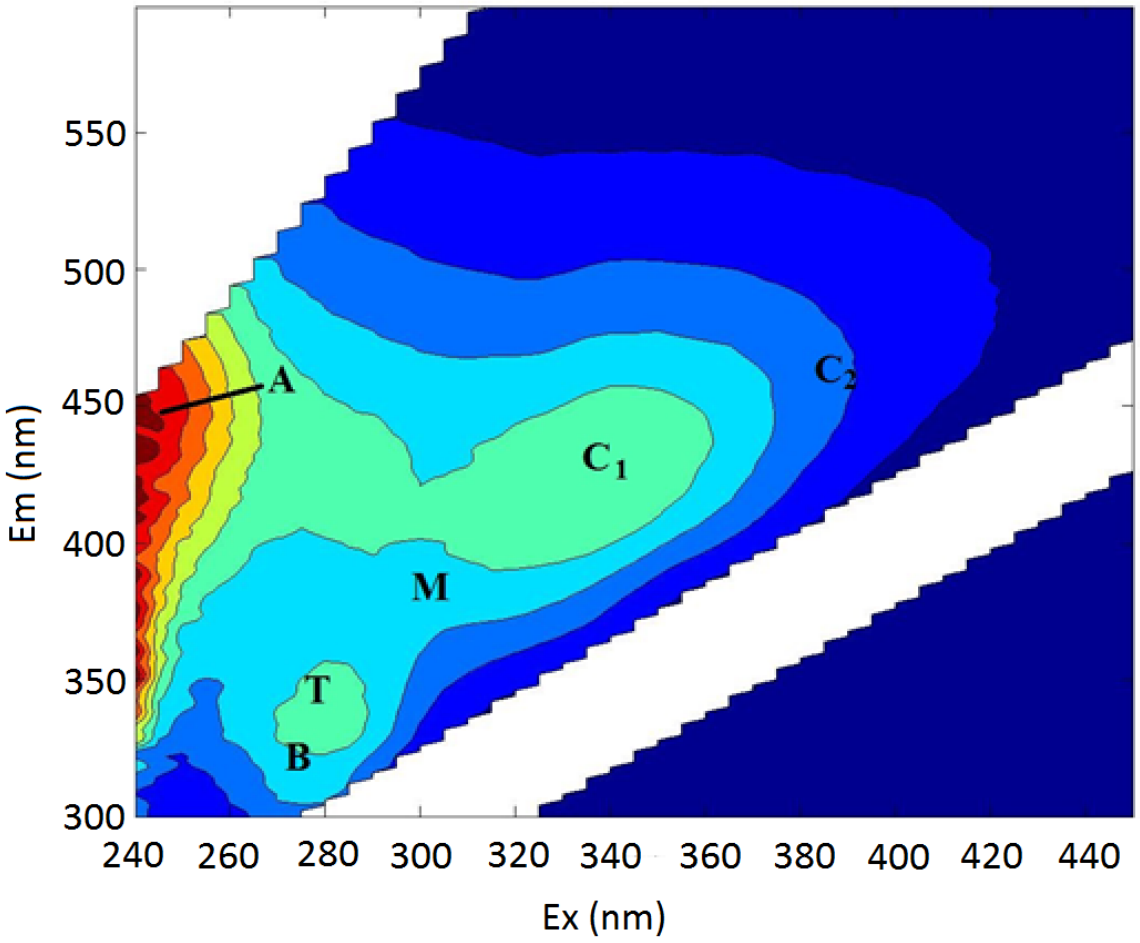

Figure 5 - Typical EEM taken from the dataset with common peak locations labelled.

Preliminary PARAFAC models were created using all samples to determine the approximate number of models necessary to capture the variance of the data and to determine potential outliers. Loadings across all wavelengths and leverages of each sample were calculated from preliminary models in order to identify potential outliers. EEMs were also visually inspected for potential instrument error or other extreme effects that could interfere with the PARAFAC modelling. During this exploratory analysis, several groups of outlier were identified based on the following characteristics (some samples appear in multiple goups):

- a very intense peak at (ex250/em350) (n=11)
- a protein peak at unusually low ex wavelengths (n=7)
- a protein peak with unusually high em wavelengths (n=13)
- a large band at em 550nm (n=6)
- instrument error (n=2)

Samples containing apparent instrument error, the large excitation band at em 500nm, and the low excitation protein peak were removed from the dataset. From this dataset 3, 4, 5 and 6 component models were split half validated according to (Stedmon and Bro, 2008). **Table 7** shows a summary of the the diagnostic information used to choose between the validated models.

The DOMFluor toolbox was used to split the data into 4 different halves. PARAFAC models were created for each half of the data containing 3 to 8 components. Each model was compared to the models created from the other half of the data. If the components identified in both models were sufficiently similar (Tucker correlation coefficients >0.95) the model was validated (Murphy et al., 2013) using Tucker congruence for factor comparison outlined in (Lorenzo-Seva and Berge, 2006).

# of Components	Split Half Validated	Random Initialization Analysis SSE	Core Consistency %
3	Yes	1224.2	74.19
4	Yes	723.4	23.55
5	Yes	372.5	9.32
6	Yes	303.1	2.53

Table 7- Summary of diagnostics used to determine appropriate number of components

Random Initialization Analysis was then run on the models because the initial sample used to create the model influences the outcome. This analysis increased the possibility of finding the universal minimum SSE for the model, rather than a local minimum. This is a common analysis for iterative fitting procedures such as PARAFAC (Stedmon and Bro, 2008).

When the SSE of the replicate models are not reasonably consistent it is a sign that the model is not stable. It may have too many components or need to be re-run with a tighter convergence criteria (Murphy et al., 2013). For this set of models, there was a large reduction in SSE between the 3 and 4 component models and the 4 and 5 component models, indicating an improved fit. The 6 component model showed variable SSE values indicating that the model is unstable.

The core consistency of the models were also evaluated. In a valid model presented by this metric, the core percent returned would be greater than 90%. This positive result would indicate that the components of the model "primarily reflect trilinear variation in the data" (Bro and Kiers, 2003). That is, that the components reflect the variation in the data in the ex, em, and fluorescence intensity directions of the EEM dataset. Models with low core consistency are possibly over fitted and the components are beginning to describe noise as well as variation caused by peaks in the EEMs. As shown in **Table 7,** the core consistency of all the models are low. Recently, (Murphy et al., 2013) has commented that core consistency typically gives larger datasets poor core consistencies. This is potentially due to the fact that larger organic carbon derived models contain covarying components (Murphy et al., 2013).

According to Murphy et al. (2013), adjacent peaks and troughs in the residuals of the modelled EEMs indicate that a single peak is being modelled by two or more components. Alternatively, it could be that a single component is trying to fit two or more narrow peaks. The

residuals from the 4 and 5 component models were investigated for this effect. The peak and trough trend was still present in the 5 component model, as shown in **Figure 6**, but was reduced relative to the 4 component model.

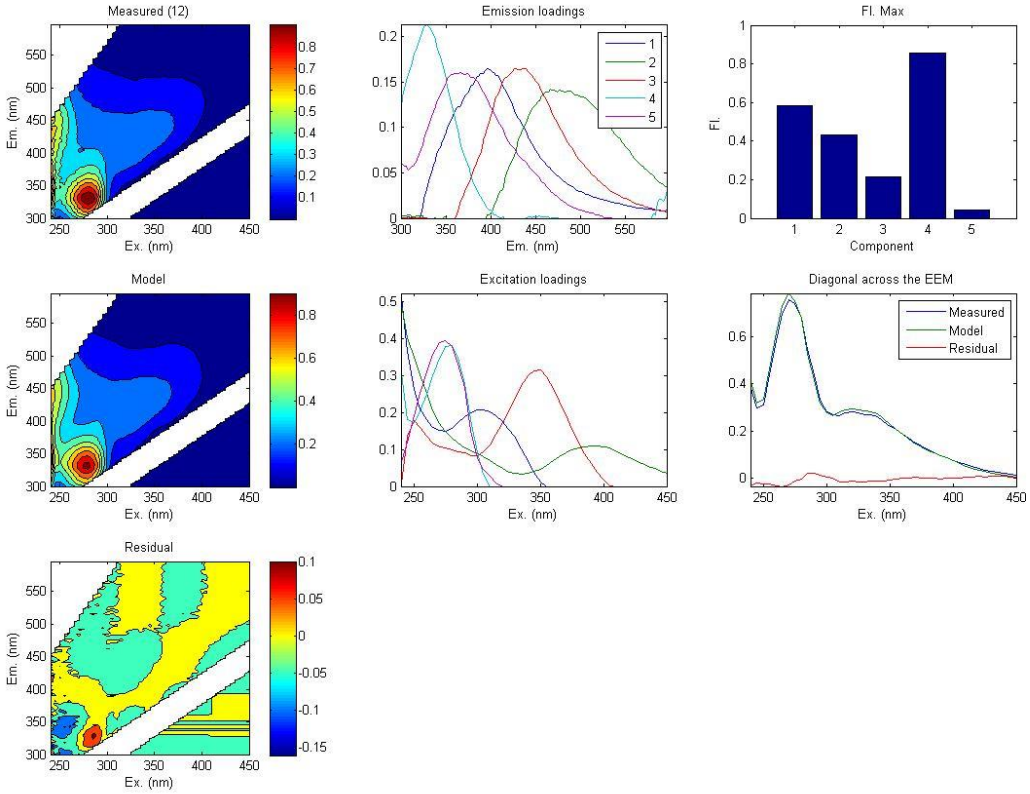

Figure 6 - Mean, modelled, residual plot of a sample in the 5 component model. Adjacent peak and trough is present in the residual plot in the lower left. The z axis of the residual plot is on a smaller scale than the measured and modelled EEMs. The residual peak shown is around 10% of the fluorescence peak in that region.

Apart from the peak and trough, the remainder of the residual EEM showed very little difference between the measured EEM and the model. It is desired that the residual EEMs show very little structure and are made up almost entirely of noise. The residuals were examined and this was the case with the 5 and 6 component models.

Given the above considerations, the 5 component model appeared to be the most appropriate. There was large improvement from the SSE of the 4 component model to the 5 component model. The peak/trough trend that was present in relatively poorly fit EEMs by the 4 component model was reduced by the 5 component model. The 6 component model appeared unstable given the large fluctuations in the SSE from the random initialization analysis and the improvement in SSE from the 5 component model was minimal.

Finally, the spectral loadings of the 5 component model were evaluated for atypical features (**Figure 7)**. This inspection was carried out to determine if the components exhibited typical spectral shapes of real fluorophores. A fluorophore should exhibit the following characteristics (Murphy et al., 2013):

1. Minimal overlap between excitation and emission spectra
2. Excitation spectra may have multiple peaks, but emission spectra has one distinct peak
3. When Ex spectra has more than one absorption peak, some absorption occurs between these bands (the spectral loading does not reach zero in between the excitation peaks of the same component)
4. Excitation and emission spectra do not exhibit abrupt changes, but rather gradual changes

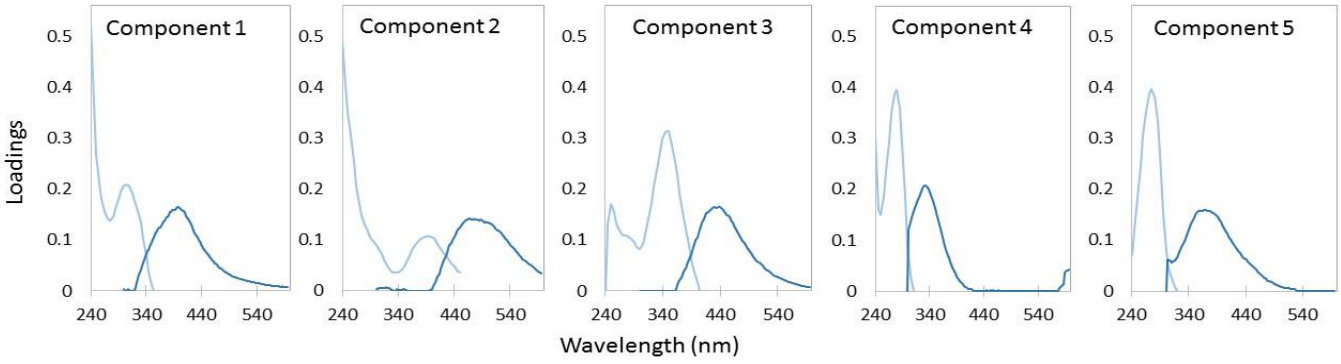

Figure 7 - Spectral Loadings of the 5 component PARAFAC model.

The desired criteria are approximately met. Component 2 shows more overlap than the other components, but this effect is still minimal. Components 3 and 5 exhibit abrupt changes in the loadings, but the sharp peaks are not large.

The components identified by the 5 component model exhibit characteristics of real fluorophores and do not show reason for rejecting the model. The outputs of the 5 component model were used for analysis.

Effluent Model

A second dataset was created from effluent EEMs. These EEMs generally contained larger humic peaks relative to protein peaks. The Effluent Model was created using the same process as the Total Model. EEMs were inspected for instrument error or other phenomena that could disrupt the modeling process. Two samples were removed from the dataset to create a final set containing n=52 EEMs. From this dataset, 3, 4, and 5 component models were split half validated according to (Stedmon and Bro, 2008). A summary of the diagnostic information of the validated models is shown in **Table 8**.

# of Components	Split Half Validated	Random Initialization Analysis SSE	Core Consistency %
3	Yes	256	39.86
4	Yes	145	70.76
5	Yes	91	46.51
6			
7			

Table 8 – Summary of diagnostic information from 3, 4, and 5 component models

The Random Initialization Analysis results and core consistencies of the models were evaluated in the same way as the Total Model. The Random Initialization SSE values showed moderate improvement between each model, but the core consistencies showed the 4 component model to be superior.

The core consistency diagnostic yielded poor results for the 3 and 5 component models. The drop in core consistency between the 4 and 5 component models hinted that the 5 component model was overfitting the data.

The 3 component model has shown poor SSE and poor core consistency and is therefore considered non suitable. To select between the 4 and 5 component models, the components themselves were evaluated to see if they exhibited common fluorophore patterns recommended by Murph et al. (2013) and appear to be fitting peaks rather than noise. The 5 component model identified an unusual peak located at excitation/emission <240/380nm and is shown in **Figure 8**. Peaks in this region of the spectra are often considered to be part of larger components with another more clearly resolved peak (Murphy et al., 2013; Stedmon et al., 2011; Yu et al., 2015).

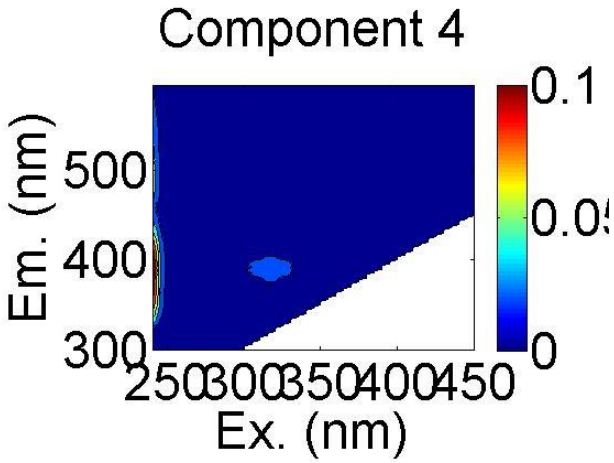

Figure 8 – Component 4 of the 5 component model

Component 4 in the 5 component model showed two emission wavelengths and the lesser, higher wavelength was in the same location as the peak in component 2. This, coupled with the low core consistency of the 5 component model, seems to indicate that the 5 component model was overfitting the data and had created a component that does not exhibit typical fluorophore patterns. Therefore, the 4 component model appeared to be the most appropriate model and was used in this study.

Data Analysis

Preliminary investigation of the data was carried out graphically in Excel (2013). Relationships between chemical parameters, PARAFAC component loadings, and component loading ratios were evaluated by linear regression and Pearson's R. Means based on sample source were also investigated graphically. Mean plots with standard deviation error bars were created to determine potentially interesting differences in source water quality.

Potentially interesting trends, relationships, and mean characteristics were examined statistically using R (3.3.1). Significance values were calculated for each linear regression coefficient and to determine significant differences in means. For regression plots and tabulated data, refer to **Appendix A - Supplementary figures.**

Contamination Detection Limit

Near the end of the sampling period (9/14/2016) a 1L sample was collected from both the effluent and the oxic tank. These samples were filtered and used to create a series of oxic tank additions to the effluent sample. Additions were made in triplicate at the following percents: 0%,

2%, 4%, 6%, 8%, 10%, 20%, 30%, 40%, and 100%. Same day effluent and oxic pairs from throughout the sampling period were used to create four additional replicates of each concentration (excluding 0% and 100% oxic water) along this gradient. This was to examine the impact that varying DOM concentrations over time would have on determining the detection limit. The oxic tank additions correspond to additions from 0.1-5.0mg C/L.

EEMs were collected from the created samples using the same methods described above. The Total Model and Effluent Model were applied to the EEMs. Component loadings from each model were examined to determine the parameter that would yield the lowest detection limit, defined as the additional TOC required to change the fluorescence characteristic of a sample two standard deviations from the mean of the pure effluent samples. Additionally, indices typically taken from EEMs and single point fluorescence data were examined for potential breakthrough monitoring capability.

These analysis use regressions to determine where the fluorescence parameter exceeds two standard deviations from the mean effluent parameter. In order to capture the uncertainty of this estimate, the 95% confidence interval for the regression was calculated according to

$$\hat{y} \pm t_{crit} \times s_{yx} \sqrt{\frac{1}{n} + \frac{(x - \bar{x})^2}{SS_x}}$$

where the values of the regression, $\hat{y}$, are bound by t_{crit} times the sample standard error of the series of dilutions used to create the regression (Zaiontz, 2016).

Chapter 4 - Results and Discussion

Data collection of the MBR system took place from late March, 2016 through the end of August. The system showed a high capacity for nutrient removal throughout the sampling period (

	Influent	Oxic Tank	Effluent	% Removal
Total Nitrogen (mg/L)	58.8 ± 16.6	504.2 ± 259.2	8.3 ± 7.5	85.9 ± 81.5
Total Phosphorus (mg/L)	7.2 ± 2.4	203.9 ± 112.4	4.3 ± 1.9	41.7 ± 23.2
Chemical Oxygen Demand (mg/L)	285.7 ± 203.69	N/A	23.6 ± 24.3	91.7 ± 115.2
Total Organic Carbon (mg/L)	35.3 ± 25.4	17.4 ± 18.4	9.6 ± 7.1	72.8 ± 75.3

Table 9). The highest and most consistent removal occurred for nitrogen, while phosphorus showed the lowest and least consistent removal.

The oxic tank showed a high concentration of nitrogen and phosphorus compared to the influent or effluent. This build up seems to reflect the capacity of the bacteria and flocc in the oxic tank to quickly absorb or retain valuable nutrients. This phenomenon is clearly seen by examining changes in nutrient concentrations over time and is covered in the following section.

	Influent	Oxic Tank	Effluent	% Removal
Total Nitrogen (mg/L)	58.8 ± 16.6	504.2 ± 259.2	8.3 ± 7.5	85.9 ± 81.5
Total Phosphorus (mg/L)	7.2 ± 2.4	203.9 ± 112.4	4.3 ± 1.9	41.7 ± 23.2
Chemical Oxygen Demand (mg/L)	285.7 ± 203.69	N/A	23.6 ± 24.3	91.7 ± 115.2
Total Organic Carbon (mg/L)	35.3 ± 25.4	17.4 ± 18.4	9.6 ± 7.1	72.8 ± 75.3

Table 9 - Mean nutrient levels for each stage of the MBR system. Percent removal is calculated from the difference in quality of sample pairs from the influent and effluent.

Detailed water quality data from the effluent revealed that the system generally produced high quality effluent. However, the effluent did not meet all EPA standards for unrestricted reuse or release to groundwater.

	Effluent	EPA Standard[1]
Total Nitrogen (mg/L)	8.3 ± 7.4	
Ammonium Nitrogen (mg/L)	2.3 ± 5.7	
Nitrate Nitrogen (mg/L)	5.2 ± 3.6	
Ortho-Phosphorus (ppm)	3.9 ± 1.9	
Total Phosphorus (mg/L)	4.2 ± 2.0	
Total Coliforms (MPN/100mL)	1.6 ± 3.0	non-detectable CFU/100mL[2,3]
E. Coli (MPN/100mL)	0.1 ± 0.6	non-detectable CFU/100mL[2,3]
pH	6.5* ± 0.7	6-9[2]
Conductivity (mS/cm)	0.6 ± 0.2	
Turbidity (mNTU)	161.2 ± 692.5	2 NTU[2,3]
Dissolved Oxygen (mg/L)	4.1 ± 2.4	
UV transmittance	74.1 ± 2.9	
Chemical Oxygen Demand (mg/L)	23.6 ± 24.3	
Total Organic Carbon (mg/L)	9.6 ± 7.1	2mg/L[3]

Table 10 - Mean effluent water quality and applicable EPS standards.
1 – (Environmental Protection Agency, 2012)
2 – Standards for unrestricted urban reuse or release to impoundment
3 – Standards for release to groundwater
* – Prior to apparent instrument failure

A greater understanding of the system's performance can be achieved by examining collected water quality data over time. As alluded to above, the buildup of nitrogen and phosphorus in the oxic tank takes place over time. Several other water quality measurements also change over time, whether over the course of the study or over the course of a pumping cycle.

Temporal Variation in MBR Function

Temporal variations in MBRs have been studied for the past decade (Zhang et al., 2006) (Hur et al., 2014; Maqbool et al., 2016, Zhang et al., 2006). These recent studies have largely focused on membrane fouling, but the present work focuses on how temporal variations can influence the monitoring of an MBR system, specifically monitoring by fluorescence spectroscopy. It has been reported that MBR systems undergo a startup period during which the bacteria in the oxic tank colonize their new environment and a biofilm develops on the membrane surface (Drews, 2010; Hur et al., 2014; Kraume et al., 2009; Zhang et al., 2006). This startup period is often defined in terms of the trans-membrane pressure of the system (Hur et al., 2014). The present study collected a wide variety of water quality parameters. The relationships between the collected parameters and time are either shown below or in **Appendix A:** Supplementary figures**.**

Shortly prior to the beginning of this study, the MBR system was cleaned with bleach and re-seeded with a live culture of wastewater. Due to this, the beginning of the study was characterized by a dramatic acclimatization of the sludge to the MBR system. This process was accompanied by an increase the trans-membrane pressure (TMP) of the system. The TMP increased with operating time according to an observable pattern. The TMP of the MBR in the present study increased during an initial startup period and held relatively constant throughout the remainder of the study period (**Figure 9**). This maturation is evident in water quality measurements as well as in fluorescence components. The startup period prior to this gray dashed line is referred to hereafter as the TMP startup period.

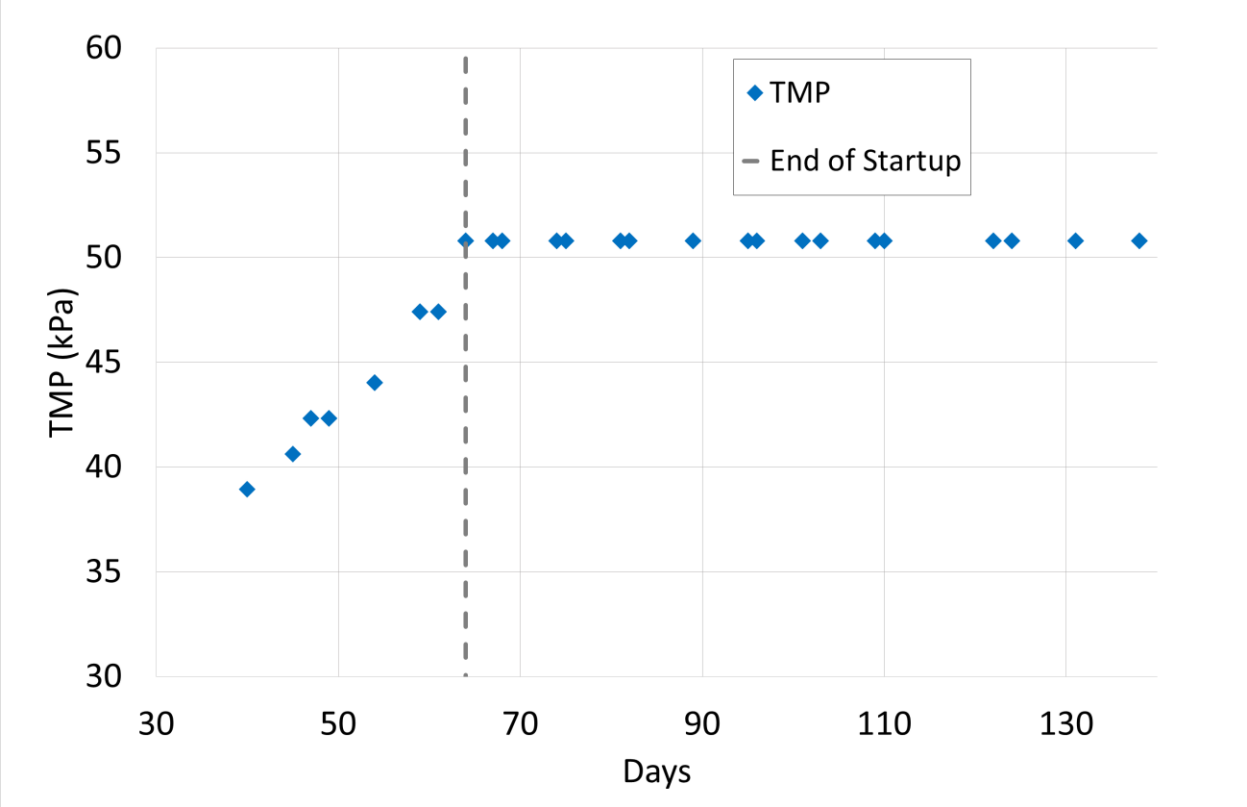

Figure 9 - Transmembrane pressure of MBR over time

Total nitrogen in the effluent showed the clearest reflection of system maturation during this startup period. At 61 days the effluent nitrogen concentration leveled off. As the seeded microorganisms acclimatized to their new environment, growth increased and fewer nutrients escaped from the system. It is also known that as a layer of sludge builds up on the membrane surface, called the cake layer, the effective pore size decreases, which can have the effect of increasing effluent quality (Mafirad, Mehrnia, Azami, and Sarrafzadeh, 2011). Both of these effects can be seen in **Figure 10**. The development of the biofilm on the membrane coincides with the decrease and leveling off of turbidity coming through in the effluent. It is unclear why there would be turbidity coming through the membrane since the pore size is 0.2µm, but apparently the biofilm layer was effective in reducing the turbidity.

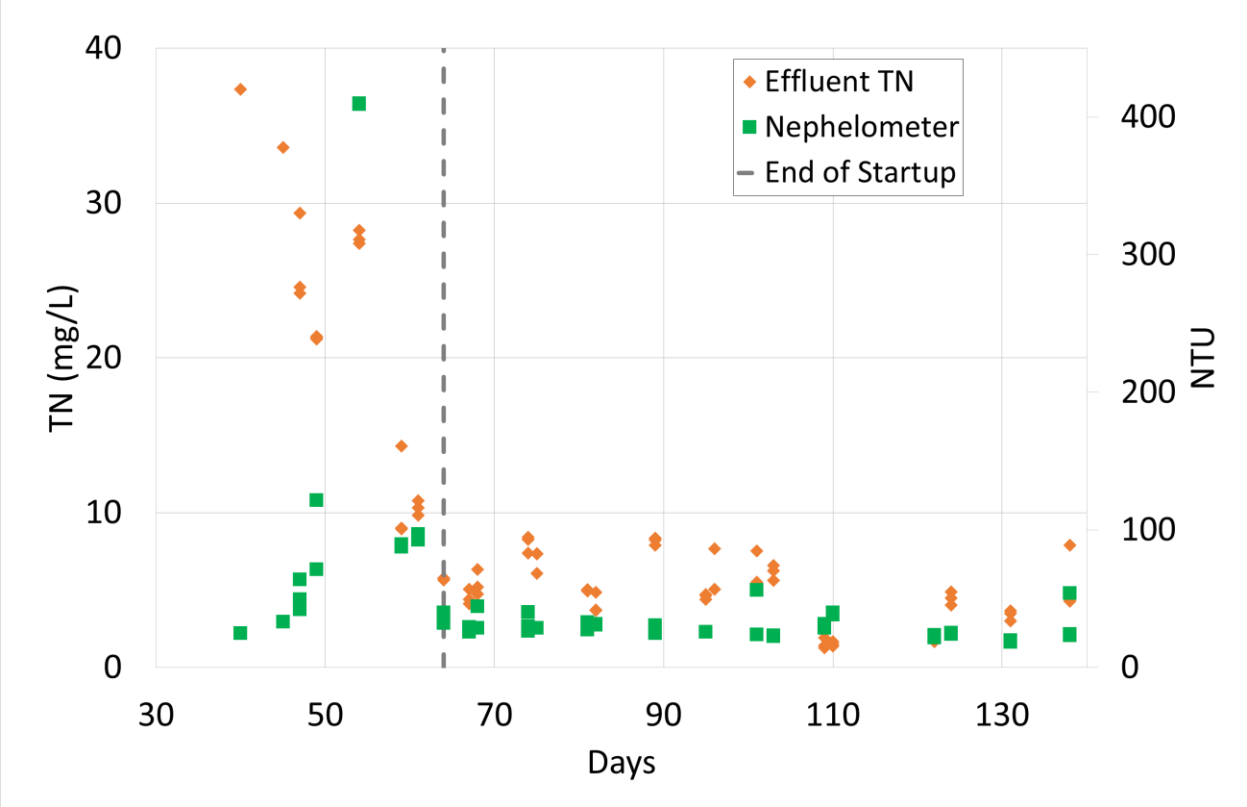

Figure 10 - Effluent total nitrogen and turbidity vs days. Dotted line shows day 61

Interestingly, there was an analogous startup phase in the oxic tank. Total nitrogen and total phosphorous are the clearest indicators of system maturation. The initial rise and then leveling off of these nutrients can be seen in **Figure 11**. The gray dashed line is the end of the startup period as determined by effluent quality and TMP. The black line demarks an apparent end of oxic tank quality development. This startup period related to oxic tank conditions is referred to as the oxic startup period.

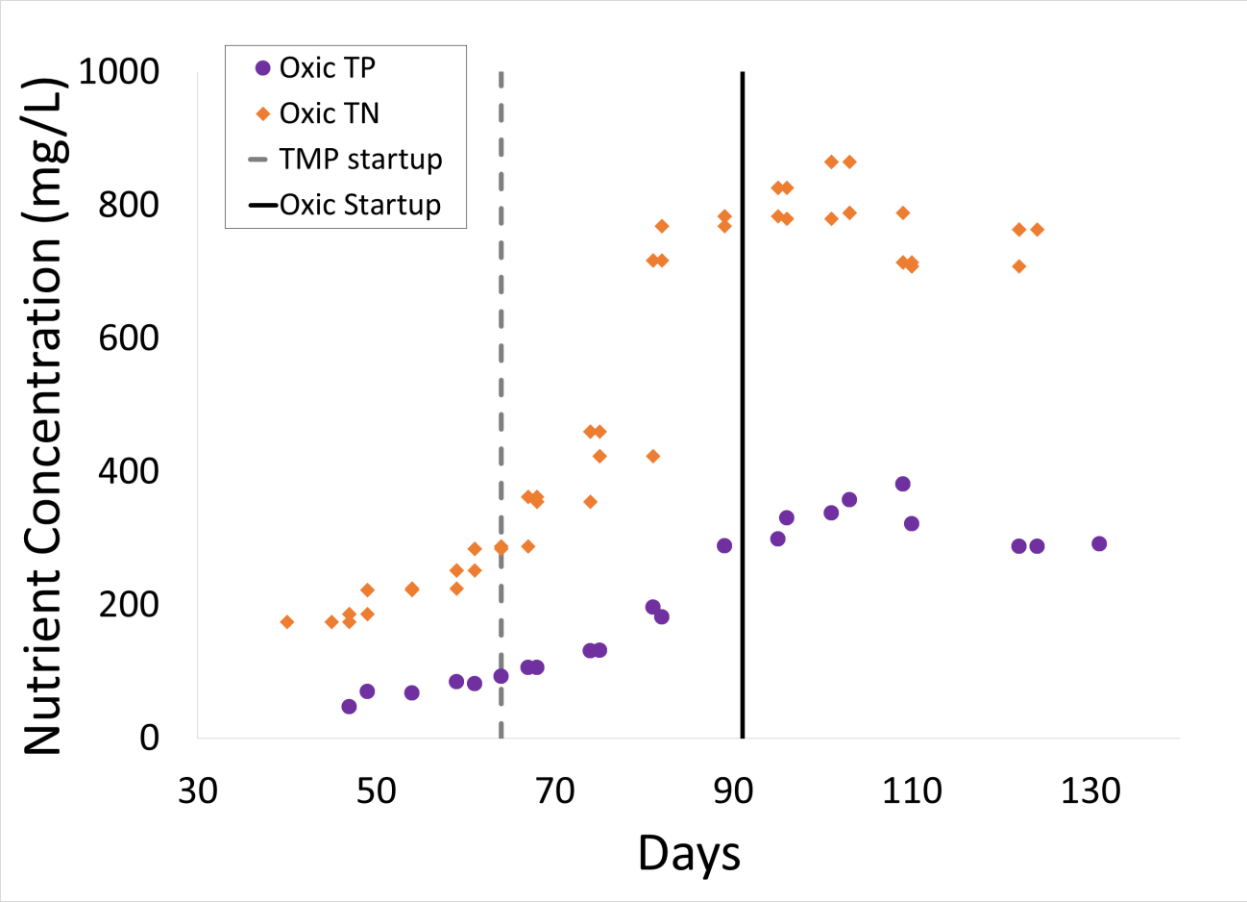

Figure 11 - Total nitrogen and phosphorus vs days the system has been running. Gray dashed line is the end of the TMP startup period and black vertical line is the end of the oxic tank startup period.

The effluent TN decreased and then leveled off as the oxic tank TN began to rapidly increase. This information supports the idea that the TMP startup period is when the biofilm layer develops on the membrane surface. The initial drop in effluent TN may have been caused by the capture of nitrogen by the biofilm. This nitrogen was then retained in the biofilm until cells died and lysed, releasing the nitrogen back into the oxic tank. This retention and release could cause the increase in TN in the oxic tank far beyond influent TN levels. For reference, the TN and TP levels for each source over time are shown in **Figure 12**. It can be seen that the oxic tank TN and TP levels far surpass those of the influent.

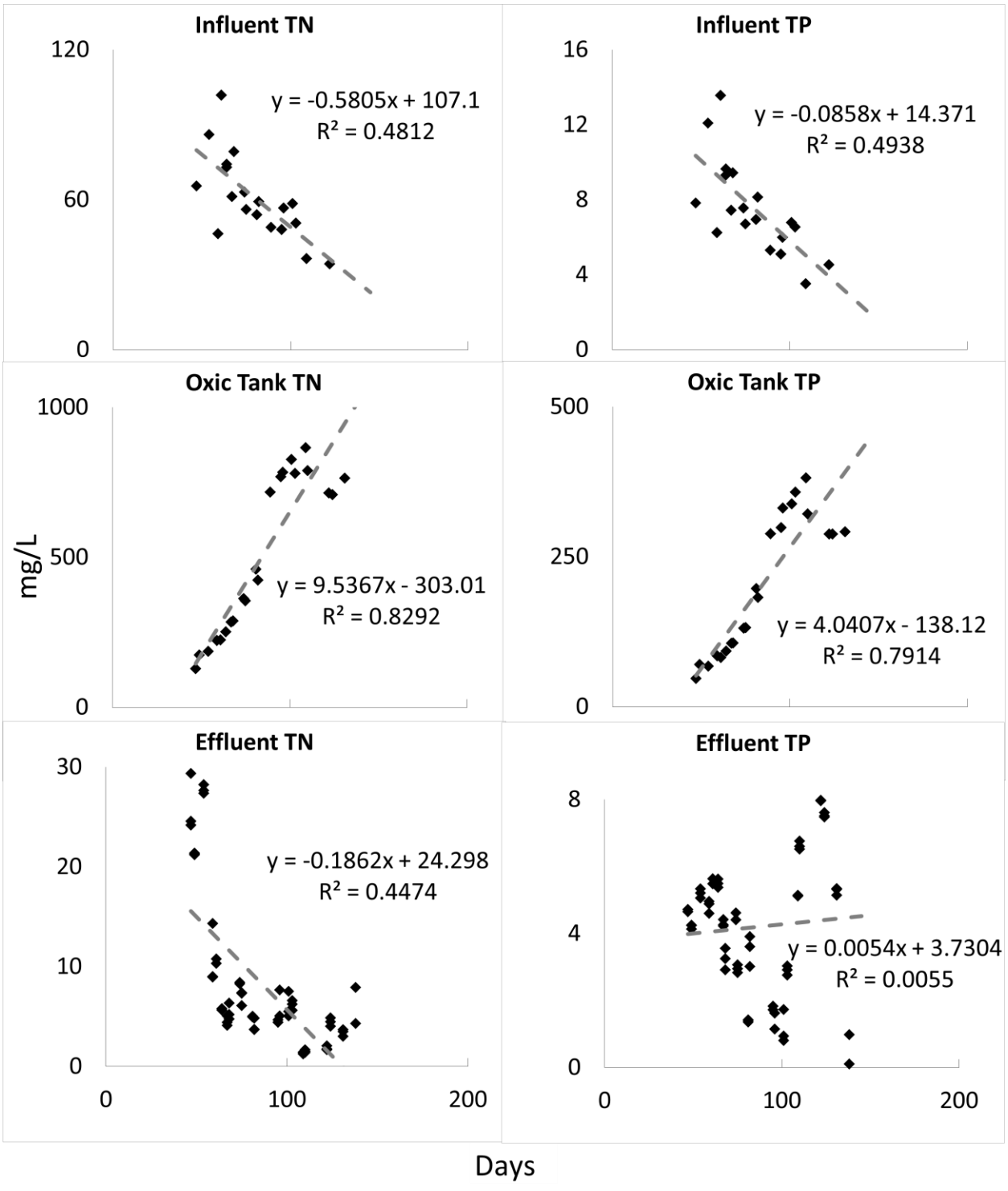

Figure 12 - TN and TP over time from each source. From top to bottom: influent, oxic tank, effluent

Variation over a Pumping Cycle

In addition to changes over a several month scale during the study, some parameters measured also changed throughout a pumping cycle. Total coliforms is a routinely checked water quality parameter because it is an indicator of fecal contamination of waters. In this study, coliforms showed a relationship to filtration time (**Figure 13**). There was a distinct peak in total coliforms for samples collected within five minutes of the beginning of a pump cycle. This indicated that effluent quality may change over a pumping cycle. In the case of coliforms, this is likely related to the membrane biofilm layer. It is possible that the biofilm layer increased in thickness or density over the course of the pumping cycle as more material was drawn through it, thereby decreasing the amount of coliforms able to slip through the membrane. This phenomenon has been reported previously (Mafirad, Mehrnia, Azami, and Sarrafzadeh, 2011).

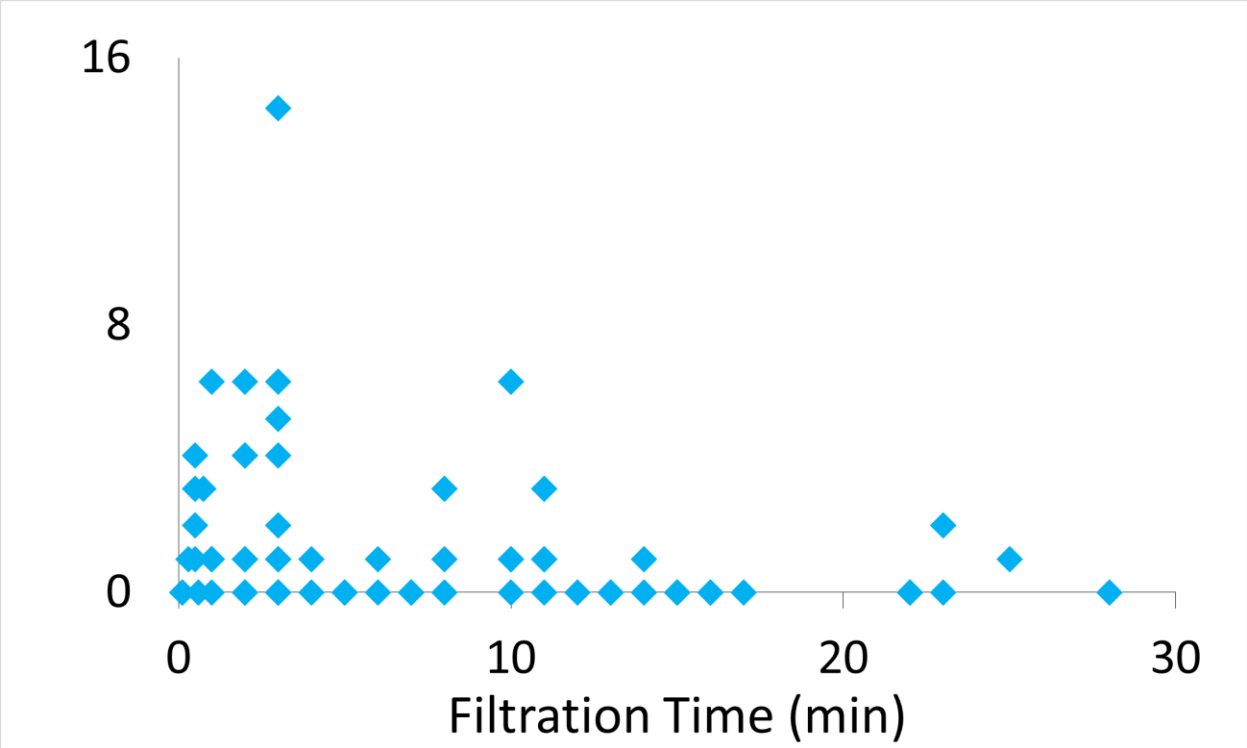

Figure 13 –Filtration time vs total coliforms for the entire startup period.

Since effluent quality was not only evaluated from grab samples, but was also monitored continuously via online instruments, these parameters were also investigated for changes over a pumping cycle. **Figure 14** shows the variations in different water quality parameters measured from the effluent line in the MBR system over the course of a week.

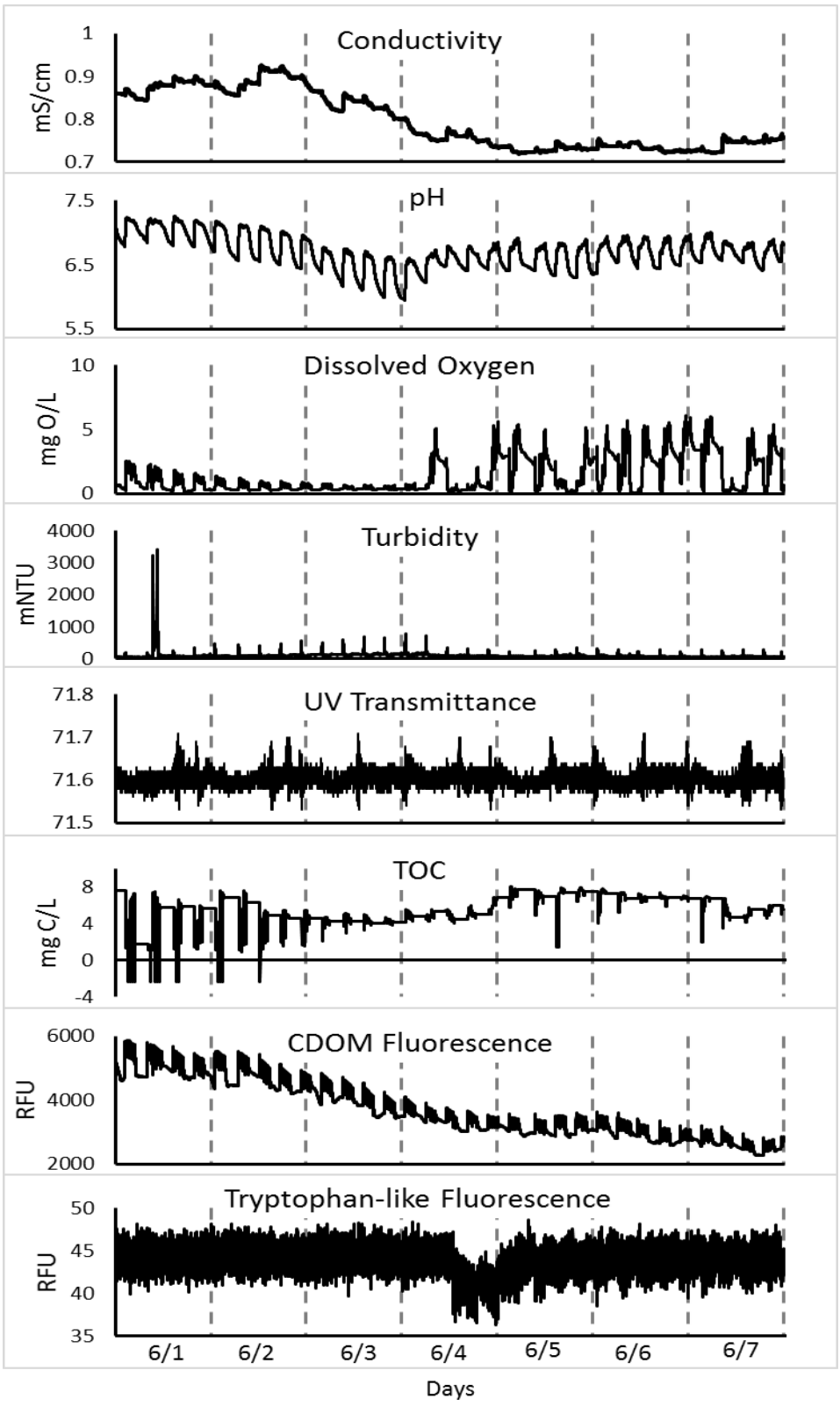

Figure 14 - Online measurements over time from 1-Jun thru 7-Jun. Dashed lines indicate days.

The cyclic nature of these data corresponded to the activation of the effluent pump. When the pump turned on, a pulse of water traveled through the instruments that was initially turbulent, then returned to laminar flow. Each instrument responded to this pulse differently.

Conductivity, turbidity, and TOC showed a sharp peak when the effluent pump started, while CDOM fluorescence, pH, and DO showed elevated values while the system was filtering and then dropped off as the water through the system stagnated between pumping periods. Additionally, the UVT and tryptophan fluorescence showed variation, but this did not appear to correlate with the pumping cycle. If using online monitoring for contamination detection or treatment monitoring, these effects must be considered on an instrument by instrument basis to allow for correct interpretation of the data.

Another effect that may impact successful online monitoring is instrument maintenance. The CDOM instrument showed little drift in **Figure 14**, but the value changes dramatically over the course of the study, decreasing according to a power law function. It appeared that the lamp intensity was diminishing rather than reflecting the character of the effluent, but this was not certain (**Figure 15)**.

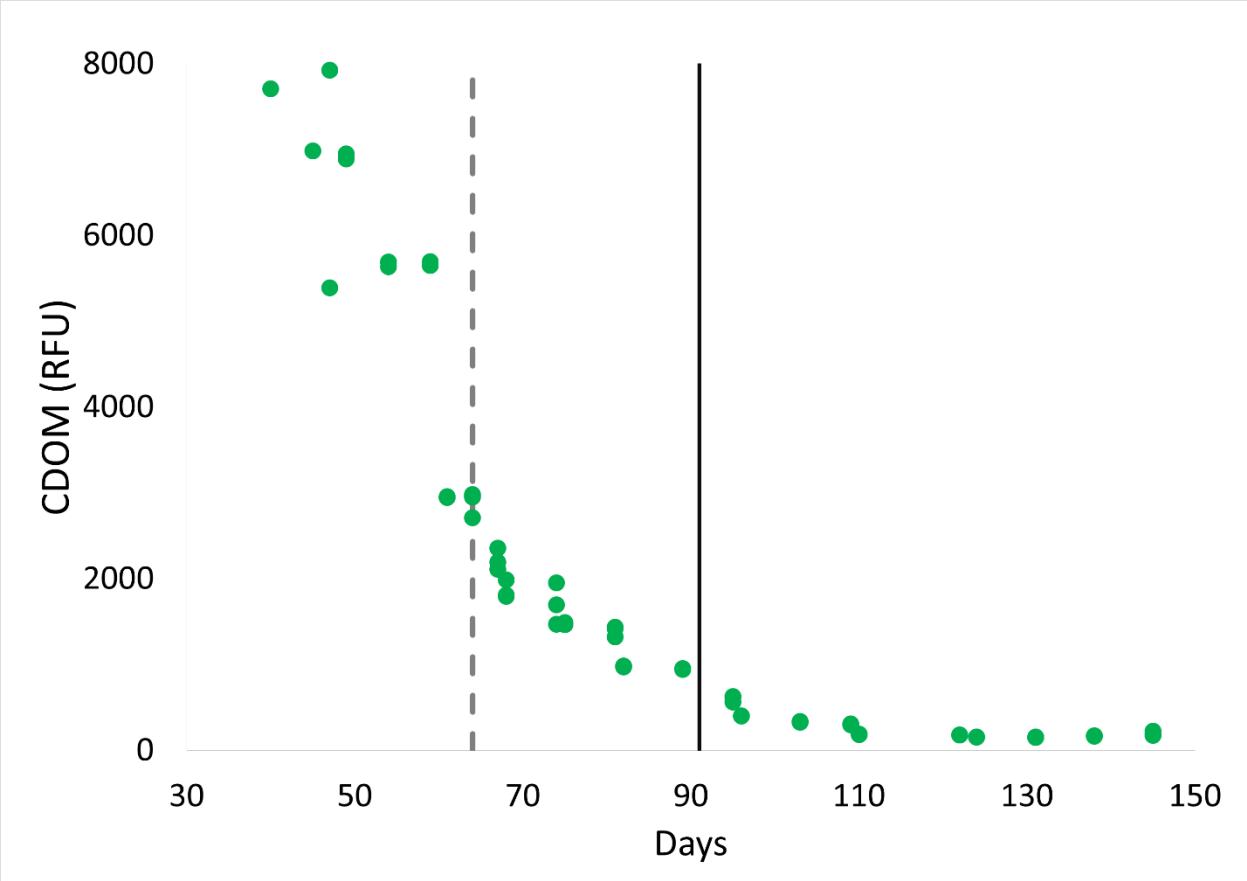

Figure 15 - CDOM intensity over the course of the study. Gray dashed line is effluent startup period. Black line is oxic tank startup period.

It is possible that the online CDOM instrument was yielding useful information rather than instrument failure. In fact, total nitrogen showed a similar decrease over time. **Figure 16** showed a strong correlation between total nitrogen and CDOM, indicating that the CDOM instrument was producing valid data. However, the CDOM fluorescence wavelengths were also measured from effluent grab samples (also shown in **Figure 16**). The two CDOM measurements did not correlate well.

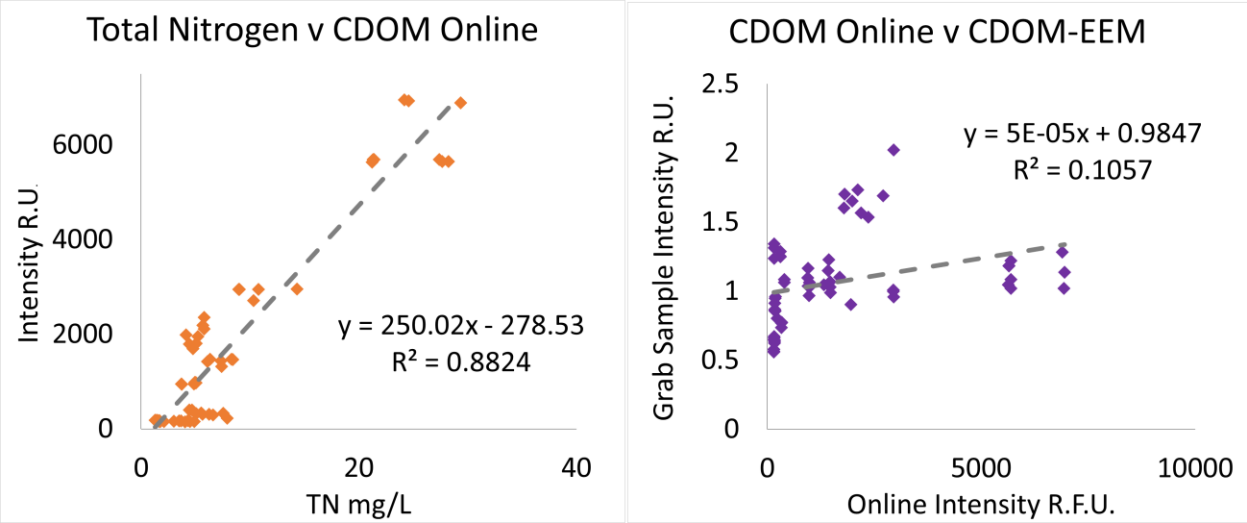

Figure 16 – Left: correlations between total nitrogen and CDOM fluorescence from the online probe (CDOM Online). Right; correlations between CDOM fluorescence from the online probe and grab samples (CDOM-EEM)

The other online fluorescence instrument measured the tryptophan-like peak. This instrument did not show the same clear decrease over time as the CDOM online peak, but did initially dropped and reached a low point at day 100 (**Figure 17**). This similar initial decrease in intensity and the correlation between the online CDOM fluorometer and total nitrogen indicate that the instrument was reflecting actual effluent quality. This indicated that one of the two measurements in each case was erroneous, or that the water measured by the benchtop fluorometer and online fluorometers were not of the same quality. This may be possible since bacterial growth was present in the effluent line after the sampling port and before the CDOM probe, however this distance was short (2ft.). It was therefore unclear whether the instrument was reflecting actual water quality or a lamp failure in both instruments.

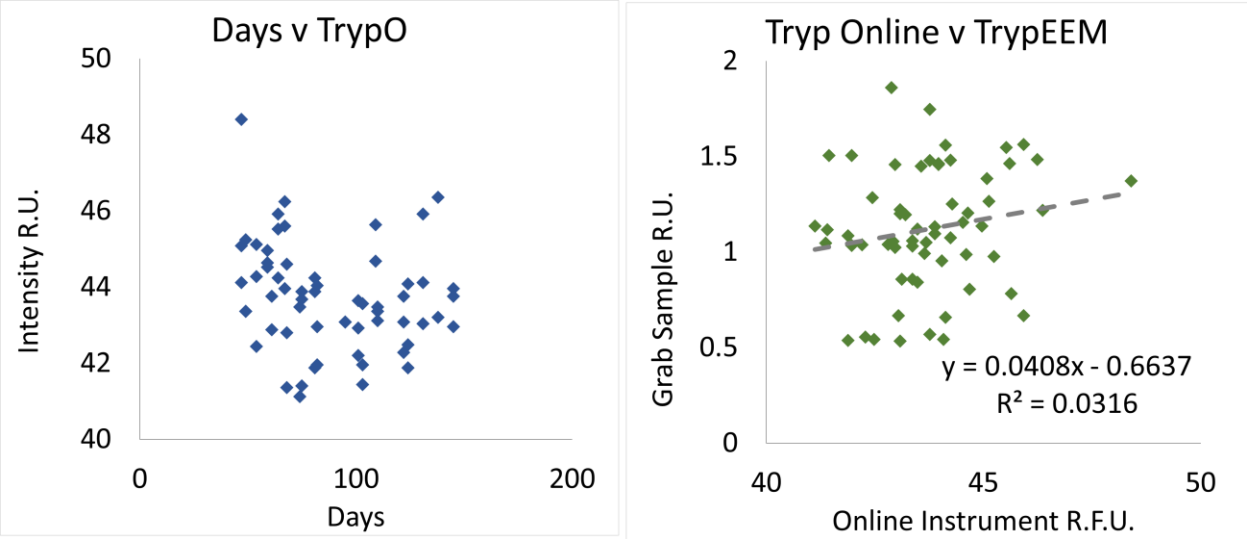

Figure 17 - Left; online tryptophan peak intensity over time. Right: correlation between online tryptophan peak and grab sample tryptophan peak.

PARAFAC

Samples taken from throughout the MBR treatment system were used to create two PARAFAC models. The Total Model was created using samples from each sampling location (n = 198) while the Effluent Model, used in the contamination detection study, was created solely from effluent samples (n = 65). Broad humic fluorescence was present in all samples with variable protein related fluorescence present depending on the source of the sample. The Total Model contained five commonly observed components. The Effluent Model consisted of four of these five components. The components were identified relative to common components published in other studies and the traditional peak locations identified by Coble (1996) (**Table 11**).

A comparison of the spectral loadings are shown below in **Figure 18**. Components 1-4 of the Total Model overlap closely with C1-C4 of the Effluent Model. This indicated that the Total Model was well able to discern the components necessary to model the effluent within a diverse

group of samples. This is the strength of the PARAFAC technique (Yu et al., 2015). **Figure 19** shows an EEM of each component. The Total Model on the left contains four components nearly identical to the components that make up the Effluent Model.

Total Model	Effluent Model	Component Reference	Peak Reference[5]
Component 1	Component 1	G2[1] - microbial humic-like, <250, (320)/400	Peak M - marine humic, 290-325/370-430
240 (305)/396	240 (295)/394	G1[3] - wastewater related microbial humic, 230 (305)/414	Peak A - UV humic-like, 260/400-460
		C2[2] - productive oceanic environments and high nutrient agricultural runoff 315/384	
Component 2	Component 2	C3[2] - terrestrial humic 270 (400)/492	Peak A - UV humic-like, 260/400-460
240 (395)/470	240 (395)/466	C3[4] - terrestrial humic 270 (360)/487	
		G6[3] - terrestrial humic-like from WW impacted waters 265 (365)/472	
		G1[1] - terrestrial humic-like from wastewater impacted waters <250 (370)/464	
Component 3	Component 3	G3[1] - wastewater related component	Peak C - humic-like, 350/420-480
350 (250)/428	345 (250)/428	C1[3] - humic-like found ubiquitously in natural waters 240 (320)/428	
		G3[4] - humic-like 245, 285, 335/420	
Component 4	Component 4	G5[1] - tryptophan-like <250/348	Peak T - tryptophan-like, 275/340
280 (240)/328	275 (240)/328	C4[2] - tryptophan-like 278/348	
		G2[3] - tryptophan-like found in wastewater impacted environments 280/332	Peak B - tyrosine like, 270-275/304-312
Component 5		G6[1] - tryptophan-like 290/352	Peak T - tryptophan-like, 275/340
280/366		C5[4] - tryptophan-like related to biological activity 280 (240)/360	
		G5[3] - free or protein bound amino acids found in surface water 245, 290/364	

Table 11 - Description of PARAFAC components identified from the Total Model and Effluent Model with similar components and peaks used for identification. Wavelengths are in nm shown as ex/em.

1 - (Murphy et al., 2013)
2 - (Stedmon et al., 2011)
3 - (Yu et al., 2015)
4 - (Stedmon, Markager, and Bro, 2003)
5 - (Coble, 1996)

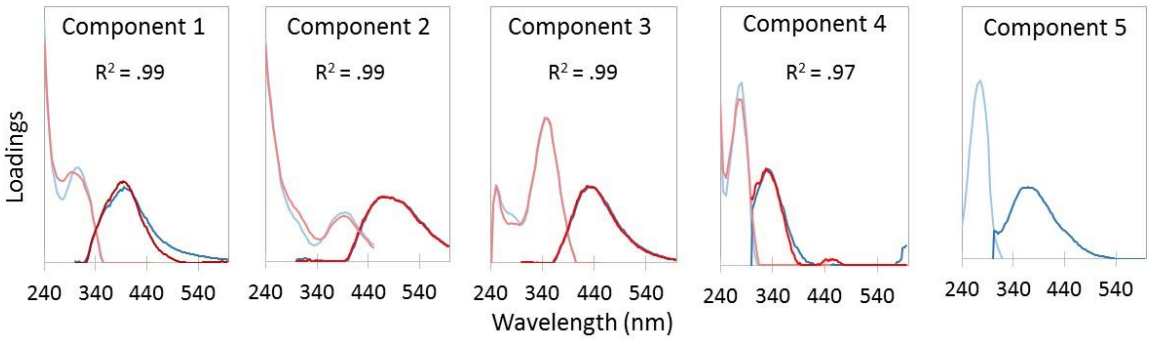

Figure 18 - Comparison of spectral loadings between the Total Model and Effluent Model. Excitation spectra are to the left of emission spectra and are lighter. Total Model spectra are blue, Effluent Model is red.

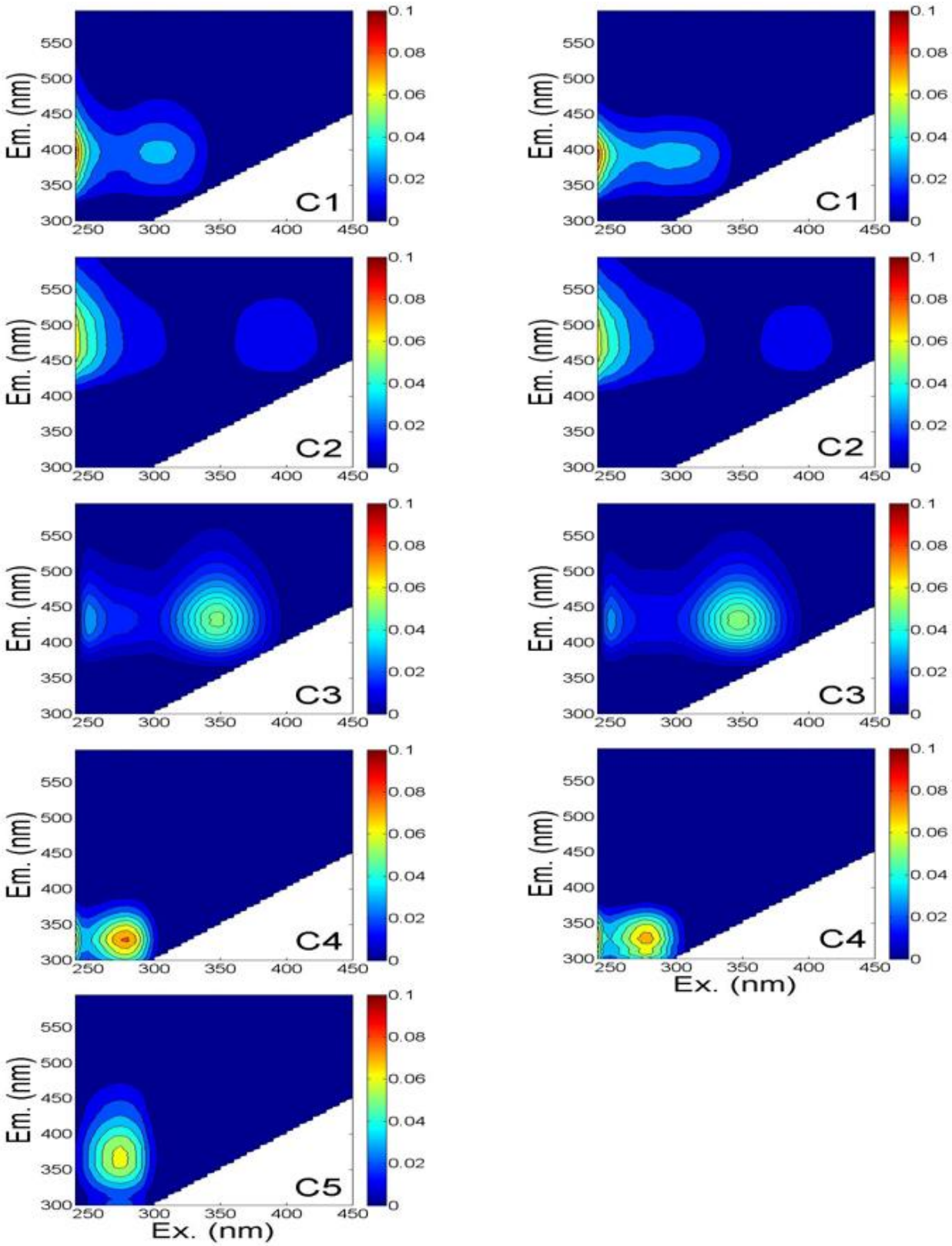

Figure 19 - Component EEMs for Total Model (left) and Effluent Model (right)

Component 1 is microbial in origin and has been associated with wastewater impacted sources (Yu et al., 2015). This component is similar to peak M described by Coble (1996). This region of the spectra was originally referred to as marine humic-like, but has since been shown to relate to microbial activity (Stedmon and Markager, 2005). Component 2 is seen in diverse environments and is thought to relate to terrestrially derived high molecular weight humic substances (Stedmon et al., 2003). This component overlaps with peak A, which is the low excitation wavelength humic-like peak. Component 3 appears ubiquitously in natural waters (Yu et al., 2015) and showed humic-like characteristics similar to peak C (Stedmon et al., 2003). This component has a broad peak centered at excitation/emission 350/425nm and is responsible for the broadest feature present in this set of EEMs, indicating the diversity of chemicals represented by the component. Component 4 exhibits fluorescent character similar to tryptophan and is protein like compounds (Yamashita and Tanoue, 2003). This region of the EEM is referred to as peak T, however this component also overlaps with peak B, the tyrosine related peak (Coble, 1996). Component 5 also exhibits fluorescence in the tryptophan-like region, but is centered at a slightly higher wavelength pair (Murphy et al., 2011; Stedmon et al., 2003). In spite of the potential shift, this component has been reported in this location by Yang et al. (2014) and has been generally referred to as amino acid related or protein like (Yang et al., 2014; Yu et al., 2015).

Mean Component Loadings

The average component loadings over the course of the study were calculated for each source (**Figure 20**). The loadings from the Total Model were used for this calculation. Due to higher DOM concentrations, the influent had higher loadings for all components. This may have

also reflected the less degraded nature of the organic matter entering the system. The loadings of the oxic tank generally decreased from the influent, and the effluent loadings decrease from the oxic tank. This trend reflects the decreasing DOM concentrations through the treatment process. The effluent loadings were generally the lowest.

The oxic tank had a much larger loading of C4 than the effluent, which indicated that some process occurring on or within the filter was responsible for the removal of C4. Similarly, the influent had a much larger loading of C5 than the oxic tank, which indicated that C5 was removed by a process occurring in the oxic tank.

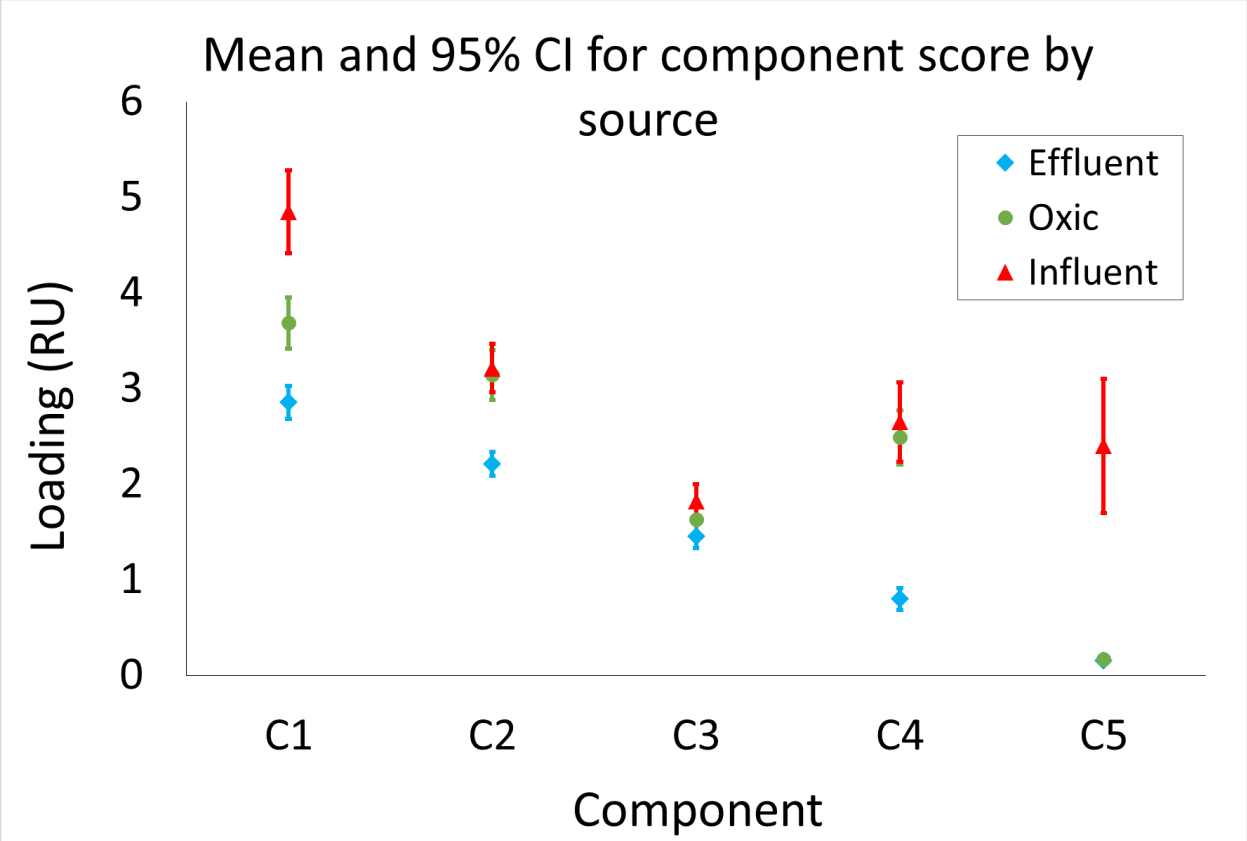

Figure 20 - Mean component loadings (Total Model) and 95% confidence intervals for each source

It was expected that the bioreactor portion of the MBR system would more effectively remove protein related components than humic-like components. As reported elsewhere (**Table 5**), bioreactors have been shown to reduce protein related fluorescence peaks T_1 and T_2. It was not expected that tryptophan-like C4 would be removed during the filtration process. It is possible that another process on the filter surface was responsible for the removal of this component.

Percent Distribution of Components

In order to remove the potential effects of changing CDOM concentrations, the percent distribution of the component loadings for each source were calculated (**Figure 21**). The percent distribution of each component was calculated as:

$$\%\ distribution = \frac{(\overline{SCN}) \times 100}{\sum_{n=1}^{5} \overline{SCn}}$$

where *S* denotes the source and may be *E* for effluent, *O* for oxic, *I* for influent. *C* denotes that the variable is a component score. *N* is a number from one to five indicating which component's percent distribution is being calculated, and *n* is a variable with a value from one to five indicating which of the five components is being considered.

The same trends were present within each source in this view of the data. Note that the percent of a given component cannot be compared across sources here. This is because the total amount of CDOM or total fluorescence may have been (and likely was) different between sources.

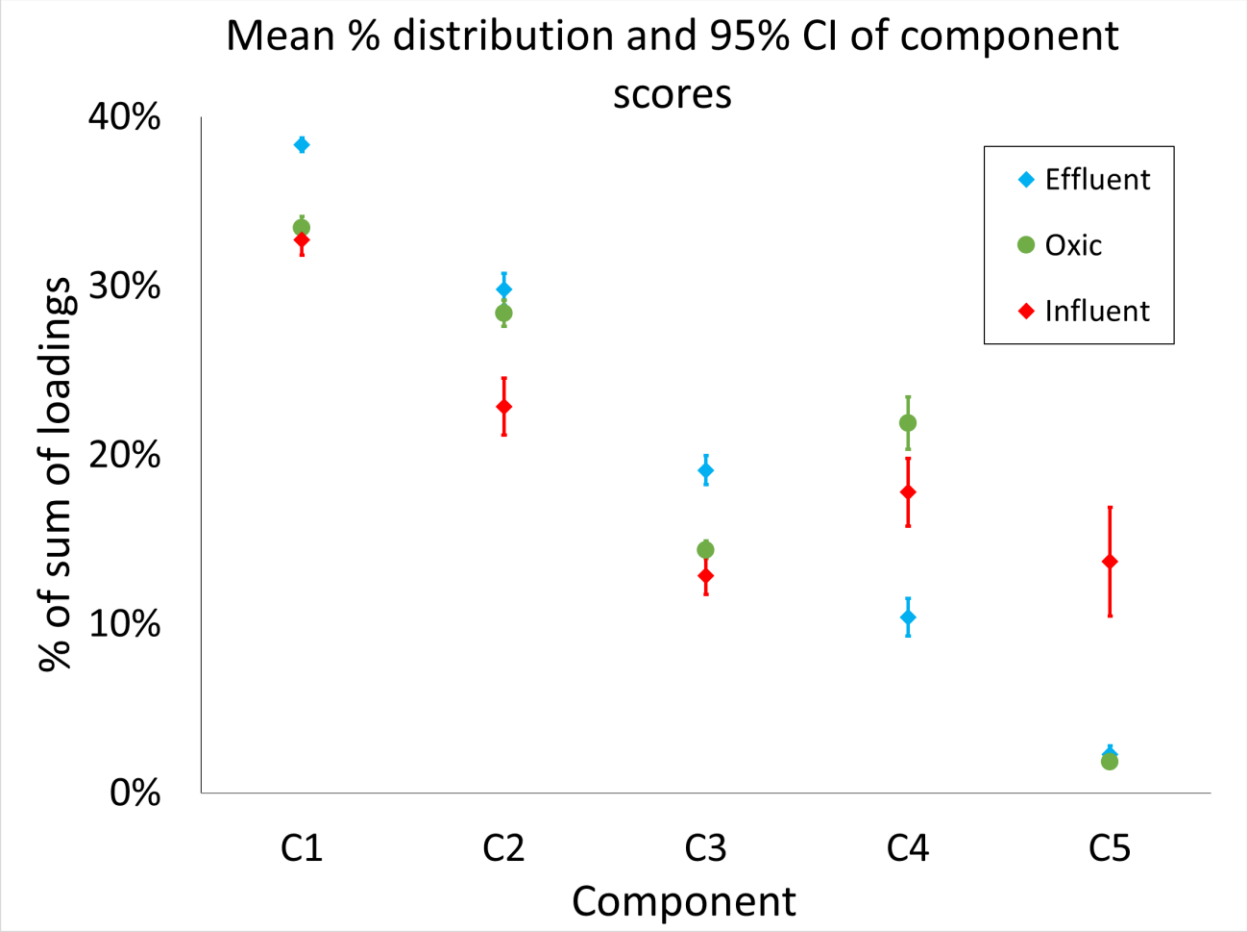

Figure 21 - Percent distribution of component loadings for each source.

Changes in DOM concentrations can influence component loadings by changing the amount of fluorescent material present in the water. This may interfere with data interpretation. It was prudent to examine loadings without the potential influence of changing concentrations of fluorescent matter.

When considering the distribution of the loadings within a source, the relative loadings were the same. Comparing the distribution of loadings between sources should be done with caution, due to the effect of changes in DOM concentration. The effluent generally had higher percent loadings of the humic-like components than the oxic tank, and the oxic tank had higher percent loadings of the humic-like components than the influent. However, this does not mean

that there was more fluorescent humic-like DOM in those sources than in the influent. This effect was a result of the removal of the protein related components C4 and C5 and the resulting decrease in total fluorescence in the effluent and oxic tank samples.

Temporal Variations in Fluorescence

There have been limited attempts to use fluorescence to investigate changes in MBR water quality over time, all of which were at benchtop or pilot scale (Hur et al., 2014; Maqbool et al., 2016; Zhou et al., 2012). In each case, the fluorescence character of the effluent changed minimally over time, while changes from within the reactor were more obvious. These changes over time reflected a cake layer formation on the membrane surface, thus dividing the membrane system performance into two periods, cake layer formation and afterward (Hur et al., 2014; Maqbool et al., 2016).

While these studies offer guidance, additional research has shown that lab scale experiments mostly offer qualitative information in regards to operation of full scale MBR systems (Kraume et al., 2009). Research suggested this was due to differences in hydrodynamic conditions, sludge freshness and composition, ambient conditions, and energy input (Kraume et al., 2009). This study allowed for investigation of temporal variations of a full scale MBR system by fluorescence spectroscopy. A notable finding in this study and others is the presence of two different start up periods related to membrane performance: the effluent startup phase defined by TMP and reflected in TN and turbidity (via the nephelometer), and the oxic tank startup phase defined by the TN and TP of the oxic tank. Evidence of these phases was also seen in the fluorescence characteristics of the system.

Figure 22 shows composite component loadings for the effluent, oxic, and influent samples taken over time. The composite loadings are the mean loading from the three samples collected from that source on the given day. Taking the mean of the three loadings from a set of concurrent samples helps to minimize the effect of outlier samples and to trim the data to a manageable number of data points. The gray and black lines represent the TMP and oxic tank startup period, respectively. The observed changes over time are related to variable influent quality, development of the sludge character in the oxic tank, and development of the biofilm on the membrane surface. As **Figure 22** reveals, the data are complex, but there does appear to be trends to the variation.

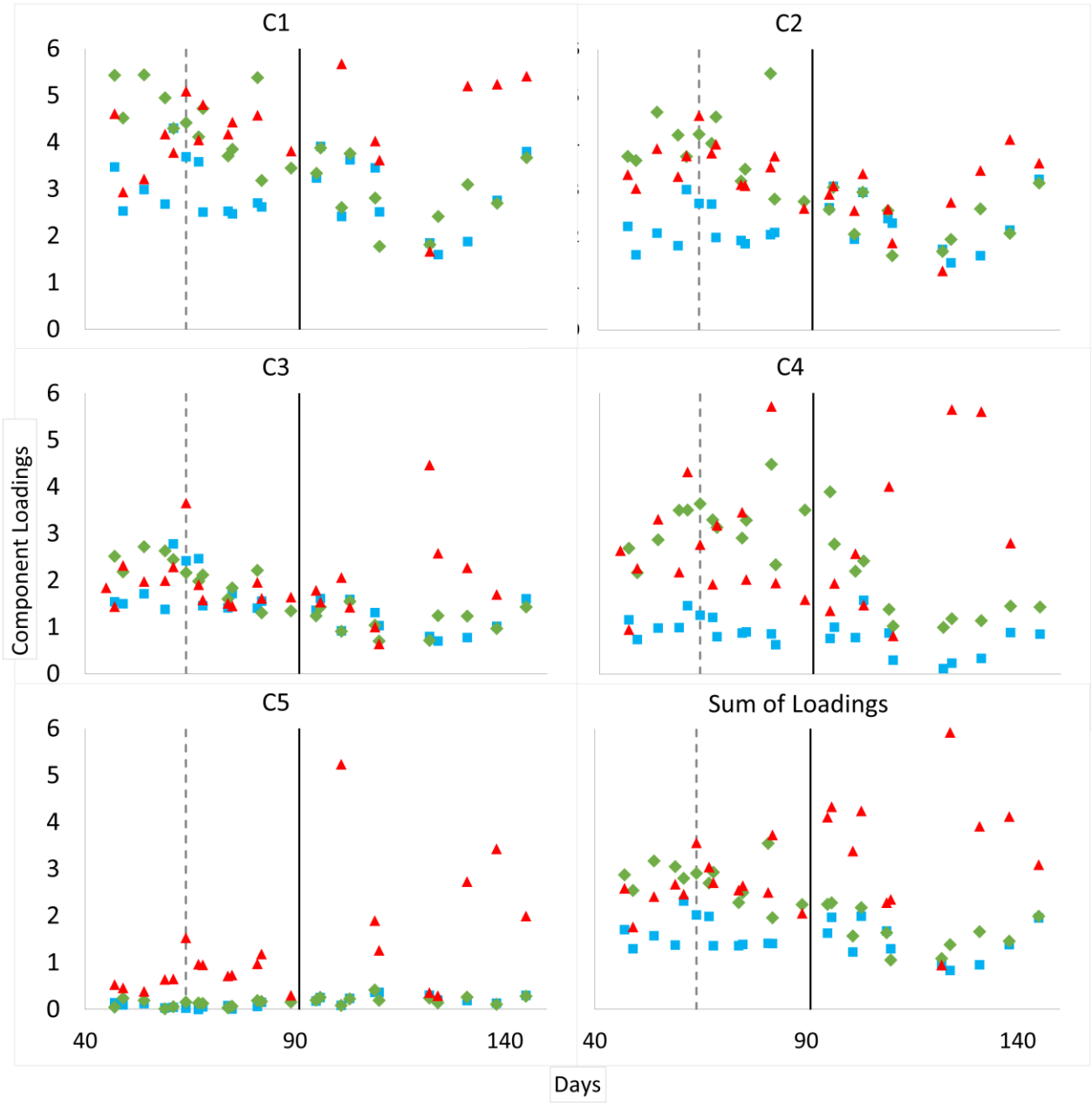

Figure 22 – Composite component loadings over time by source. Effluent components are blue squares, oxic tank components are green diamonds, and influent components are red triangles. Gray dashed line denotes TMP startup period and black vertical line denotes oxic startup period

There are not many clear trends when only considering individual components, but there are some. Humic-like components C1, C2, and C3 decrease over time in the oxic tank (green diamonds). These same components also have an increasing tail near the end of the sampling

period, starting around day 125. Terrestrial humic-like C2 also exhibited this hockey stick shaped trend in the influent (red triangles), which may be a cause to the trend in the other humic-like components. Also in the influent (red triangles), amino acid related component C5 increased after the oxic tank startup period.

Looking at trends in individual components, however, can be misleading. Each of the sample sources are influenced by the quality of the water coming from previous sources. For example, terrestrial humic C2 decreased in the oxic tank (green diamonds) during the same period that C2 decreased in the influent (red triangles). It is not possible to determine a cause for this decreasing trend, but it is likely that the trend in the oxic tank is related to the trend in the influent. Therefore, comparisons between the component loadings are more valuable as these can take into account the water quality upstream of the source being considered.

Removal of PARAFAC components over time

Figure 22 is useful for examining the differences in component loadings and assessing the removal or buildup of components over time. Differences between influent loadings (red) and oxic tank loadings (green) may indicate that a component is biodegraded or retained in the oxic tank. Similarly, differences between oxic tank loadings (green) and effluent loadings (blue) may indicate that the biofilm on the filter is removing a component or leeching it through the filter.

In the period between water entering the MBR system as influent and travelling through the oxic tank, the only process that may influence the DOM is biodegradation since settling is minimized by a mixing pump and blower within the MBR system. From the reactor, through the membrane, to the effluent there are three processes that may affect DOM. These are adsorption to the membrane surface, biosorption into the matrix of bacteria and organic material (biofilm)

forming on the membrane surface, and biodegradation by the biofilm. The TMP startup period was defined as a period of increasing TMP (up to day 61 in the present study), after which the TMP remained constant for the remainder of the study period. During the TMP startup period, the processes that acted at the membrane surface to remove components were likely the same processes that increased TMP. However, after this period, there was still removal of some components without the effect of increasing the TMP. These processes are discussed below.

Removal of microbial humic C1

During the oxic tank startup phase, microbial humic C1 had a higher loading in the oxic tank (green) than in the effluent (blue) (**Figure 23**). This result indicated that this component was removed by membrane related processes. This phenomenon has been reported previously (Hur et al., 2014; Maqbool et al., 2016). Since C1 was removed by membrane related processes during the TMP startup period, this component may have contributed to increasing the system TMP. Of the potential membrane processes, adsorption to the membrane surface likely has the greatest influence on TMP as this process leads directly to pore narrowing, even prior to the buildup of biofilm (Iorhemen, Hamza, and Tay, 2016).

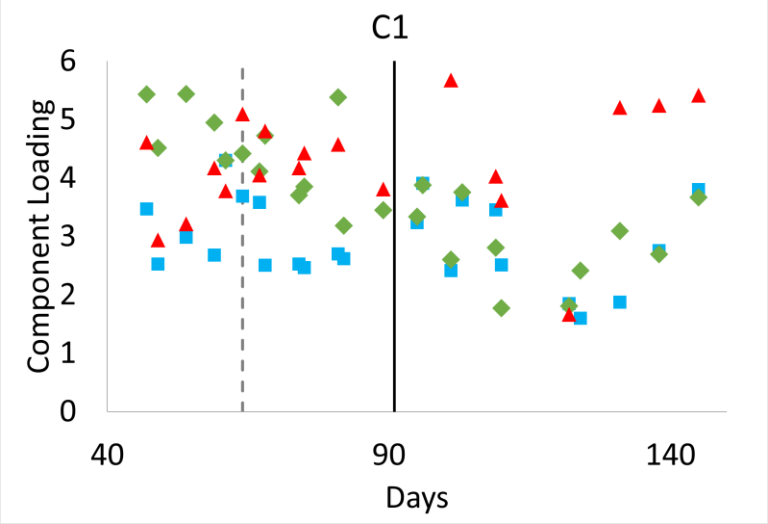

Figure 23 - Microbial humic C1 loading over time. Gray dashed line indicates end of TMP startup period. Black line indicates end of oxic tank startup period. The source of each component loading is indicated as follows: red triangles represent influent, green diamonds represent oxic tank, blue squares represent effluent.

After the TMP startup period when the biofilm was established, C1 was removed at the membrane surface by a process that did not affect TMP. This was possibly biosorption to the biofilm rather than adsorption to the membrane surface and pore space. This may explain why the TMP stopped increasing. A similar phenomenon was observed by Arora and Davis (1994) and reviewed by Le-Clech et al. (2006). Arora and Davis (1994) added yeast to a MBR containing bovine serum albumin. The yeast was found to create a type of pre-filter that inhibited the BSA from binding to the membrane pores, resulting in greatly decreased membrane fouling.

During the period after the TMP startup and still during the oxic startup period (days 61-91), the oxic tank C1 loading began to decrease, while influent loadings remained high. This indicated a decrease in filter retention over time, which has been previously reported by Maqbool et al. (2016). It appears that as the biofilm was growing, biodegradation began to increase in the oxic tank, eventually dominating the removal of C1.

After the oxic startup period, the oxic tank and effluent loadings for C1 began to mirror each other. It may be that biodegradation in the oxic tank removed the components to such a level that the membrane surface processes no longer removed the material. Biodegradation of C1 has been reported elsewhere (Cohen et al., 2014; Murphy et al., 2011).

Removal of terrestrial humic C2

Terrestrial humic-like C2 exhibited similar patterns of removal as compared to microbial humic C1 (**Figure 24**). During the oxic tank startup phase, this component had higher loadings in the oxic tank (green) than in the effluent (blue), which indicated that C2 was initially removed by membrane related processes, similar to C1. Filtration related removal of C1 has been reported (Hur et al., 2014; Maqbool et al., 2016), but C2 was reported to be resistant to filtration (Ishii and Boyer, 2012). This difference between the results of the present study and those of previous studies may due to the operational stage of these other systems, which were all past system startup. For example, initially C2 showed removal by filter related processes, but afterward C2 no longer appeared to be retained by the membrane. Since C2 was removed by membrane related processes during the TMP startup period, it too may have contributed to the increasing TMP of the system.

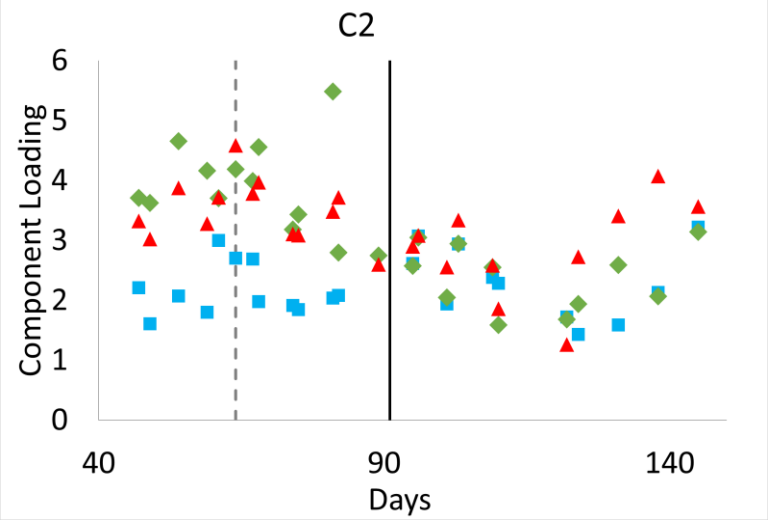

Figure 24 - Terrestrial humic C2 loading over time. Gray dashed line indicates end of TMP startup period. Black line indicates end of oxic tank startup period. The source of each component loading is indicated as follows: red triangles represent influent, green diamonds represent oxic tank, blue squares represent effluent.

During this period after the TMP startup and still during the oxic startup period, the oxic tank loading began to decrease. In the case of C1, this decrease appeared to be due to increasing biodegradation, however C2 appeared to be simply mirroring the influent score. C2 did not exhibit biodegradation until the final days of the study period. Biodegradation of C1 has been reported elsewhere (Cohen et al., 2014; Murphy et al., 2011), but C2 is generally reported to show minimal biodegradation (Cohen et al., 2014; Ishii and Boyer, 2011; Murphy et al., 2011), which is in agreement with the current study.

Removal of microbial humic C3

During the TMP startup phase, microbial humic C3 had higher loadings in the oxic tank than in the effluent (**Figure 25**). This indicated that C3 was removed by membrane related processes. Since C3 was only removed during the period when TMP was increasing, it seems

that this component was only removed by adsorption to the membrane surface. This is consistent with another study which reported the fluorescence peak in the same location as C3 to be found in membrane foulants (Wang et al., 2009).

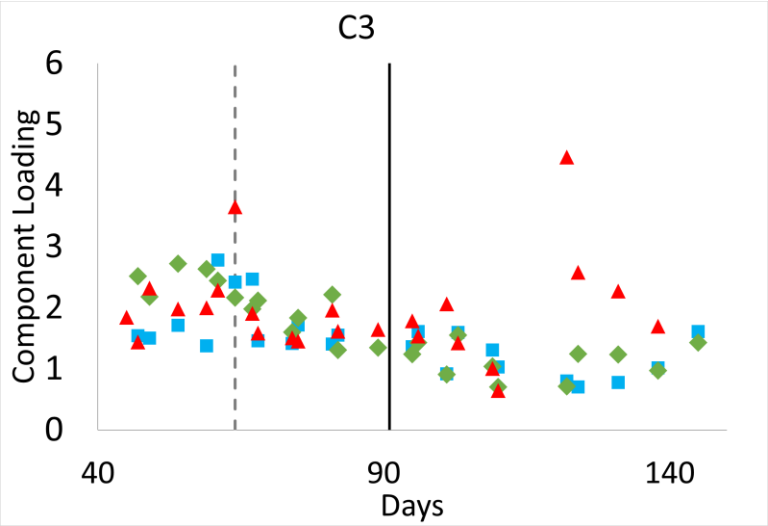

Figure 25 - Microbial humic C3 loading over time. Gray dashed line indicates end of TMP startup period. Black line indicates end of oxic tank startup period. The source of each component loading is indicated as follows: red triangles represent influent, green diamonds represent oxic tank, blue squares represent effluent.

At the end of the TMP startup period, the effluent loading quickly converged to the oxic tank loading and both closely followed the influent loadings for this component over time. It appears that initially the component was binding to the membrane surface, but after the initial 60 days binding sites to the membrane surface were filled, or conditions in the tank changed that inhibited binding to the membrane surface. This would explain why the effluent loading and the oxic tank loading were approximately the same around day 60. In the instances where the influent brought a higher amount of C3 than usual, the component was biodegraded in the oxic tank to normal levels. Apart from the instances of unusually high C3 inputs from the influent, the

component showed very little biodegradability. This result was consistent with previous literature (Cohen et al., 2014; Murphy et al., 2011).

Removal of tryptophan-like C4

Initially, tryptophan-like C4 removal was entirely accomplished by membrane related processes (**Figure 26**). The removal of this component was consistent through the TMP startup phase (day 1-61) and oxic tank startup phase (day 1-90). Therefore, the component was likely removed by biosorption to the biofilm forming on the membrane surface rather than adsorption to the membrane itself. This result is supported by many studies that found tryptophan-like fluorescence to be related to membrane fouling by biosorption to the biofilm (Hur et al., 2014, Meng et al., 2011; Tang et al., 2010; Wang et al., 2009). If adsorption was the primary process for removal of C4, then the removal would have decreased after the TMP startup period similar to the humic components C1 and C3.

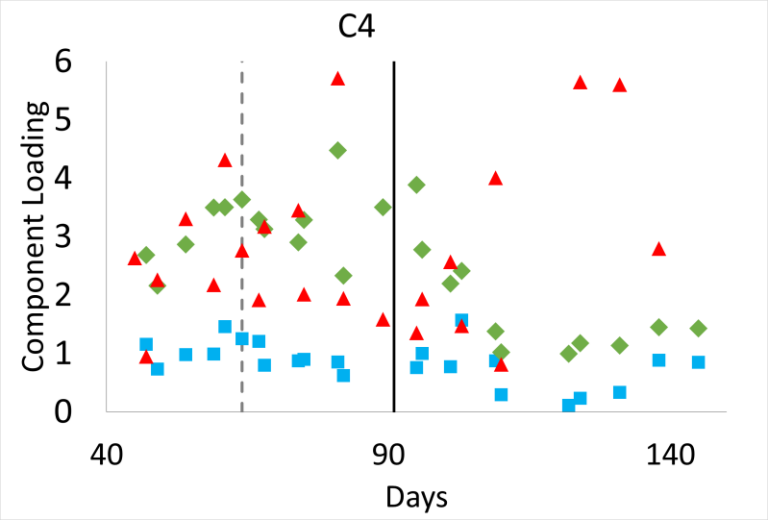

Figure 26 – Tryptophan-like C4 loading over time. Gray dashed line indicates end of TMP startup period. Black line indicates end of oxic tank startup period. The source of each component loading is indicated as follows: red triangles represent influent, green diamonds represent oxic tank, blue squares represent effluent.

The transfer from membrane related removal of this component to biodegradation in the oxic tank does not occur neatly at the end of one of the startup phases, but 10 days or so after the oxic tank startup period. C4 has been reported to be removed by biodegradation (Baker and Inverarity, 2004) as well as by membrane related processes (Hur et al., 2014; Maqbool et al., 2016). The present study indicated that under different operational stages, the component may be removed by different processes. Initially, C4 was removed by membrane related processes, but afterward the removal switched to biodegradation in the oxic tank.

While biodegradation of this component increased, examining the percent removal of this component, rather than the absolute removal reveals that the filter was still removing a comparable fraction of this component, but this removal was less obvious because the levels of C4 in the oxic tank had dropped. This can be seen by comparing the mean component loadings and influent relative component loadings in a later section (**Figure 28**).

Removal of amino acid related C5

C5 is the amino acid related peak and its removal appeared to be entirely accomplished by biodegradation (**Figure 27**). The effluent component loading consistently matched the oxic tank loading indicating no removal from membrane related processes. This is consistent with literature (Yang et al, 2014). Protein like components are considered primarily responsible for membrane fouling due to their retention on membrane surfaces (Drews et al., 2007; Hur et al., 2014; Maqbool et al., 2016). This study has shown one protein like component to be highly biodegradable, while the other is retained by the membrane initially, but is increasingly biodegraded as operation continues.

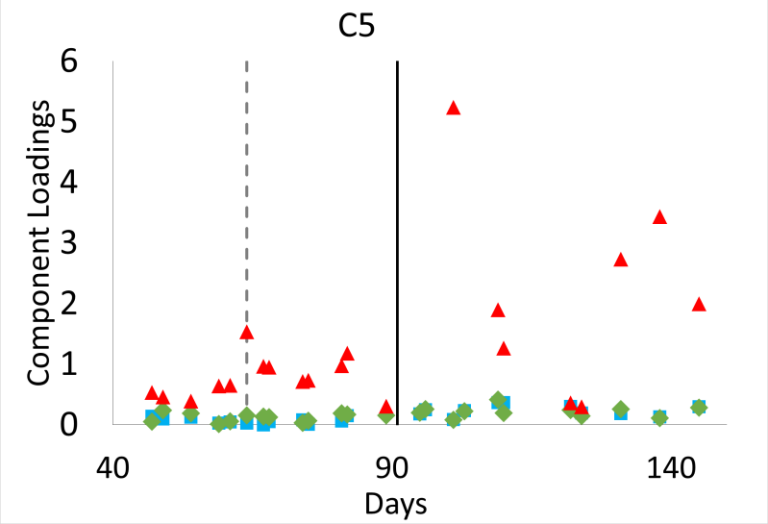

Figure 27 – Amin acid-like C5 loading over time. Gray dashed line indicates end of TMP startup period. Black line indicates end of oxic tank startup period. The source of each component loading is indicated as follows: red triangles represent influent, green diamonds represent oxic tank, blue squares represent effluent.

Relative component loadings

While removals and trends are present in the composite loadings, they are also difficult to visualize. The mean component loadings were taken during and after the two startup periods for easy comparison between startup and afterward and between sources. These means are shown in **Figure 28**. Along with the means are the influent relative component loadings. These were calculated by dividing the component loadings by the corresponding influent component loading from the same day and calculating averages over the four time periods. This presentation of the data removes extraneous information to easily identify the effects that MBR processes have on component scores.

$$influent\ relative\ component\ loading = \frac{(\overline{SCN})}{\overline{ICN}}$$

An additional advantage of examining component loadings relative to influent component loadings is that effects of changing influent quality on the data are mitigated. One of the differences between a full scale MBR system and a benchtop system is the consistency of influent quality. Often benchtop studies will use synthetic wastewater of a consistent quality throughout the duration of the study (Hur et al., 2014; Maqbool et al., 2016). Since full size MBR systems treating real wastewater encounter variabilities in water quality, this variability could contribute to unexpected system behavior and should be accounted for when analyzing data from real systems. **Figure 28** shows that the same general trends are present when considering component loadings compared to the influent.

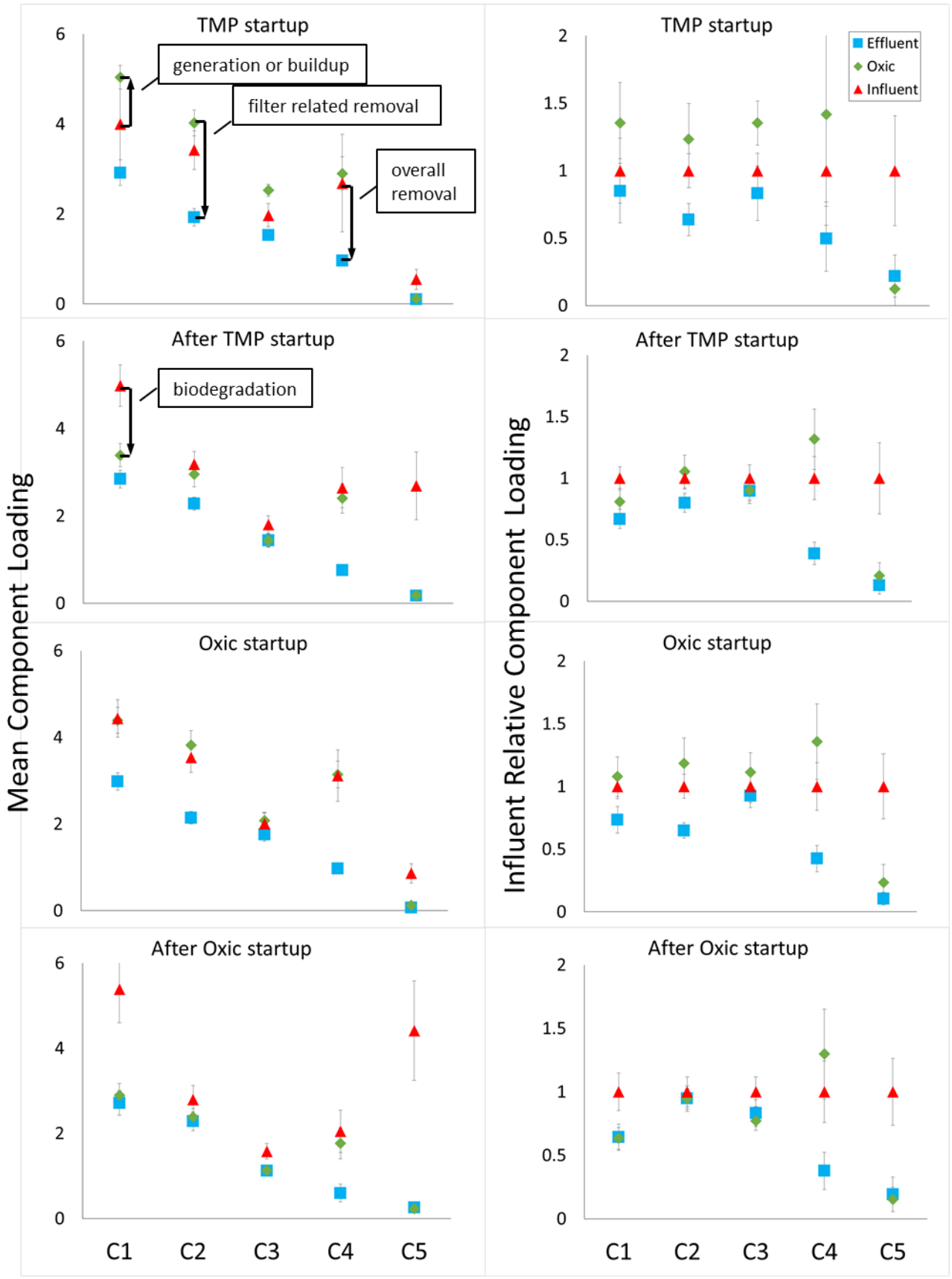
TMP startup
generation or buildup
filter related removal
overall removal
TMP startup
Effluent
Oxic
Influent
After TMP startup
biodegradation
After TMP startup
Oxic startup
Oxic startup
After Oxic startup
After Oxic startup
Mean Component Loading
Influent Relative Component Loading
C1
C2
C3
C4
C5
Components

Figure 28 - Mean component loadings and mean relative component loadings for startup periods and post-startup. Mean component loadings for the given time period are on the left. Mean influent relative component loadings are on the right. A buildup of DOM is indicated where oxic tank loadings are greater than influent loadings. Biodegradation is indicated by a decrease in component loading from influent to oxic tank. Membrane related removal is indicated by a decrease in loading from the oxic tank to the effluent. The total removal for a given component is indicated by the difference in loading from the influent to effluent.

Figure 28 clearly shows an increase in some component loadings from the influent to the oxic tank. This is especially evident during the TMP startup phase. It is unusual to see components increase through the treatment process, but this has been reported previously (Hur et al., 2014; Saadi, Borisover, Armon, and Laor, 2006; Yang et al., 2014). This likely indicated a buildup of these components in the oxic tank rather than generation of these components. This could have been caused by retention of the components by the membrane coupled with low biodegration of the material due to acclimation of the bacteria to the new environment. Additionally, **Figure 28** shows the same relationships as the composite loadings do in **Figure 22**. For composite loadings shown as percent distributions, refer to **Appendix A**: Supplementary figures.

Fluorescence Correlation to TOC Removal

Fluorescence peaks have been previously shown to relate to TOC concentrations in wastewater streams (Baker, 2002; Hudson et al., 2008; Reynolds et al., 2002; Vasel and Praet, 2002). This is a valuable information as organic matter poses several obstacles to efficient treatment of wastewater such as membrane fouling, increased oxidant demand, disinfection byproduct formation, and poor coagulation efficiency (Ishii and Boyer, 2012; Wang et al., 2009a; Yang et al., 2014). A fluorescence metric was found to correlate strongly to TOC removal

after the oxic tank startup phase for this MBR system. A linear regression was created between the ratio of humic components over protein like components from the influent and TOC removal between influent and effluent (**Figure 29**).

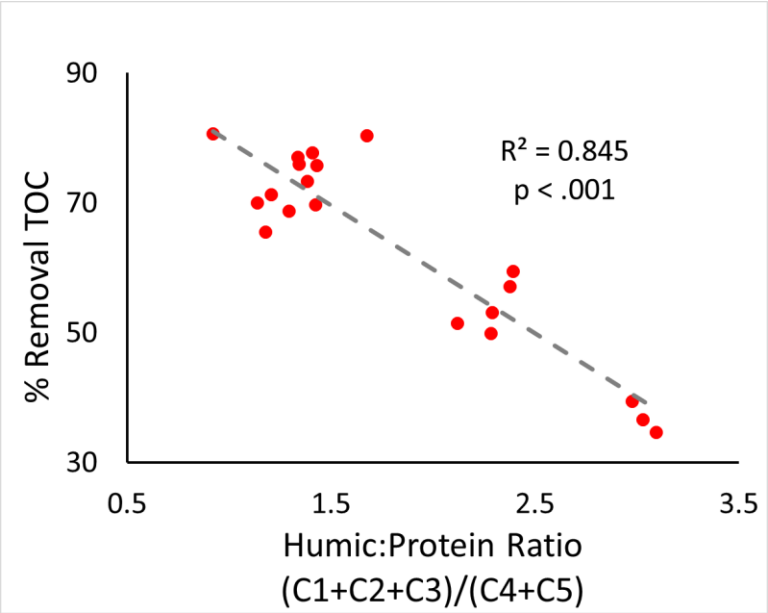

Figure 29 - Linear regression of humic:protein ratio to % removal of TOC

The humic:protein ratio has been developed by (Kulkarni et al., 2016) for determination of arsenic mobilization in groundwater in Bangladesh, however the ratio is also shown to be meaningful in this context. The more protein like character the DOM in the influent had, the higher the percent removal of TOC. This is expected as protein like fluorescent components were highly removed throughout MBR operation (**Figure 22**).

It is desirable that single wavelength peaks could be used to replace the need of developing a PARAFAC model, so the ratio of peak M (ex 312nm/ em 450nm) to a peak corresponding to C5 (ex 275nm/ em 360nm) was evaluated. **Figure 30** shows the regression between this peak ratio and percent removal TOC.

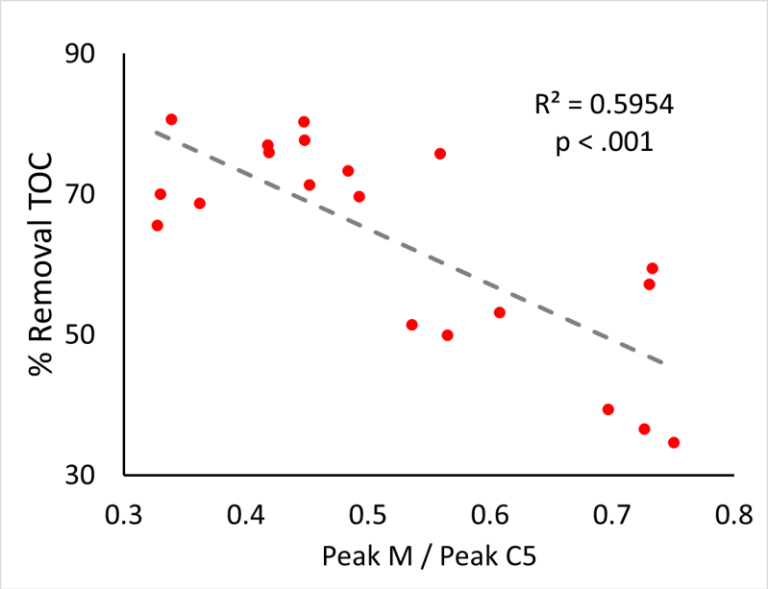

Figure 30 - Linear regression of peak M/peak at C5 to % removal of TOC

The peak M to peak at C5 ratio is similar to the humic:protein ratio in that it is a ratio of fluorescence related to humic-like material to that of protein-like material. The peak M to peak at C5 ratio does not show as strong of a correlation to TOC removal as the humic:protein ratio, but this ratio is far easier to obtain. The value of this ratio is in its simplicity as an indicator of protein-like character in the DOM.

Contamination Detection

Much work has been done in the development of fluorescence spectroscopy as a means for contamination detection in water treatment systems. These studies have elaborated on the strengths and weaknesses of fluorescence (Hambly et al., 2012; Henderson et al., 2009; Hudson et al., 2008), and also on the possible detection limits of this technique (Hambly et al., 2010; Stedmon et al., 2011). These prior detection limit studies have focused on drinking water systems. This study applies contamination detection methods in a water reuse scenario, where

treated water is much closer in quality to untreated water than in drinking water scenarios. This Is to determine if fluorescence based monitoring is useful in these scenarios.

Upon analysis, it was determined that the single effluent and oxic tank samples used to create the standard curve were of unusual water quality. Most notably, the tryptophan-like C4 component loading in the effluent sample used in these dilutions was calculated to be 0 RU. The average C4 component loading for all other effluent samples is 2.95 RU. This seemed to indicate that the effluent sample used was an outlier and therefore, the detection limit determined via this single sample standard curve cannot be considered to apply to the system.

These series of dilutions do have some value, however. They may be used to determine the variability intrinsic to the standard dilution method and to compare the precision of the Total Model vs the Effluent Model. The detection limits of the two models applied to the dilution series is shown in **Figure 31**. From analyzing this data, the ratio between tryptophan C4 and humic-like C3 showed to have the greatest response to oxic tank carbon addition. This reflects the large difference between the loadings of C4 in the oxic tank and effluent, making the C4 loading a good indicator of contamination. C3 was chosen as a reference because it showed no significant difference between oxic tank and effluent.

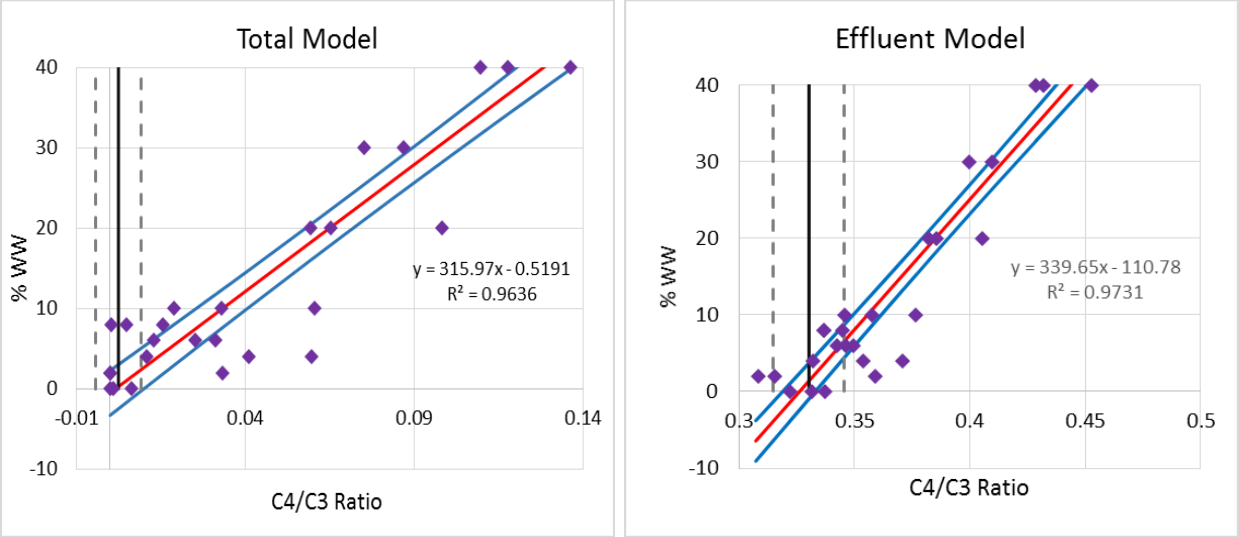

Figure 31 – Comparison of the detection limit of the Total Model and Effluent Model. Red and blue lines are the linear regression of the single sample dilution series and 95% CI of the regression, respectively. The black vertical line and gray hashed lines are the mean C4/C3 Ratio of the effluent sample and 2 standard deviations from the mean, respectively. Purple diamonds are the dilution series used to create the plots.

The regression line of the standard dilution series is shown in red. The linear regression for this series of dilutions shows very high R^2 values, similar to (Stedmon et al., 2011). The R^2 values given are for the full range of the dilutions, which include a triplicate measurement at the 100% oxic tank sample level. This sample is not shown in figure for clarity near the detection limit. Without the inclusion of this extreme sample, the R^2 for the Total Model and Effluent Model dilution series are .81 and .86, respectively. The blue lines in **Figure 31** are 95% confidence intervals of the regression. That is, if the experiments were to be repeated with an infinite number random samples from the same source, there is a 95% probability that the best fit line would fall within this interval. The confidence interval for the regression was applied in order to determine a measure of the uncertainty of this estimate. The regression lines were compared to the mean C4/C3 ratio taken from the triplicate measurements of the pure effluent

sample used in the dilution series. Two standard deviations from this mean are shown by gray vertical lines.

The detection limit is determined where the regression lines exceed two standard deviations from the mean effluent value. This range of percent wastewater values are the range in which there is a 95% probability that the true detection limit of the C4/C3 ratio lies. Based on the detection limits determined in this ideal case, the Total Model shows lower detection limits than the model based solely on the effluent.

To find a detection limit that was valid for this system, these detection limit methods were applied to the series of dilutions created using effluent and oxic tank sample pairs. In order to account for the variations in carbon concentration between the samples selected, the linear regressions were run between TOC (mg C/L) and the fluorescence component to be analyzed, rather than percent wastewater like the previous regressions. Again, the ratio between the tryptophan-like C4 and the humic-like C3 components showed the best response to the amount of oxic tank TOC added (**Figure 32**).

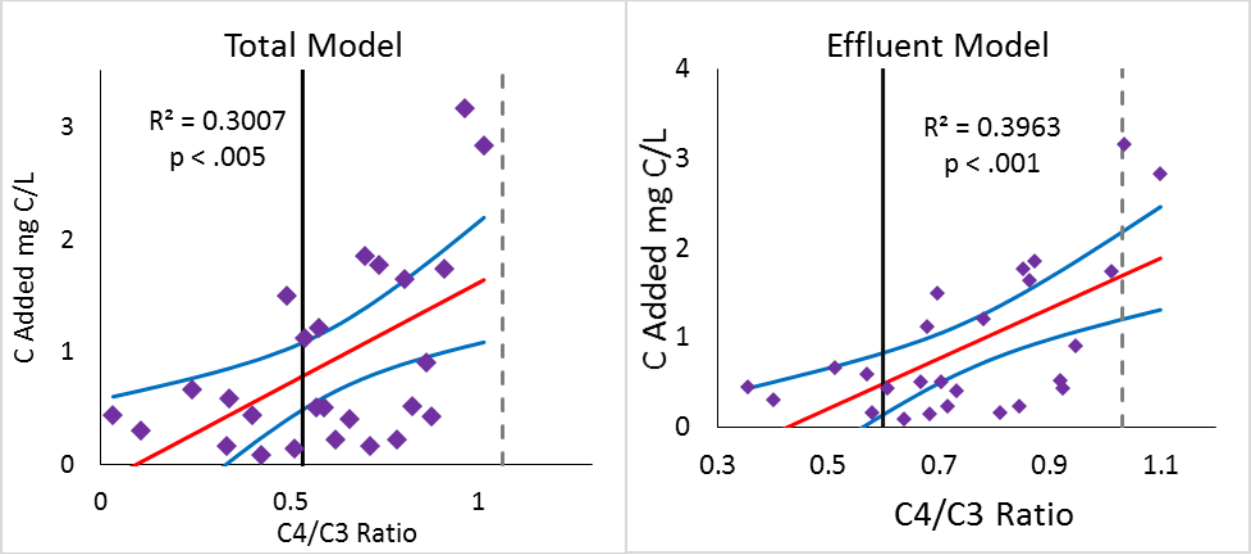

Figure 32 - Detection limit regression of the Total Model and Effluent Model using real samples from the oxic tank and effluent. Red and blue lines are the linear regression of the single sample dilution series and 95% CI of the regression, respectively. The black vertical line and gray hashed lines are the mean C4/C3 Ratios of the pure effluent samples and two standard deviations from the means, respectively. Purple diamonds are the dilution series used to create the plots.

When using a variety of samples, the Effluent Model yielded the lowest detection limit. The Total Model response was similar to that of the Effluent Model, but the standard deviation of the average C4/C3 Ratio in the effluent was larger using the Total Model. This reflects the improved fit of the model using samples taken only from the effluent. For the Total Model, two standard deviations from the mean was outside the range of the standard dilution curve and no detection limit was determined. Using the C4/C3 Ratio of the Effluent Model yielded a mean detection limit of 1.70±0.49 mg C/L from the oxic tank. This amounts to ~31% of the average TOC of the treated effluent.

PARAFAC component loadings require a large sample dataset and are labor intensive to acquire. For this reason they do not lend themselves to online monitoring. Fortunately, single wavelength pairs have been shown to correlate strongly to PARAFAC component loadings

(Murphy et al., 2011; Yu et al., 2015). Single wavelength pairs were selected that monitor wavelengths in the same region as tryptophan-like C4 and humic-like C3. These wavelengths correspond to peaks T and C, respectively. Also, in the case of a single wavelength pair, peak B was shown to have the largest response (**Figure 33**).

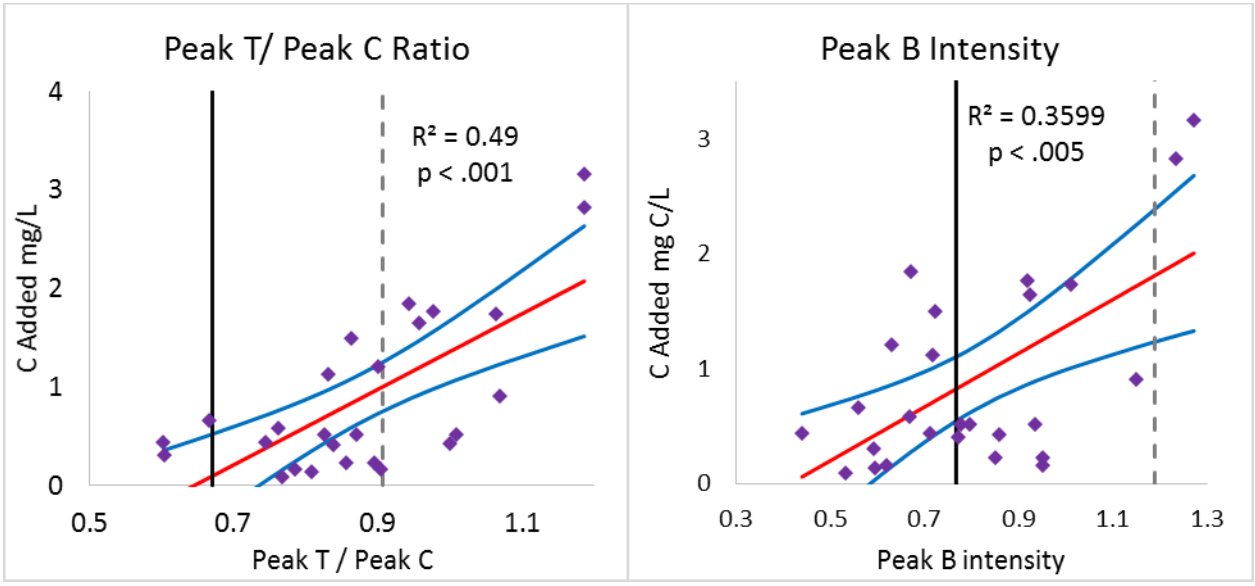

Figure 33 - Detection limit regressions using wavelength pairs identified from PARAFAC. The black vertical lines are mean peak T to peak C ratio and peak b intensities. Gray hashed lines are two standard deviations from these means. Purple diamonds are the dilution series used to create the plots.

Peak T / Peak C ratio yielded a mean detection limit of 0.99±0.25mg C/L and examining only peak B yielded a mean detection limit of 1.72±0.53mg C/L. The detection limit using a single wavelength was equal to that of using the PARAFAC components and the ratio of peaks showed even greater detection limits. This result is surprising, yet it has been reported that peak picking could have the advantage of being minimally affected by shifts in peak location compared to PARAFAC loadings (Yu et al., 2015). This is possibly the cause of the increase in sensitivity observed as the oxic tank conditions and effluent quality of the system under

consideration has been shown to be variable. It is for this reason that (Yu et al., 2015) recommends only using PARAFAC for monitoring contamination from a source that has components or peaks that are not normally present in the monitored water.

It should also be considered that while the fluorescence peak related methods yielded lower detection limits, the Pearson's R of these regressions was much lower than those of the PARAFAC based techniques. Therefore, the reliability of these relationships is in question. In this area, the PARAFAC based methods can provide greater confidence in the determined detection limit.

Twenty six pairs of samples were used in this study which had the effect of drastically lowering the R^2 of the regression of this dilution series compared to the single sample dilution series. This is due to the increased variability in the sample set. This is the difference between using a single sample to create a series of dilutions, as done by Stedmon et al. (2011), and using multiple samples. As shown above, the conditions in the oxic tank and the quality of the effluent change over time and even show variation between samples collected at the same time. Additionally, as was seen from the dilution experiment run with a single pair of samples, the single sample pair may not be representative of the system. This result indicates that the variability of the water treatment system over time should be taken into account when determining contamination detection limits and multiple samples should be used whenever possible. Future contamination detection limit studies should be careful to consider the variability of the system being studied.

Fluorescence as a Monitoring Technique for Wastewater Treatment

Fluorescence was shown to be an effective tool to monitor the removal of carbon throughout the waste stream for a full scale MBR (**Figure 22**) and to correlate to TOC removal for a given source of waste (**Figure 29**). While fluorescence did relate to the safety of reclaimed water in that untreated oxic tank water was detectable in the effluent of the MBR system (**Figure 32**), the fluorescence parameters did not correlate directly to *Escherichia coli* or total coliform measurements. These bacteria are used as indicator species for the contamination of a water source by fecal material.

The relationships between fluorescence parameters and coliform measurements were investigated and are shown in **Appendix A** at **Total coliforms** and **E. Coli**. Unfortunately, no significant correlations were found between these coliform measurements and any fluorescence measurement. This may be the related to the very low amounts of coliforms in the effluent of the MBR system. The majority of the coliform tests returned 0 MPN total coliforms and 0 *E. coli*. Perhaps at high coliform loadings, a direct relationship could develop. It is also important to consider that coliforms and *E. coli* make up only a portion of the bacteria present in wastewater. Efforts to quantify other bacterial counts may have been more fruitful. This is not to say that fluorescence techniques do not offer useful information about water treatment, but simply that they do not directly measure these pathogens.

Chapter 5 - Conclusions

The world's water resources are under pressure and increasingly so (Millennium Ecosystem Assessment, 2005). Failure to respond to these pressures results in increased water security risks. As much as 80% of the world's population has been reported to be in areas of high water security risk due to a convergence of factors, such as watershed disturbance, pollution, water resource development and biotic factors (Voeroesmarty et al., 2010).

Communities in developed nations are highly shielded from the impacts of diminished water security by the ability to offset risk through investments in infrastructure (Voeroesmarty et al., 2010), yet in the U.S. this infrastructure is rapidly aging and reaching the end of designed lifetimes. For example, the American Water Works Association's report, *Buried No Longer: Confronting America's Water Infrastructure Challenge*, predicts that restoring and expanding the existing drinking water infrastructure in the U.S. will cost at least 1 trillion USD over the next 25 years (Raucher et al., 2012). These costs, coupled with government restrictions on water use provide strong incentive for the development and implementation of water reuse technologies at decentralized locations near consumers (Li et al., 2011).

With the implementation of water reuse systems, there comes increased risk and an increase in perceived risk by the public (Hambly et al., 2012; Henderson et al., 2009). This risk can be mitigated by rapid and sensitive water treatment monitoring technologies. Fluorescence spectroscopy has shown much promise in this regard due to its sensitivity, selectivity, and ability to be placed online in water treatment streams (Hambly et al., 2010; Henderson et al., 2009).

The goal of the present study was to further evaluate the effectiveness of fluorescence spectroscopy as a water quality monitoring technique. To this end, a full scale MBR system treating wastewater from a military barracks in Fort Riley, KS was monitored using fluorescence

spectroscopy along with other water quality measurements over a period of three months in 2016. Fluorescence was employed online to the effluent of the system and grab samples were collected periodically for the generation of full EEMs. From these EEMs, two PARAFAC models were created for the comparison of PARAFAC, EEM analysis, and online fluorescence as monitoring techniques.

From the examination of the online data and grab samples, two startup periods were identified instead of a typical single startup period. During the first 60 days of the study, the TMP increased steadily and then levelled off. This change in pressure across the membrane reflected the development of a biofilm on the membrane surface. During the first 91 days, the nitrogen and phosphorus levels of the oxic tank increased and then levelled off. Additionally, as the nutrient levels began to stabilize the biodegradation of DOM in the oxic tank began to increase. Both of these startup phases showed value in predicting trends over time in fluorescence components and the removal of those components.

From the grab samples, a series of dilutions were made to simulate contamination in the effluent from the oxic tank. A comparison of fluorescence related monitoring techniques showed that the most sensitive parameter for detecting effluent contamination was a ratio of the intensities of peak T/ peak C, which yielded a detection limit of 0.99 ± 0.25mg C/L. It is possible that the peak T / peak C ratio correlated more closely to the amount of oxic tank in the diluted sample because the peaks were less susceptible to slight variations in peak location, and therefore more able to reflect the true signal, rather than noise. The finding that a ratio of peaks showed greater sensitivity than a ratio of two component from a PARAFAC model has important implications for water reuse monitoring. The use of peak intensity data is much less time consuming and requires less processing after data collection.

Also, a simple parameter was shown to relate to treatment efficacy of the studied MBR system. The ratio of the influent humic-like components to protein-like components was shown to correlate well with TOC removal ($R^2 = .845$, $p < .001$). Due to the time consuming nature of PARAFAC and the necessity of a large number of samples to create the PARAFAC model, single peaks were evaluated that monitored fluorescence intensity at wavelengths correlated to a humic-like component (C1) and a protein-like component (C5). The ratio of these peaks showed lowed correlation, but was still shown to have a significant relationship with TOC removal ($R^2 = .595$, $p < .001$). The more protein-like character the DOM had in this system, the greater the TOC removal the system was able to accomplish.

Fluorescence was shown to be useful for treatment monitoring over time, contamination detection, and to relate to TOC removal, but was not shown to relate directly to the presence of water borne pathogens. In addition to verifying the two phase startup period identified in this research, future needs in the evaluation of fluorescence spectroscopy in water treatment monitoring include: a greater understanding of the effects of dynamic influent quality on wastewater treatment and how this influences fluorescence based monitoring techniques, broadening the types of systems for which fluorescence based contamination detection limits have been investigated, and futher investigation of the sources of temporal variation in treatment efficacy in MBR systems. While much work in this area has been accomplished, there is still need for improved water treatment monitoring technologies.

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Appendix A - Supplementary figures

Percent distributions

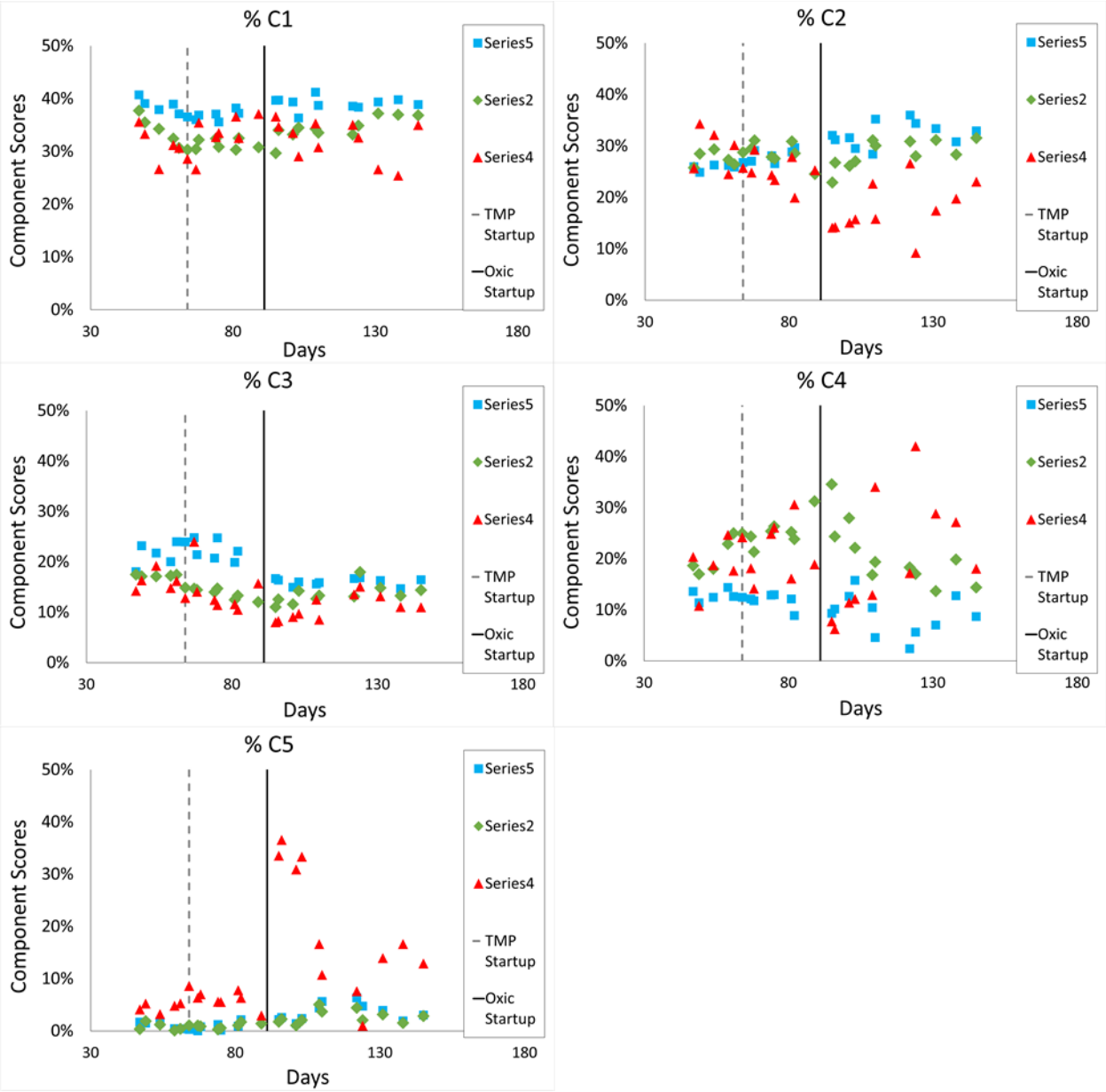
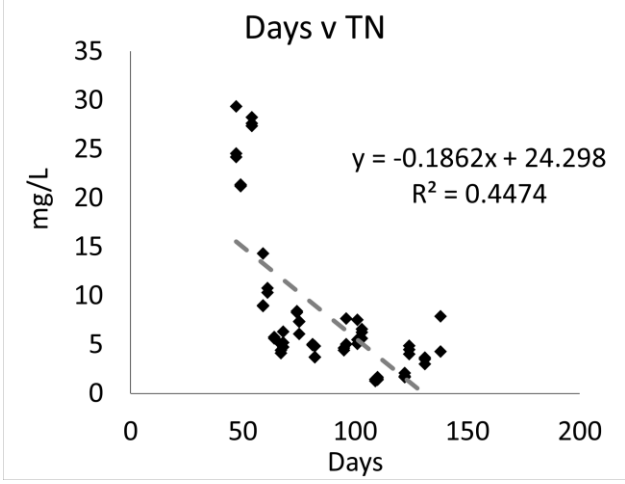


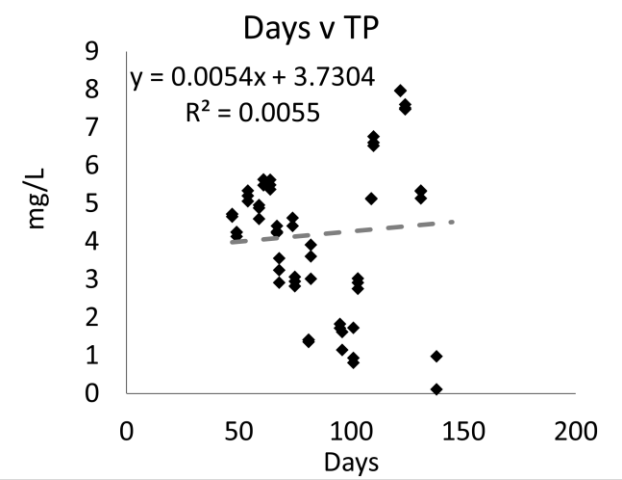
Figure 34 - Percent distribution of components over time by source

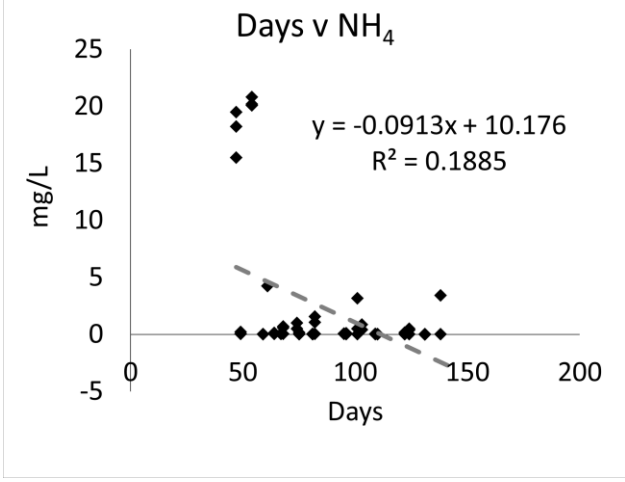
Data correlations

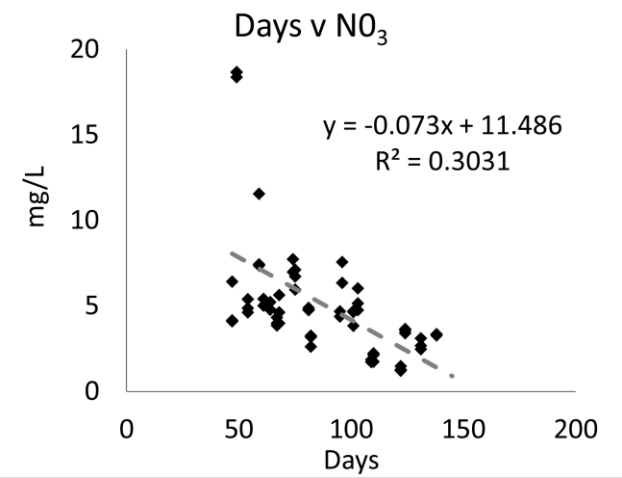
Days

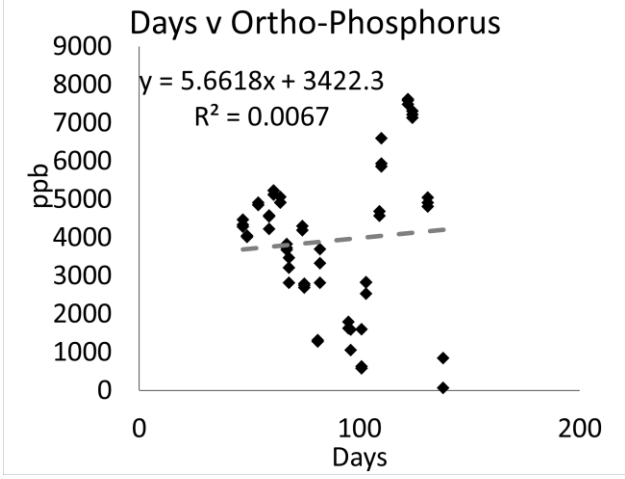
Effluent

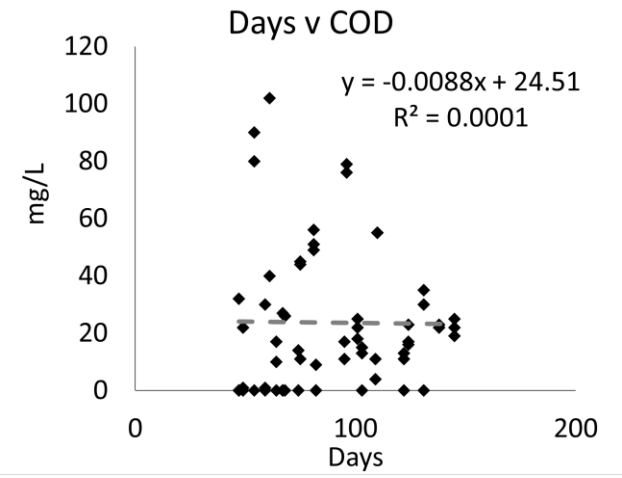

Days v TN
y = -0.1862x + 24.298
R² = 0.4474
mg/L
Days

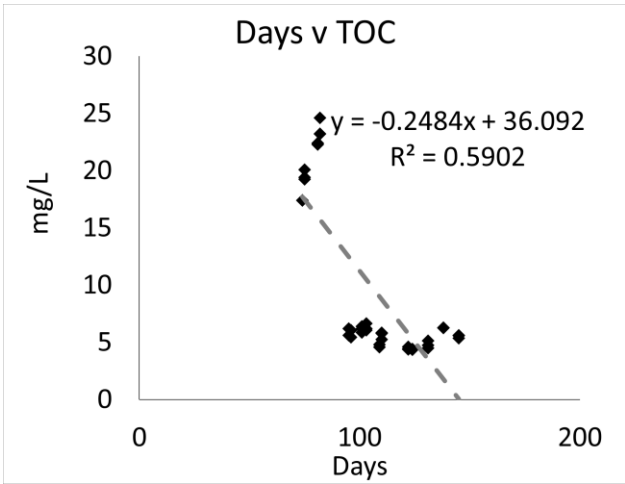

Days v TP
y = 0.0054x + 3.7304
R² = 0.0055
mg/L
Days

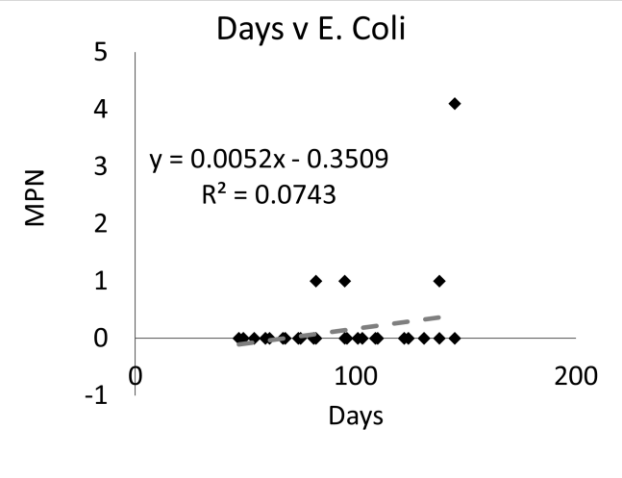

Days v NH4
y = -0.0913x + 10.176
R² = 0.1885
mg/L
Days

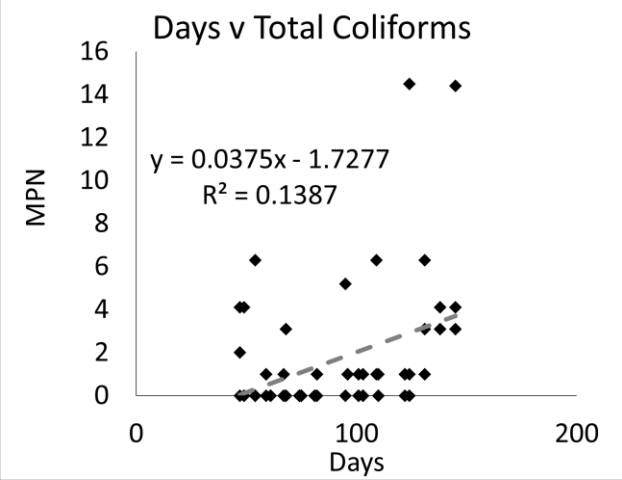

Days v NO3
y = -0.073x + 11.486
R² = 0.3031
mg/L
Days

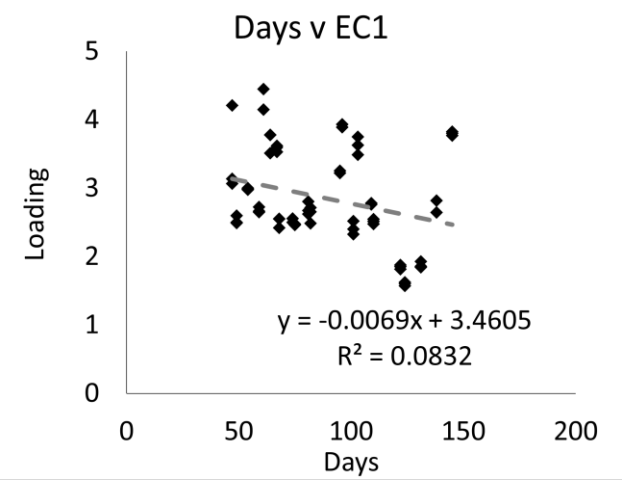

Days v Ortho-Phosphorus
y = 5.6618x + 3422.3
R² = 0.0067
ppb
Days

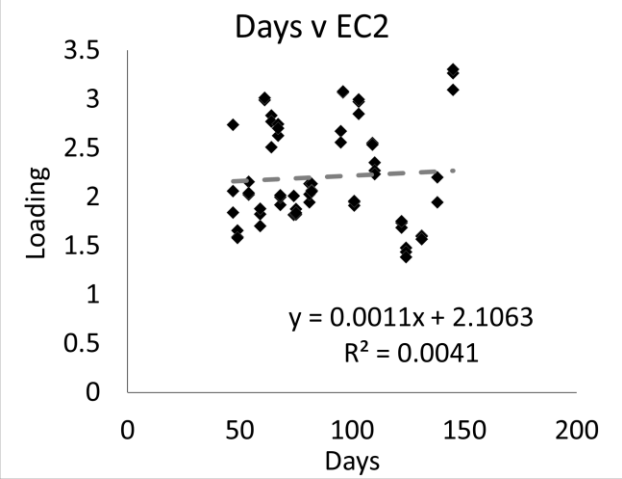

Days v COD
y = -0.0088x + 24.51
R² = 0.0001
mg/L
Days

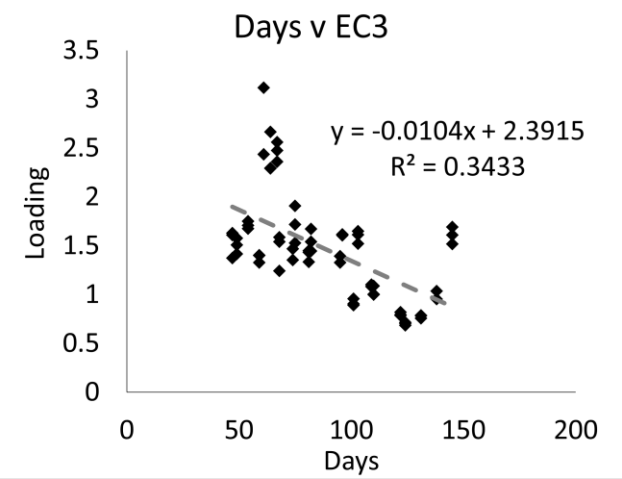

Days v TOC
y = -0.2484x + 36.092
R² = 0.5902
mg/L
Days
0
5
10
15
20
25
30
0
100
200

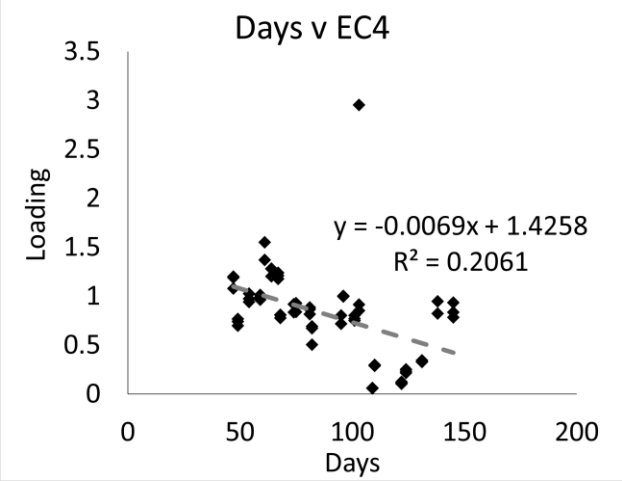

Days v E. Coli
y = 0.0052x - 0.3509
R² = 0.0743
MPN
Days
-1
0
1
2
3
4
5
0
100
200

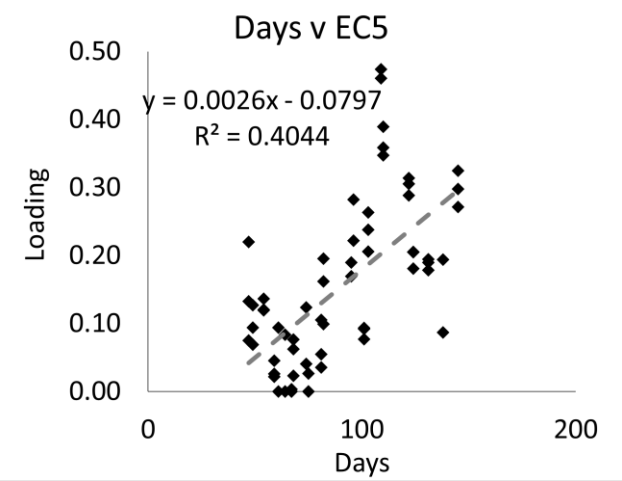

Days v Total Coliforms
y = 0.0375x - 1.7277
R² = 0.1387
MPN
Days
0
2
4
6
8
10
12
14
16
0
100
200

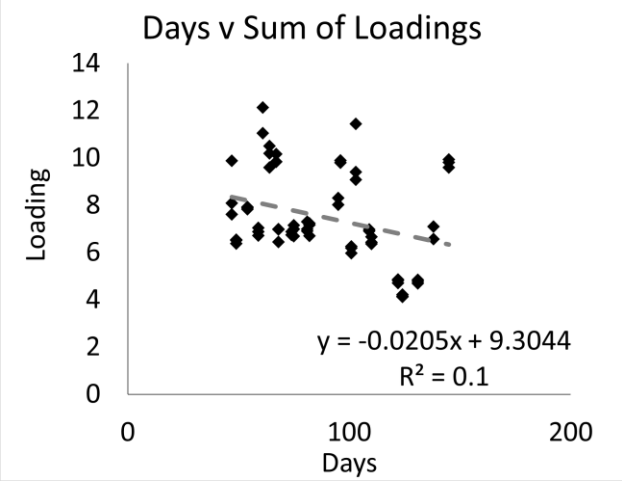

Days v EC1
y = -0.0069x + 3.4605
R² = 0.0832
Loading
Days
0
1
2
3
4
5
0
50
100
150
200

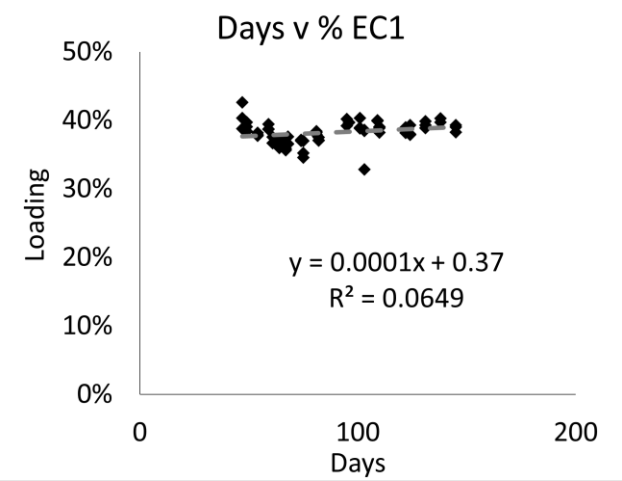

Days v EC2
y = 0.0011x + 2.1063
R² = 0.0041
Loading
Days
0
0.5
1
1.5
2
2.5
3
3.5
0
50
100
150
200

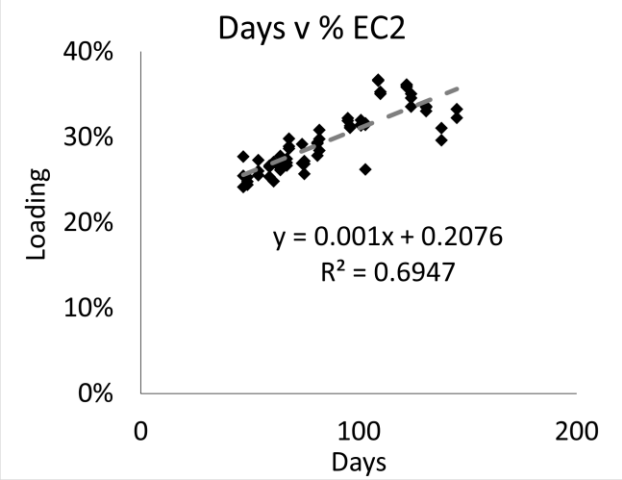

Days v EC3
y = -0.0104x + 2.3915
R² = 0.3433
Loading
Days
0
0.5
1
1.5
2
2.5
3
3.5
0
50
100
150
200

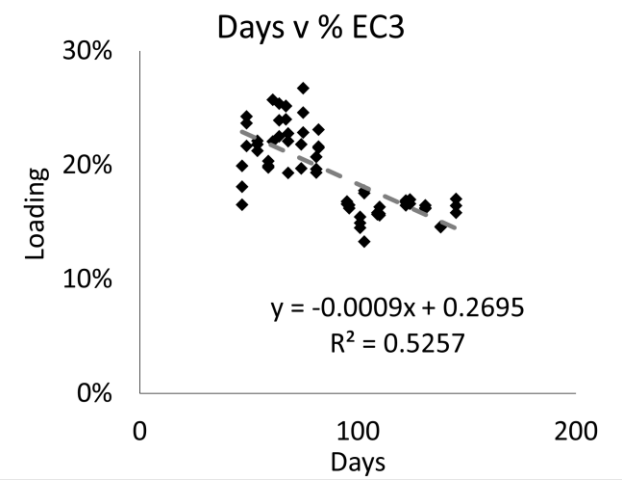

Days v EC4
Loading
Days
y = -0.0069x + 1.4258
R² = 0.2061
3.5
3
2.5
2
1.5
1
0.5
0
0
50
100
150
200

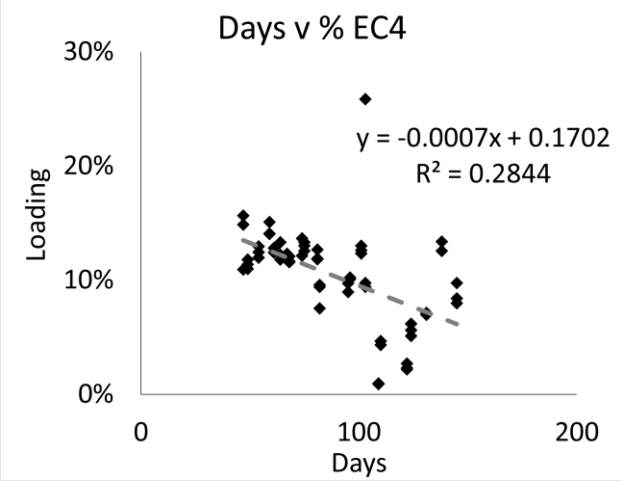

Days v EC5
Loading
Days
y = 0.0026x - 0.0797
R² = 0.4044
0.50
0.40
0.30
0.20
0.10
0.00
0
100
200

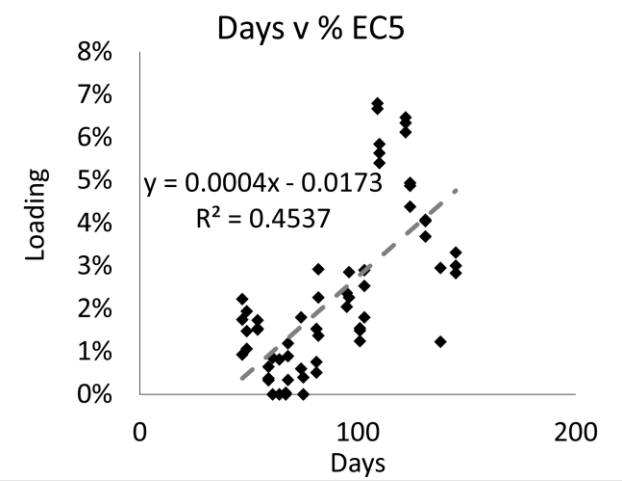

Days v Sum of Loadings
Loading
Days
y = -0.0205x + 9.3044
R² = 0.1
14
12
10
8
6
4
2
0
0
100
200

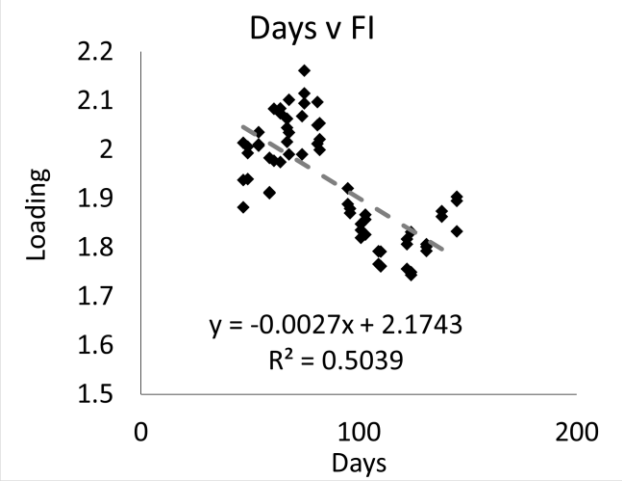

Days v % EC1
Loading
Days
y = 0.0001x + 0.37
R² = 0.0649
50%
40%
30%
20%
10%
0%
0
100
200

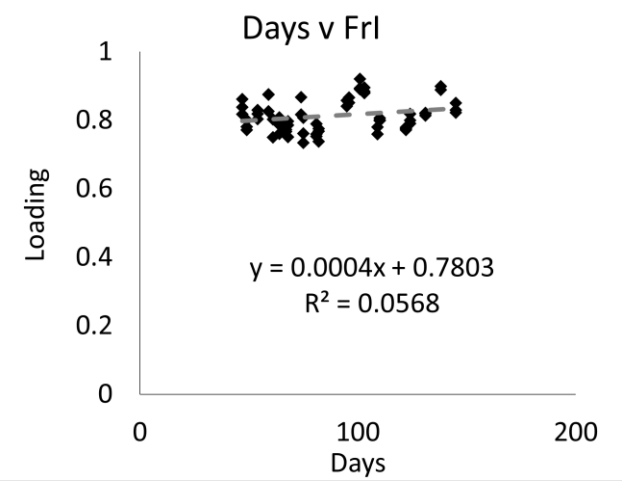

Days v % EC2
Loading
Days
y = 0.001x + 0.2076
R² = 0.6947
40%
30%
20%
10%
0%
0
100
200

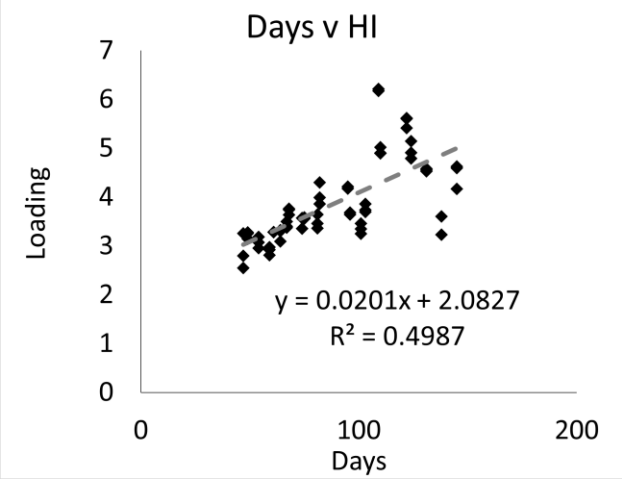

Days v % EC3
Loading
Days
y = -0.0009x + 0.2695
R² = 0.5257
30%
20%
10%
0%
0
100
200

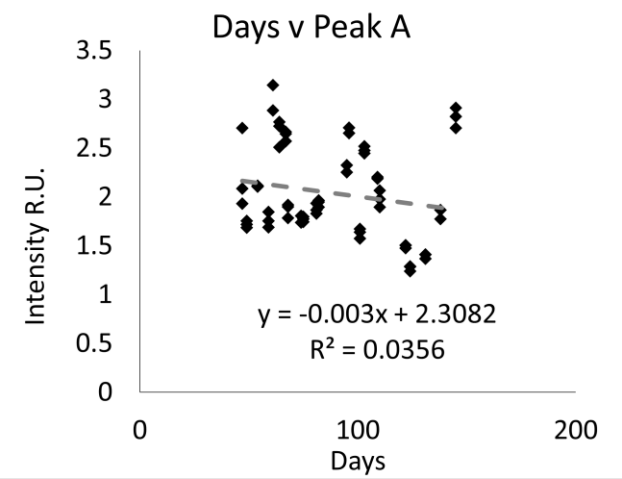

Days v % EC4
y = -0.0007x + 0.1702
R² = 0.2844
Loading
Days
30%
20%
10%
0%
0
100
200

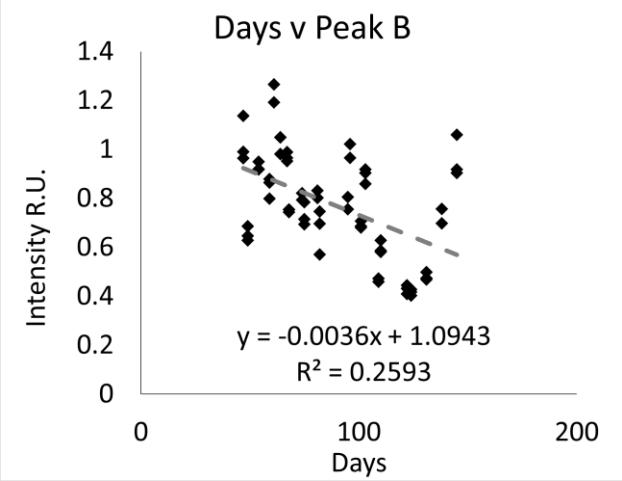

Days v % EC5
y = 0.0004x - 0.0173
R² = 0.4537
Loading
Days
8%
7%
6%
5%
4%
3%
2%
1%
0%
0
100
200

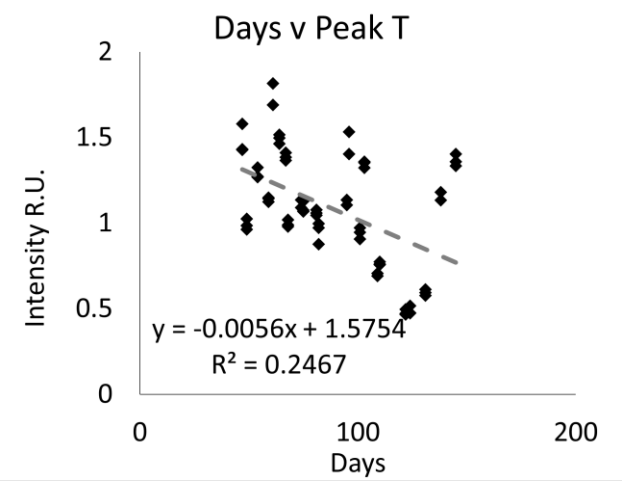

Days v FI
y = -0.0027x + 2.1743
R² = 0.5039
Loading
Days
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
0
100
200

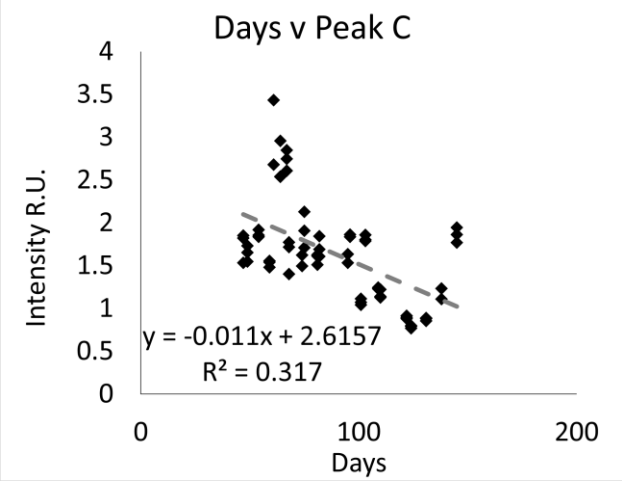

Days v FrI
y = 0.0004x + 0.7803
R² = 0.0568
Loading
Days
1
0.8
0.6
0.4
0.2
0
0
100
200

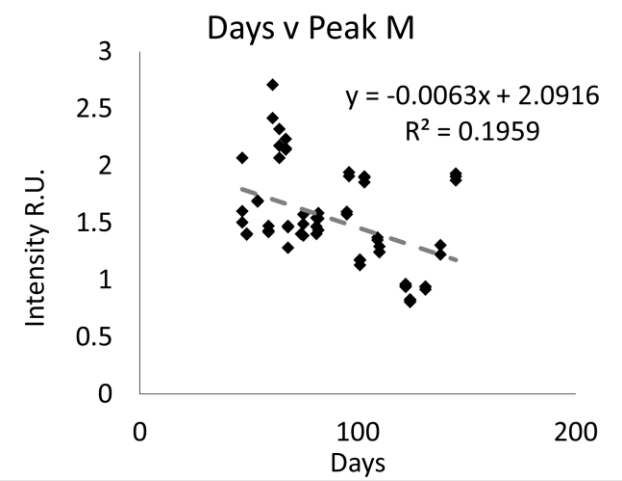

Days v HI
y = 0.0201x + 2.0827
R² = 0.4987
Loading
Days
7
6
5
4
3
2
1
0
0
100
200

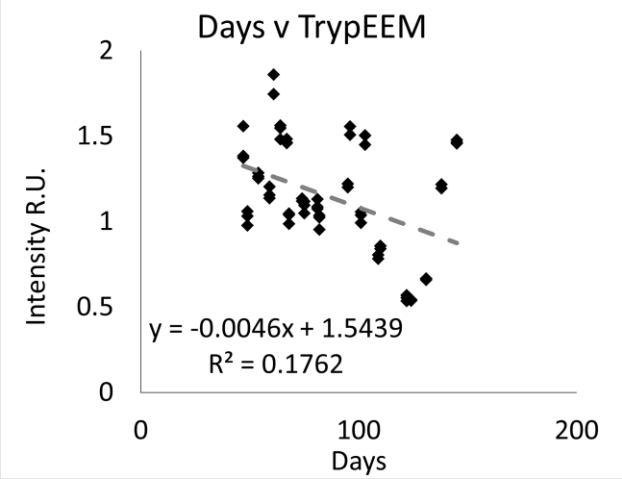

Days v Peak A
y = -0.003x + 2.3082
R² = 0.0356
Intensity R.U.
Days
3.5
3
2.5
2
1.5
1
0.5
0
0
100
200

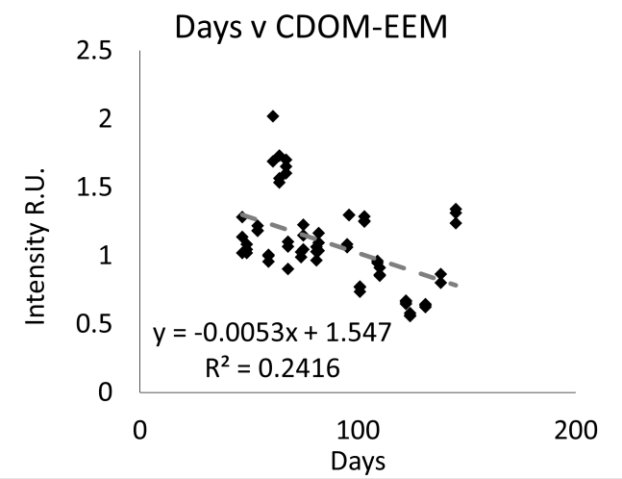

Days v Peak B
Intensity R.U.
Days
y = -0.0036x + 1.0943
R² = 0.2593

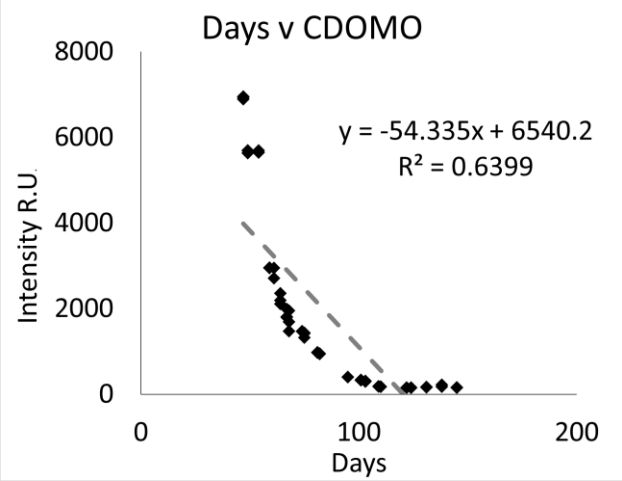

Days v Peak T
Intensity R.U.
Days
y = -0.0056x + 1.5754
R² = 0.2467

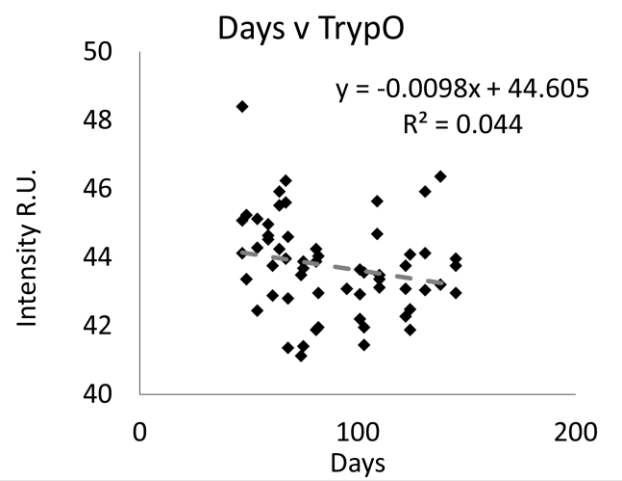

Days v Peak C
Intensity R.U.
Days
y = -0.011x + 2.6157
R² = 0.317

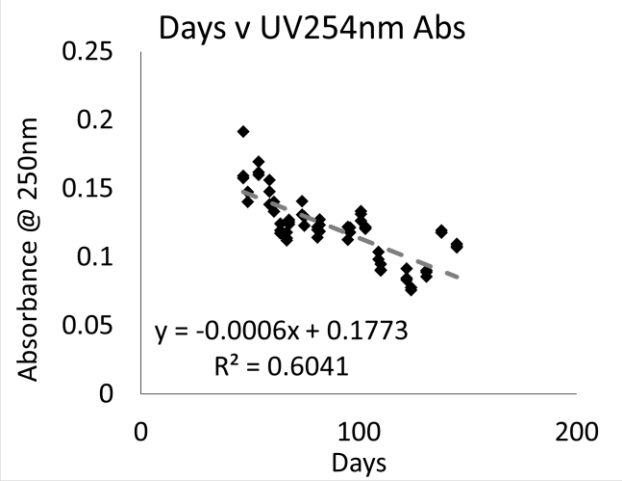

Days v Peak M
Intensity R.U.
Days
y = -0.0063x + 2.0916
R² = 0.1959

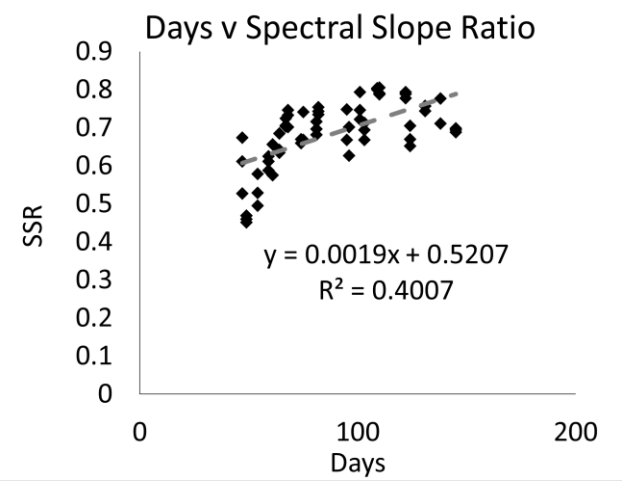

Days v TrypEEM
Intensity R.U.
Days
y = -0.0046x + 1.5439
R² = 0.1762


Days v CDOM-EEM
Intensity R.U.
Days
y = -0.0053x + 1.547
R² = 0.2416

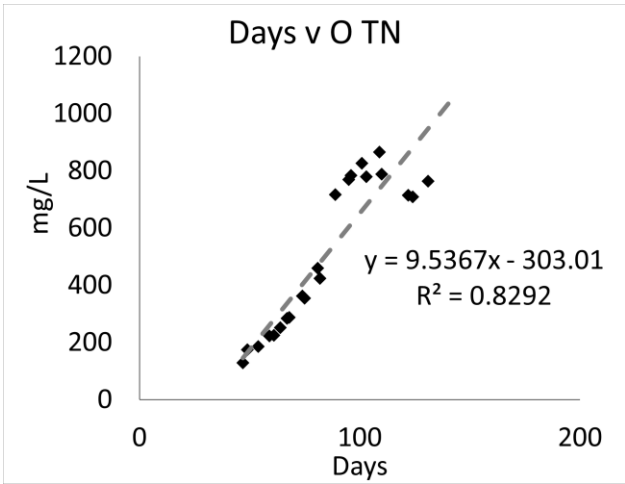

Days v CDOMO
Intensity R.U.
8000
6000
4000
2000
0
0
100
200
Days
y = -54.335x + 6540.2
R² = 0.6399

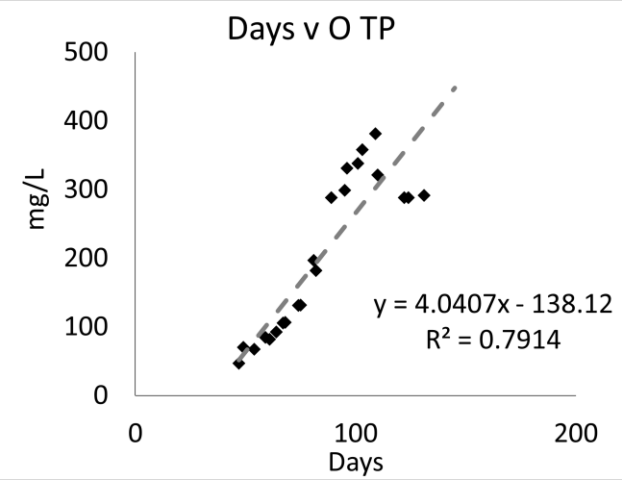

Days v TrypO
Intensity R.U.
50
48
46
44
42
40
0
100
200
Days
y = -0.0098x + 44.605
R² = 0.044

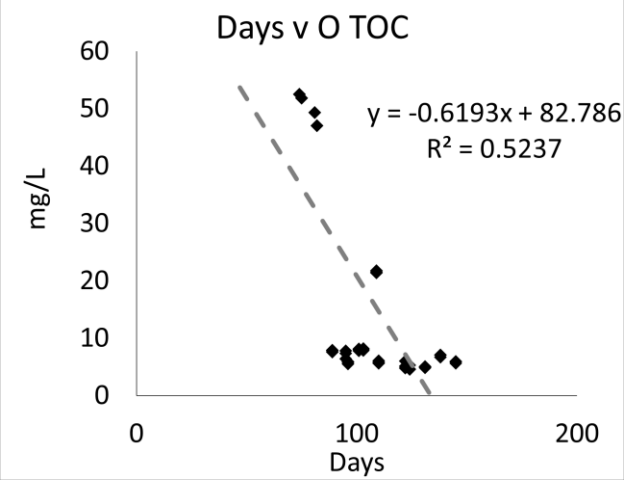

Days v UV254nm Abs
Absorbance @ 250nm
0.25
0.2
0.15
0.1
0.05
0
0
100
200
Days
y = -0.0006x + 0.1773
R² = 0.6041

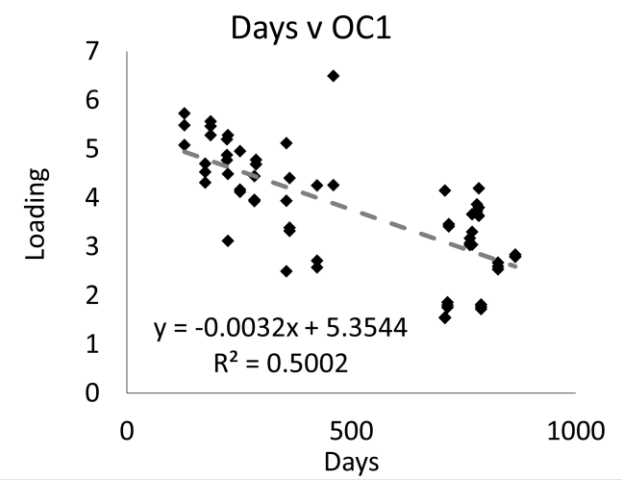

Days v Spectral Slope Ratio
SSR
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
100
200
Days
y = 0.0019x + 0.5207
R² = 0.4007

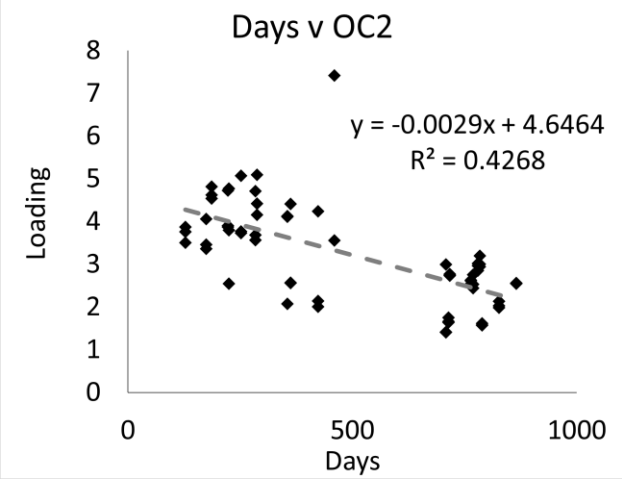
Oxic

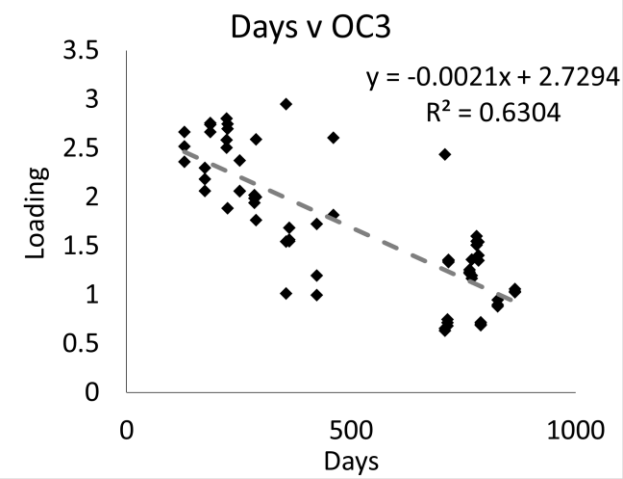

Days v O TN
mg/L
Days
y = 9.5367x - 303.01
R² = 0.8292
0
200
400
600
800
1000
1200
0
100
200

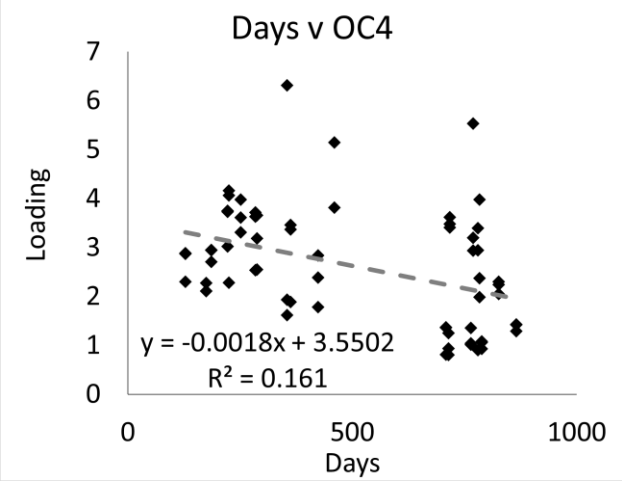

Days v O TP
mg/L
Days
y = 4.0407x - 138.12
R² = 0.7914
0
100
200
300
400
500
0
100
200

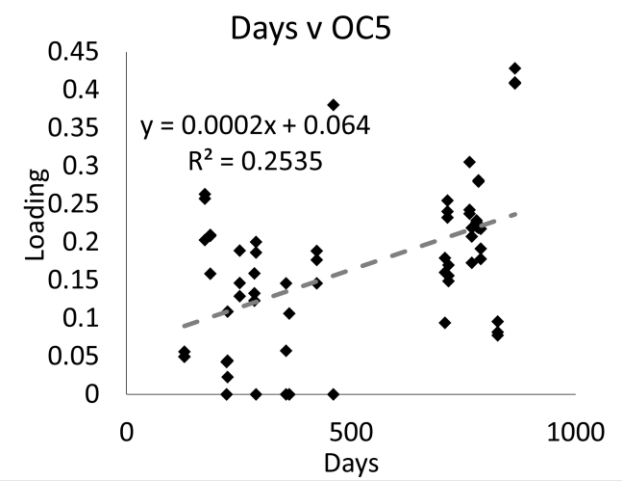

Days v O TOC
mg/L
Days
y = -0.6193x + 82.786
R² = 0.5237
0
10
20
30
40
50
60
0
100
200

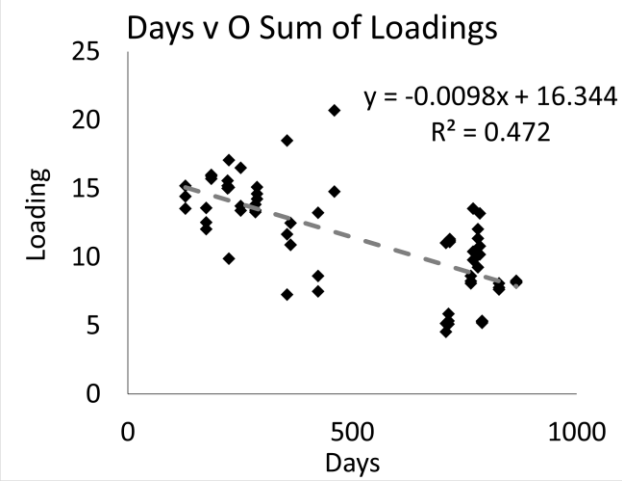

Days v OC1
Loading
Days
y = -0.0032x + 5.3544
R² = 0.5002
0
1
2
3
4
5
6
7
0
500
1000

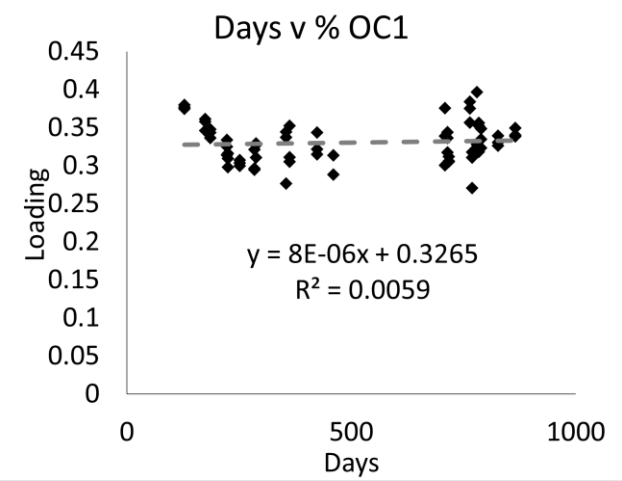

Days v OC2
Loading
Days
y = -0.0029x + 4.6464
R² = 0.4268
0
1
2
3
4
5
6
7
8
0
500
1000

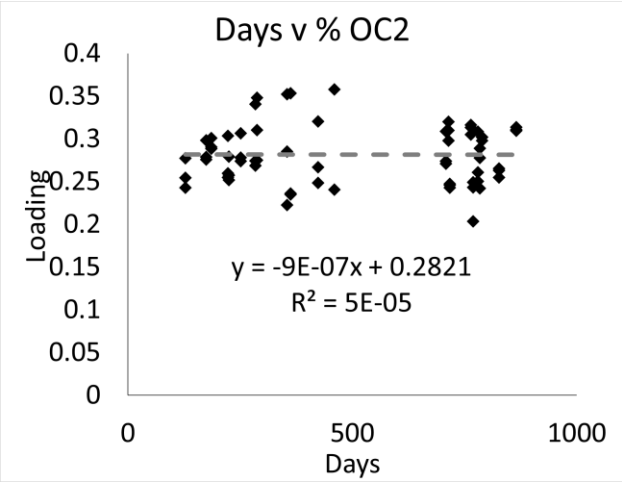

Days v OC3
Loading
Days
y = -0.0021x + 2.7294
R² = 0.6304
0
0.5
1
1.5
2
2.5
3
3.5
0
500
1000

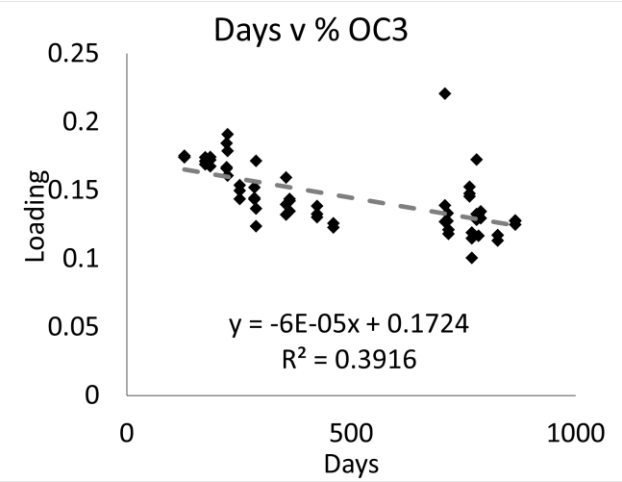

Days v OC4
Loading
Days
y = -0.0018x + 3.5502
R² = 0.161
0
1
2
3
4
5
6
7
0
500
1000

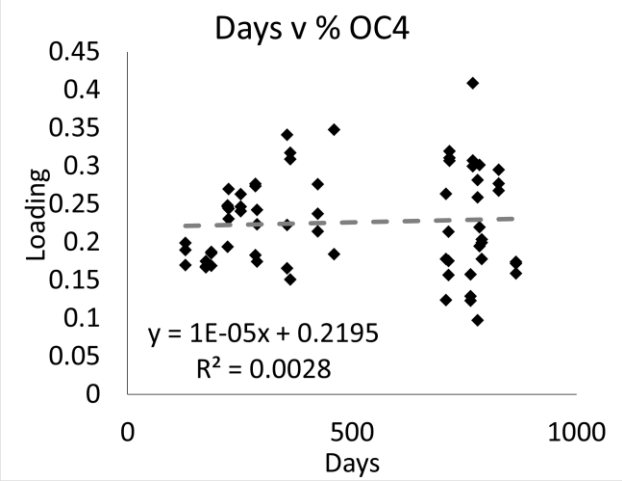

Days v OC5
Loading
Days
y = 0.0002x + 0.064
R² = 0.2535
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0
500
1000

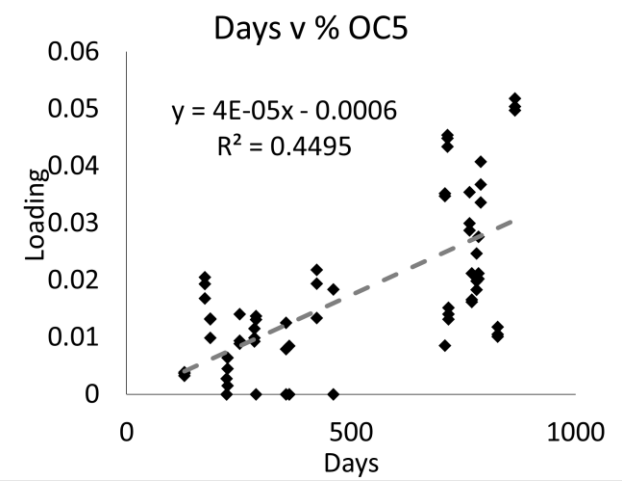

Days v O Sum of Loadings
Loading
Days
y = -0.0098x + 16.344
R² = 0.472
0
5
10
15
20
25
0
500
1000

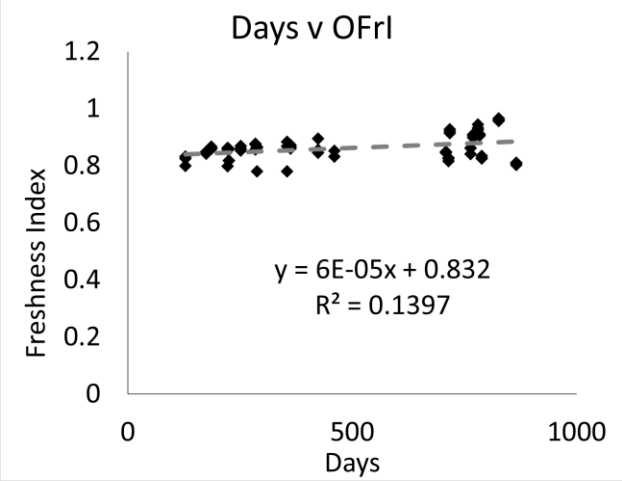

Days v % OC1
Loading
Days
y = 8E-06x + 0.3265
R² = 0.0059
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0
500
1000

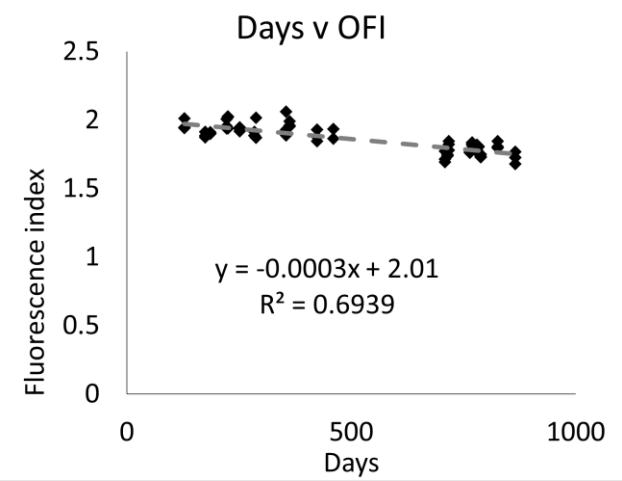

Days v % OC2
Loading
Days
y = -9E-07x + 0.2821
R² = 5E-05
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0
500
1000

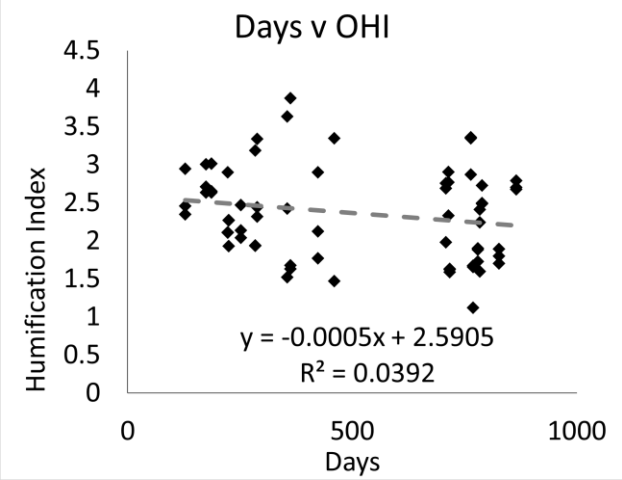

Days v % OC3
Loading
Days
y = -6E-05x + 0.1724
R² = 0.3916
0
0.05
0.1
0.15
0.2
0.25
0
500
1000

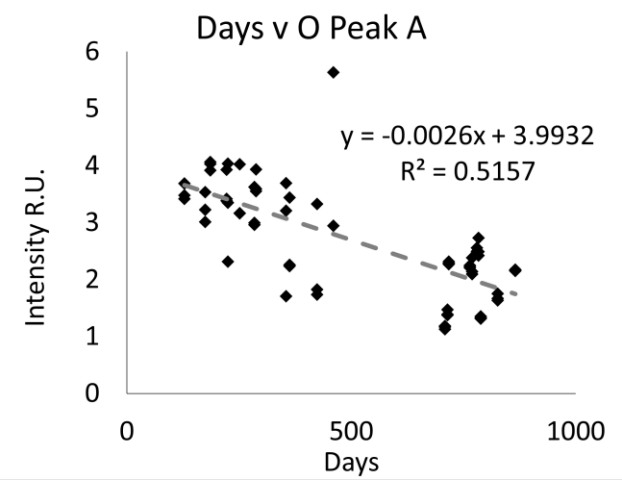

Days v % OC4
Loading
Days
y = 1E-05x + 0.2195
R² = 0.0028
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
500
1000

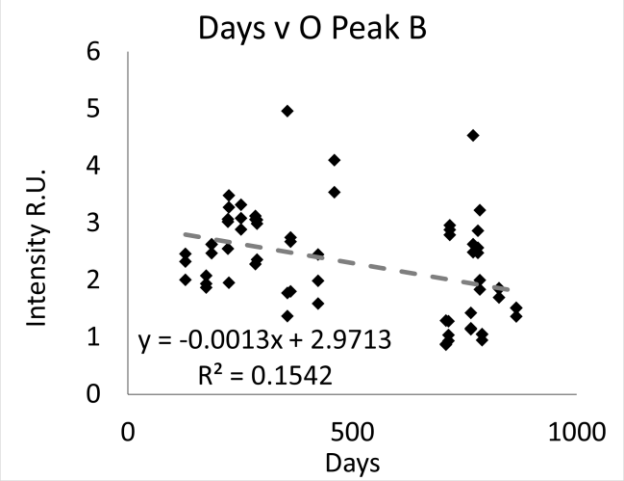

Days v % OC5
Loading
Days
y = 4E-05x - 0.0006
R² = 0.4495
0.06
0.05
0.04
0.03
0.02
0.01
0
0
500
1000

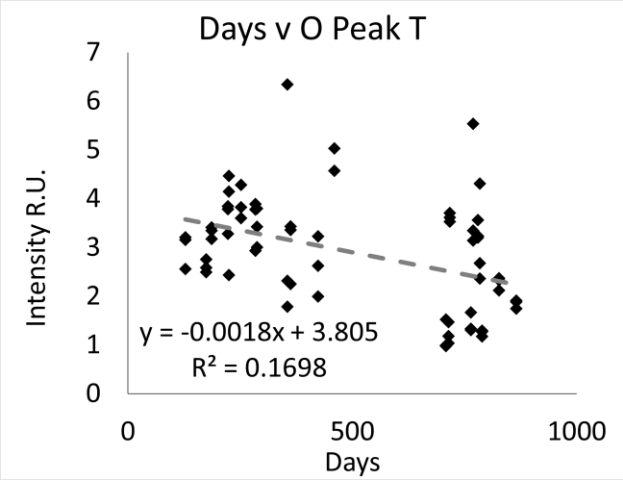

Days v OFrI
Freshness Index
Days
y = 6E-05x + 0.832
R² = 0.1397
1.2
1
0.8
0.6
0.4
0.2
0
0
500
1000

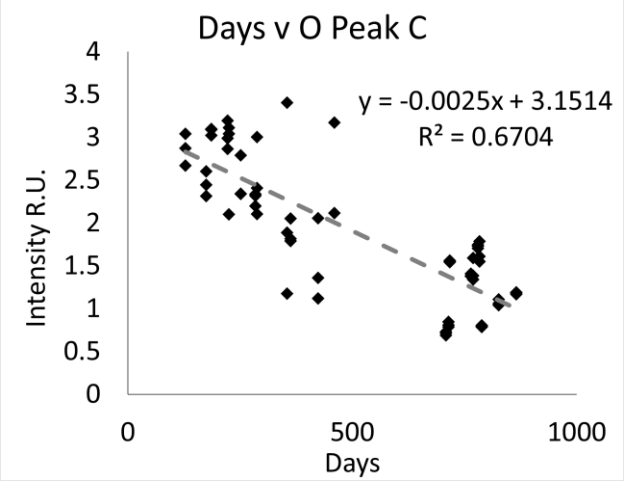

Days v OFI
Fluorescence index
Days
y = -0.0003x + 2.01
R² = 0.6939
2.5
2
1.5
1
0.5
0
0
500
1000

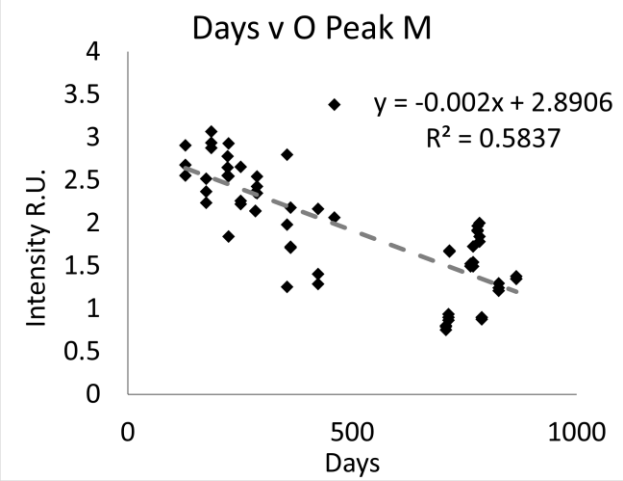

Days v OHI
Humification Index
Days
y = -0.0005x + 2.5905
R² = 0.0392
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
0
500
1000

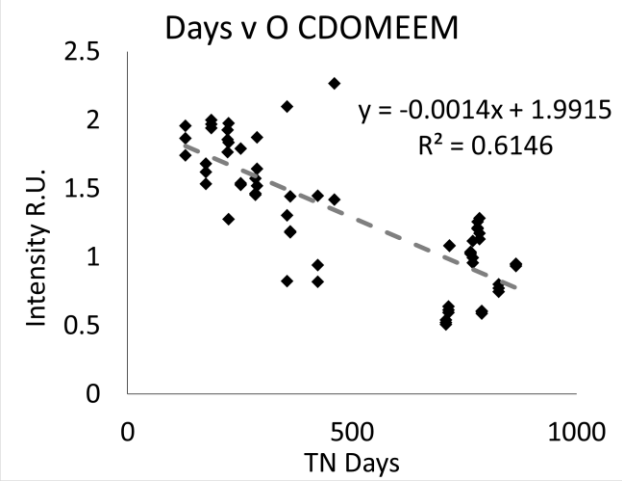

Days v O Peak A
Intensity R.U.
Days
y = -0.0026x + 3.9932
R² = 0.5157
6
5
4
3
2
1
0
0
500
1000

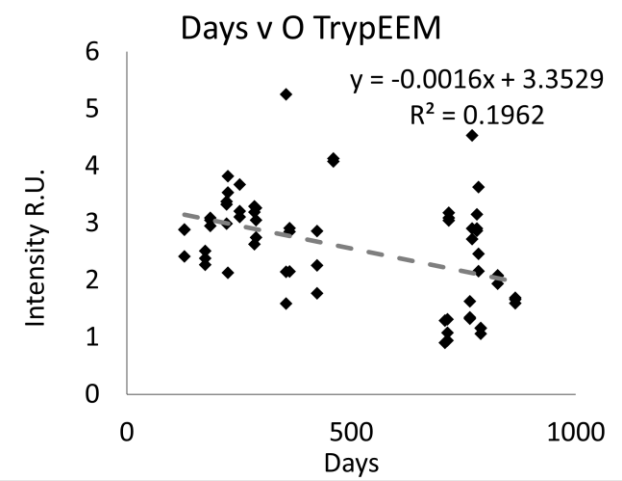

Days v O Peak B
Intensity R.U.
Days
y = -0.0013x + 2.9713
R² = 0.1542
0
1
2
3
4
5
6
0
500
1000

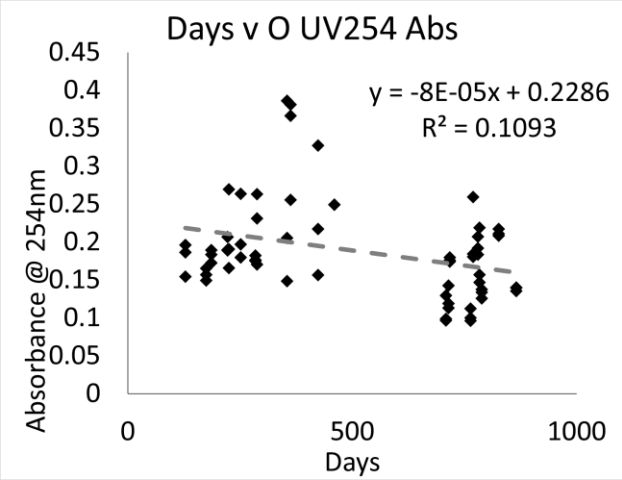

Days v O Peak T
Intensity R.U.
Days
y = -0.0018x + 3.805
R² = 0.1698
0
1
2
3
4
5
6
7
0
500
1000

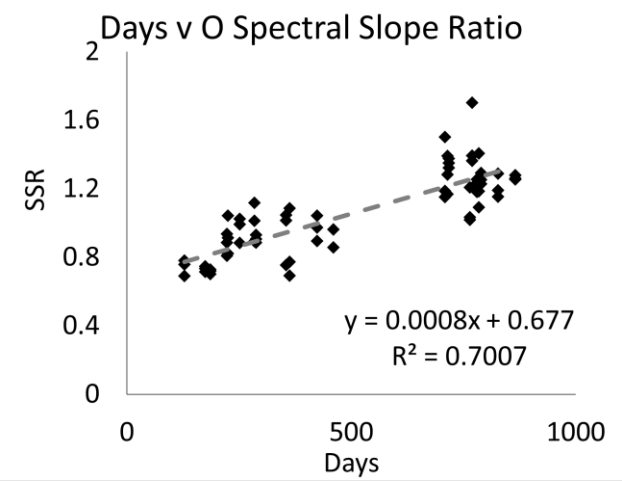

Days v O Peak C
Intensity R.U.
Days
y = -0.0025x + 3.1514
R² = 0.6704
0
0.5
1
1.5
2
2.5
3
3.5
4
0
500
1000


Days v O Peak M
Intensity R.U.
Days
y = -0.002x + 2.8906
R² = 0.5837
0
0.5
1
1.5
2
2.5
3
3.5
4
0
500
1000

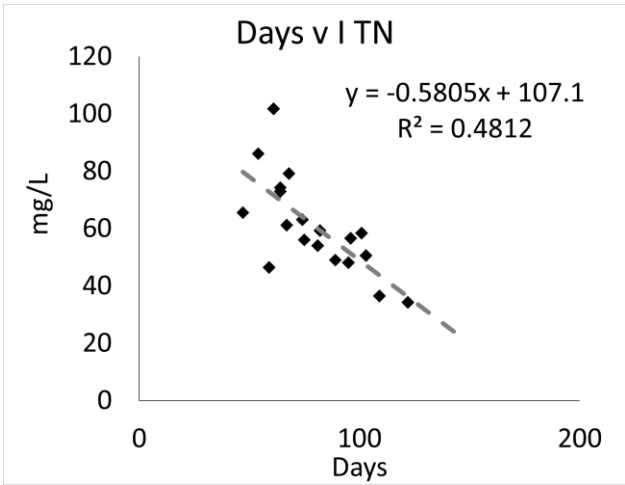

Days v O CDOMEEM
y = -0.0014x + 1.9915
R² = 0.6146
Intensity R.U.
TN Days
0
0.5
1
1.5
2
2.5
0
500
1000

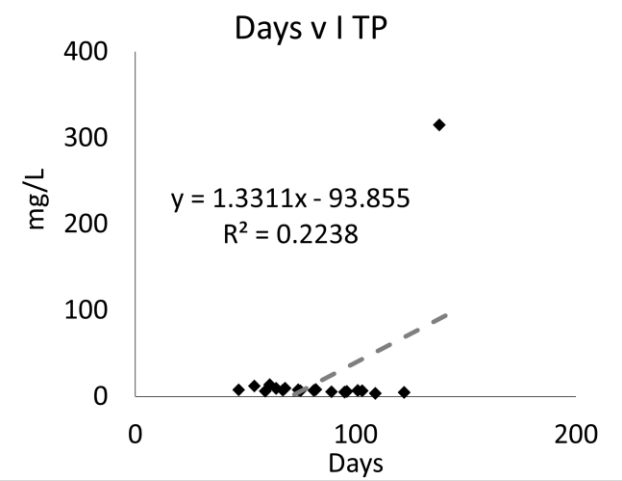

Days v O TrypEEM
y = -0.0016x + 3.3529
R² = 0.1962
Intensity R.U.
Days
0
1
2
3
4
5
6
0
500
1000

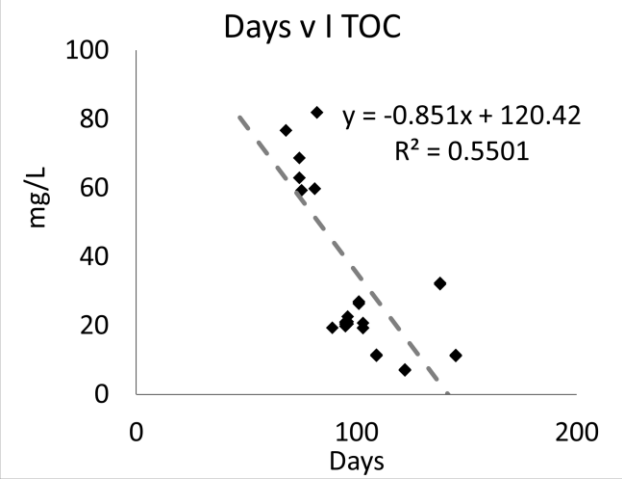

Days v O UV254 Abs
y = -8E-05x + 0.2286
R² = 0.1093
Absorbance @ 254nm
Days
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0
500
1000

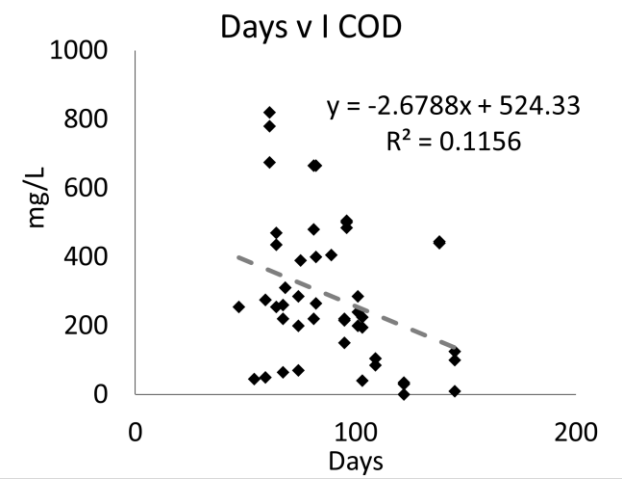

Days v O Spectral Slope Ratio
y = 0.0008x + 0.677
R² = 0.7007
SSR
Days
0
0.4
0.8
1.2
1.6
2
0
500
1000

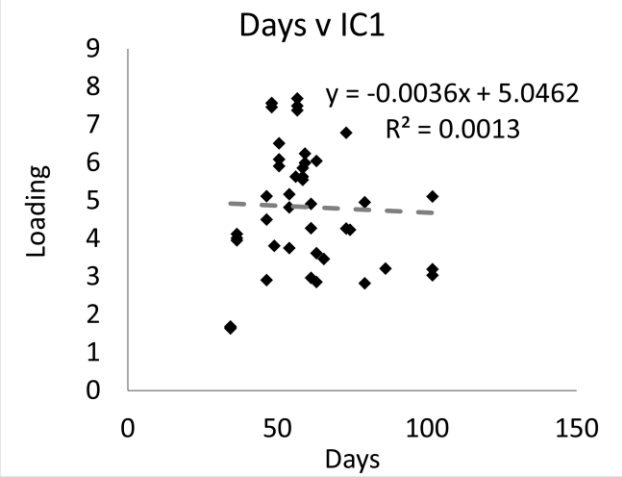
Influent

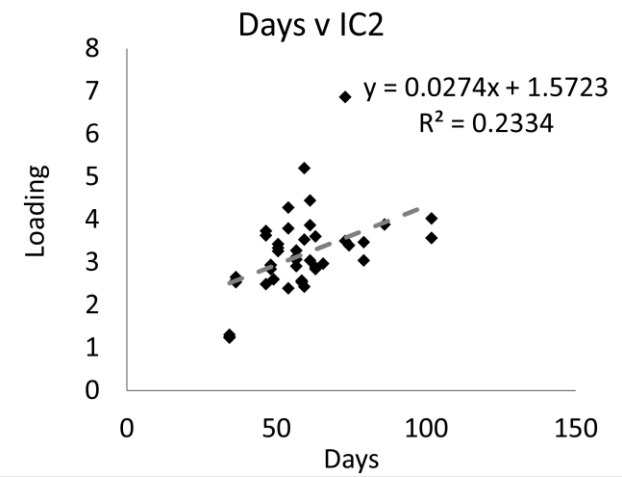

Days v I TN
y = -0.5805x + 107.1
R² = 0.4812
mg/L
Days
0
20
40
60
80
100
120
0
100
200

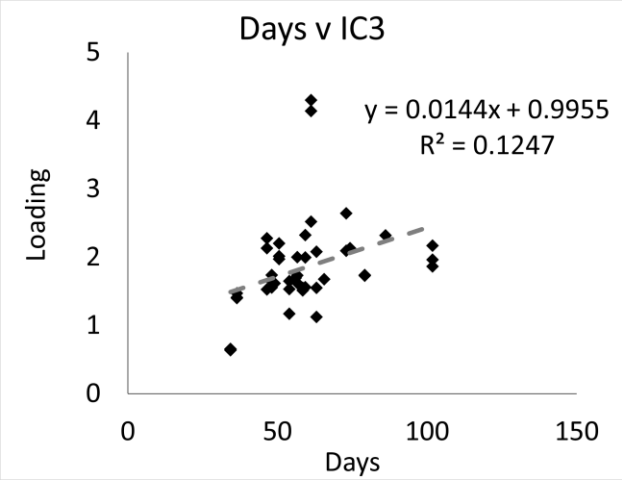

Days v I TP
y = 1.3311x - 93.855
R² = 0.2238
mg/L
Days
0
100
200
300
400
0
100
200

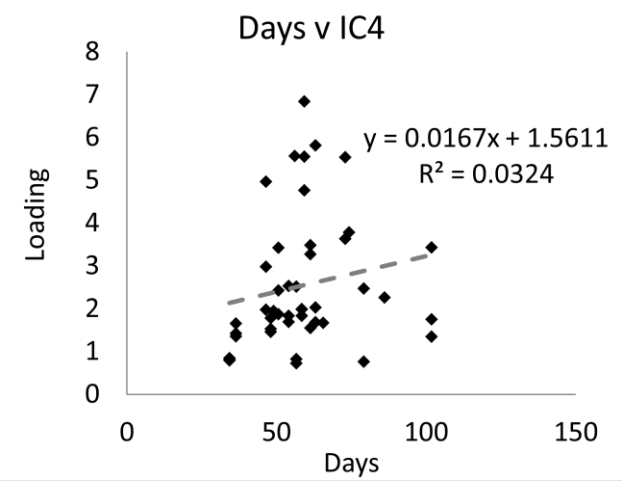

Days v I TOC
y = -0.851x + 120.42
R² = 0.5501
mg/L
Days
0
20
40
60
80
100
0
100
200

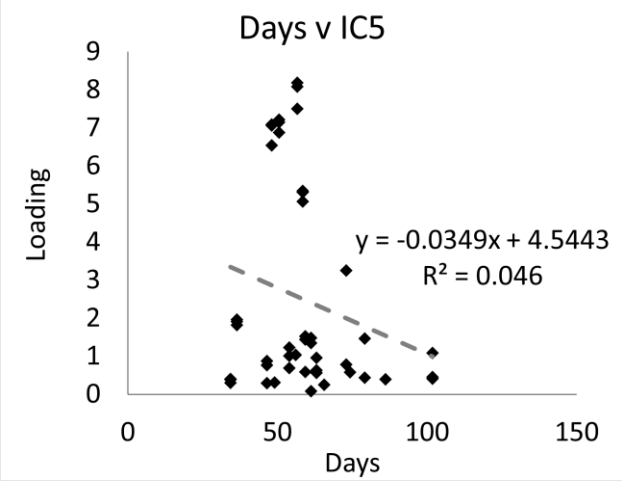

Days v I COD
y = -2.6788x + 524.33
R² = 0.1156
mg/L
Days
0
200
400
600
800
1000
0
100
200

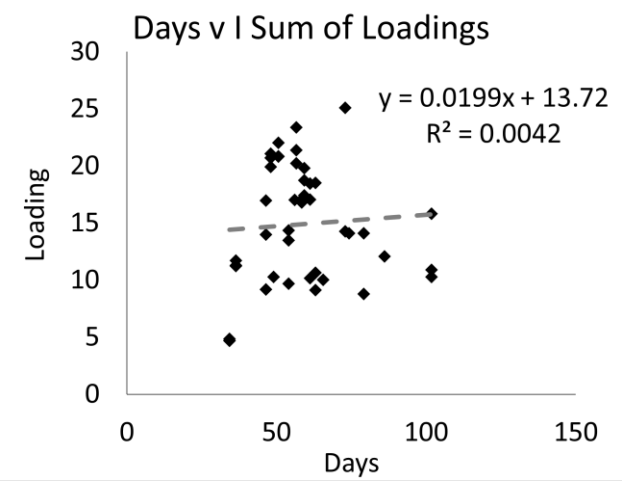

Days v IC1
y = -0.0036x + 5.0462
R² = 0.0013
Loading
Days
0
1
2
3
4
5
6
7
8
9
0
50
100
150

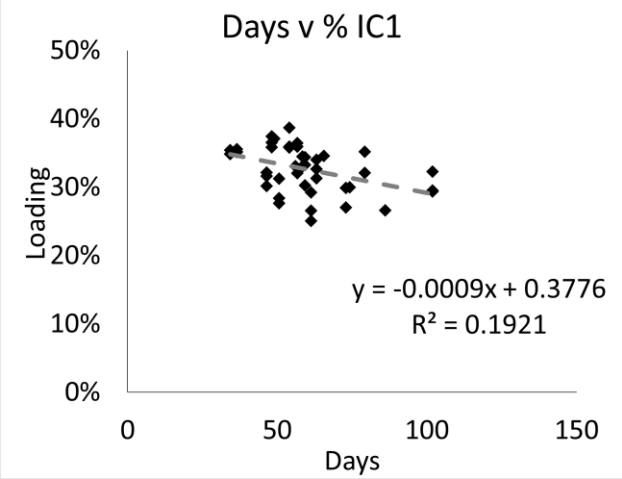

Days v IC2
y = 0.0274x + 1.5723
R² = 0.2334
Loading
Days
0
1
2
3
4
5
6
7
8
0
50
100
150

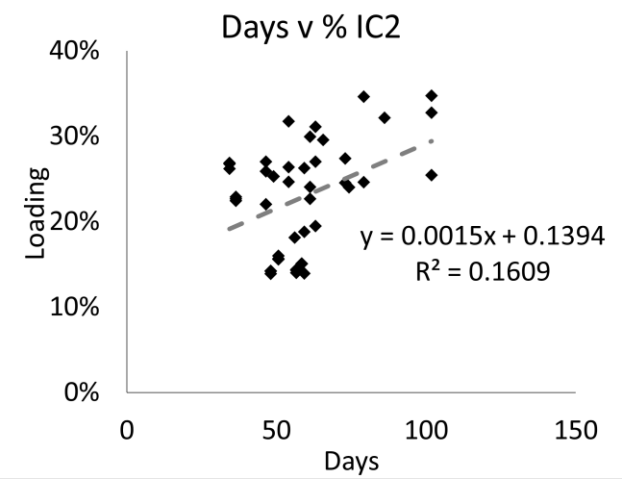

Days v IC3
y = 0.0144x + 0.9955
R² = 0.1247
Loading
Days
0
1
2
3
4
5
0
50
100
150

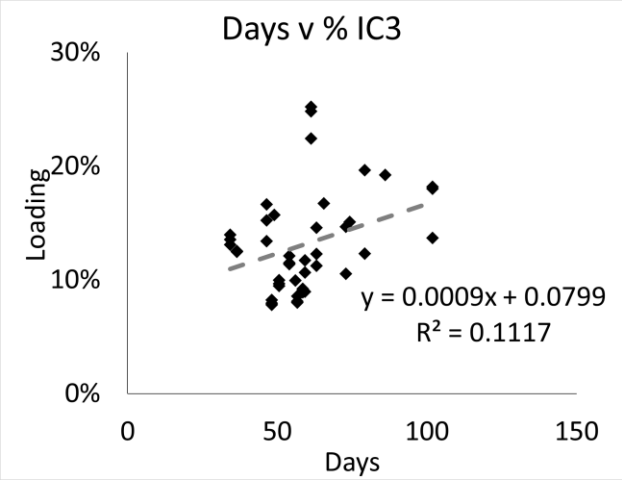

Days v IC4
y = 0.0167x + 1.5611
R² = 0.0324
Loading
Days
0
1
2
3
4
5
6
7
8
0
50
100
150

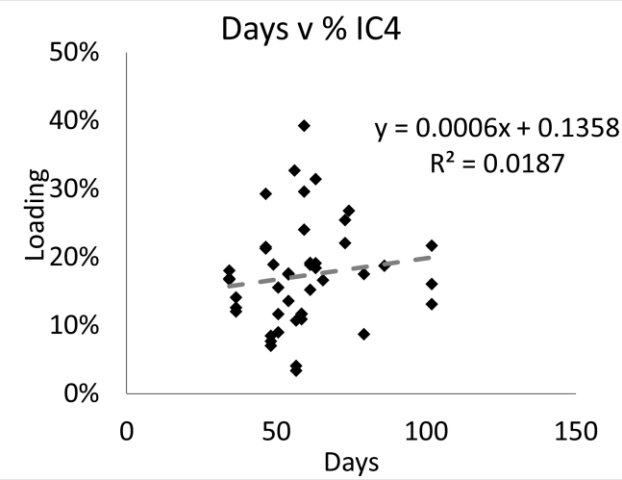

Days v IC5
y = -0.0349x + 4.5443
R² = 0.046
Loading
Days
0
1
2
3
4
5
6
7
8
9
0
50
100
150

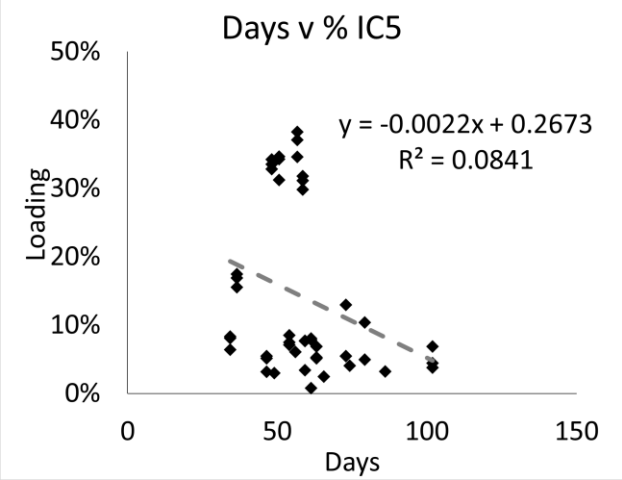

Days v I Sum of Loadings
y = 0.0199x + 13.72
R² = 0.0042
Loading
Days
0
5
10
15
20
25
30
0
50
100
150

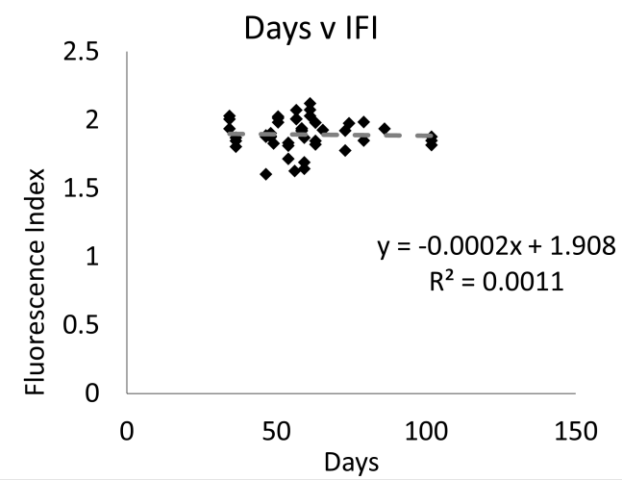

Days v % IC1
y = -0.0009x + 0.3776
R² = 0.1921
Loading
Days
0%
10%
20%
30%
40%
50%
0
50
100
150

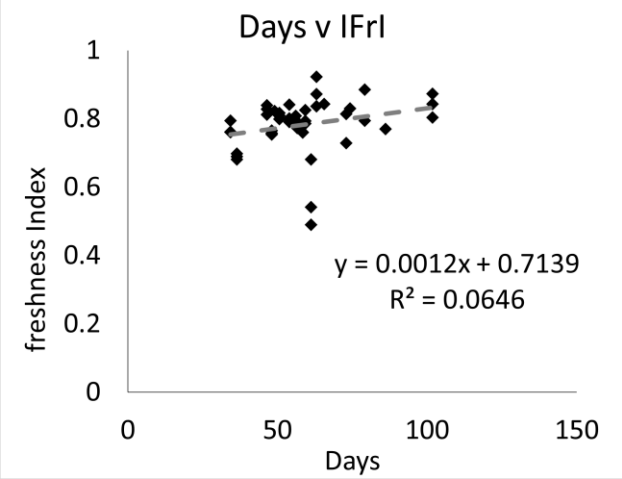

Days v % IC2
y = 0.0015x + 0.1394
R² = 0.1609
Loading
Days
0%
10%
20%
30%
40%
0
50
100
150

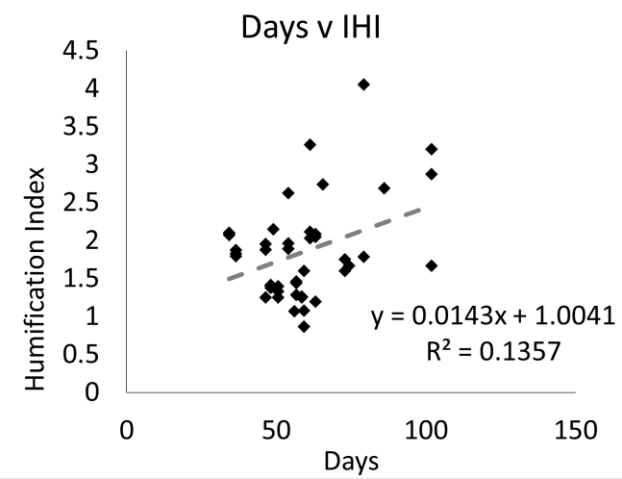

Days v % IC3
30%
20%
10%
0%
Loading
0
50
100
150
Days
y = 0.0009x + 0.0799
R² = 0.1117

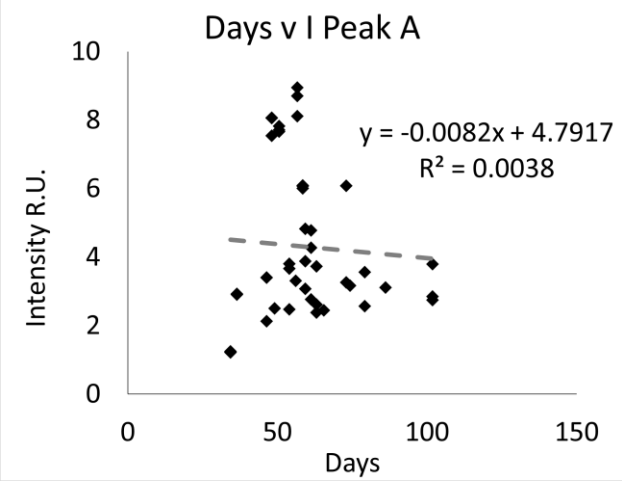

Days v % IC4
50%
40%
30%
20%
10%
0%
Loading
0
50
100
150
Days
y = 0.0006x + 0.1358
R² = 0.0187

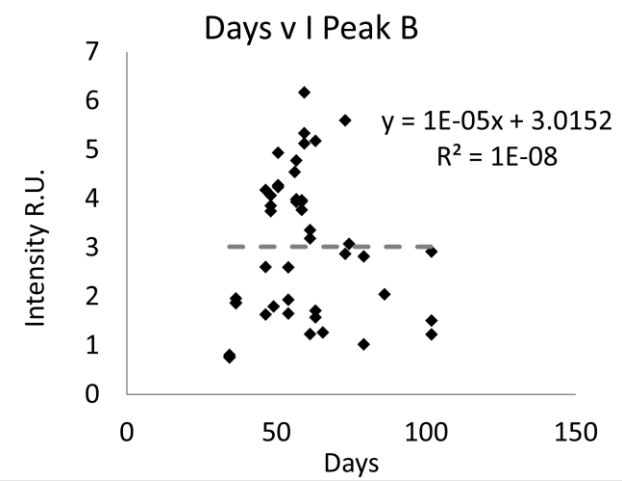

Days v % IC5
50%
40%
30%
20%
10%
0%
Loading
0
50
100
150
Days
y = -0.0022x + 0.2673
R² = 0.0841

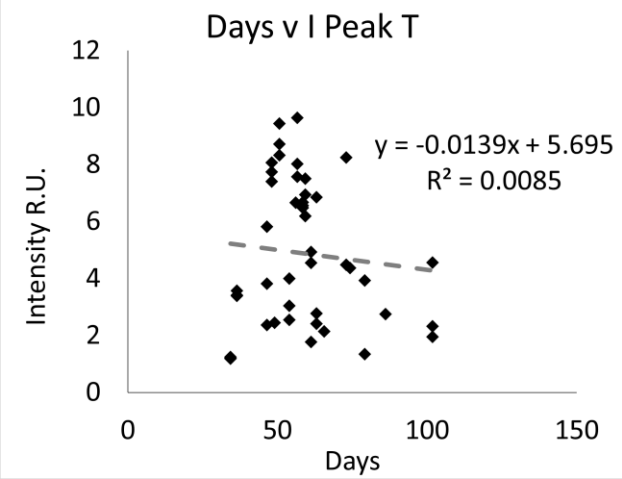

Days v IFI
2.5
2
1.5
1
0.5
0
Fluorescence Index
0
50
100
150
Days
y = -0.0002x + 1.908
R² = 0.0011

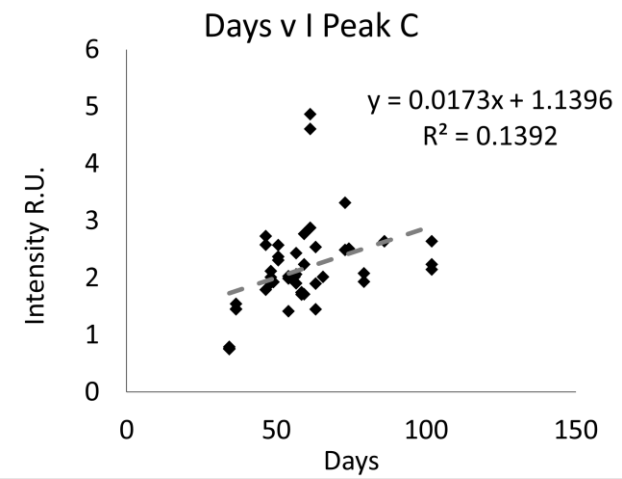

Days v IFrI
1
0.8
0.6
0.4
0.2
0
freshness Index
0
50
100
150
Days
y = 0.0012x + 0.7139
R² = 0.0646

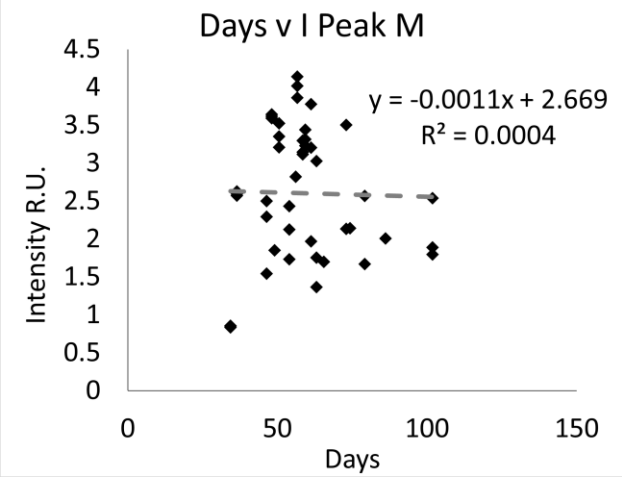

Days v IHI
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Humification Index
0
50
100
150
Days
y = 0.0143x + 1.0041
R² = 0.1357

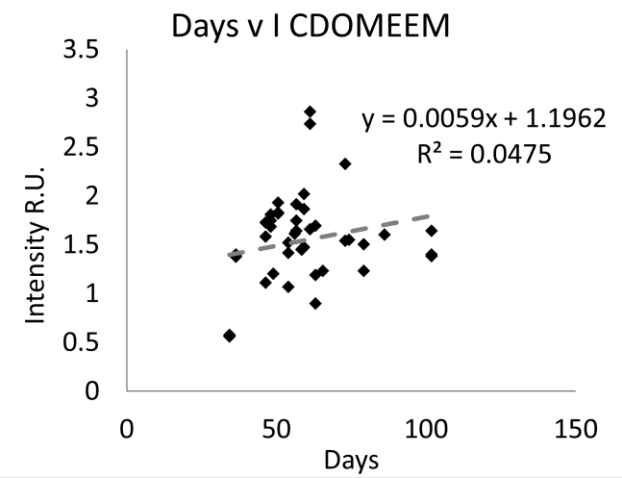

Days v I Peak A
y = -0.0082x + 4.7917
R² = 0.0038
Intensity R.U.
Days
0
2
4
6
8
10
0
50
100
150

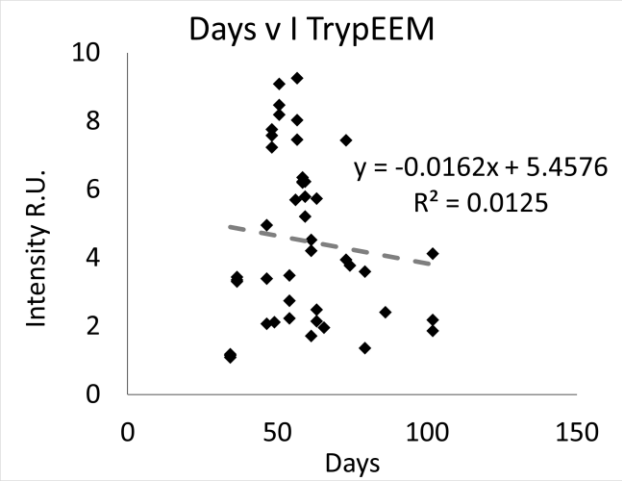

Days v I Peak B
y = 1E-05x + 3.0152
R² = 1E-08
Intensity R.U.
Days
0
1
2
3
4
5
6
7
0
50
100
150

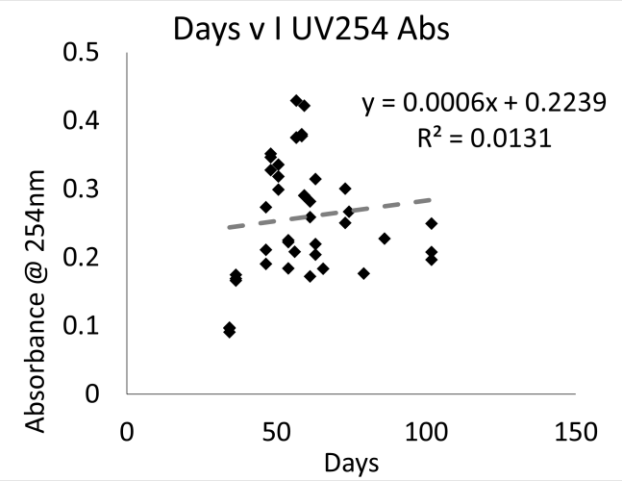

Days v I Peak T
y = -0.0139x + 5.695
R² = 0.0085
Intensity R.U.
Days
0
2
4
6
8
10
12
0
50
100
150

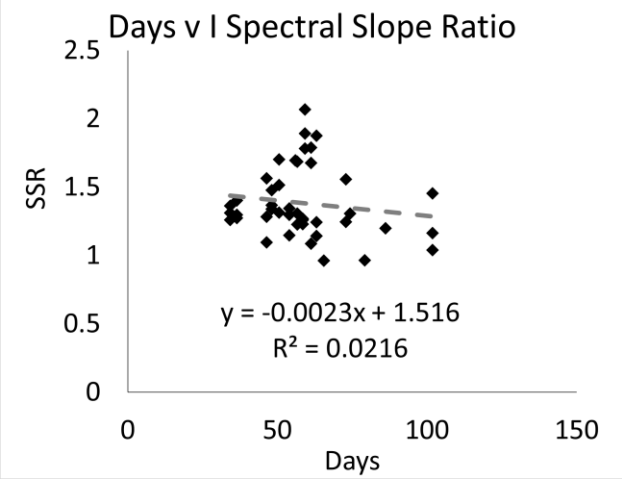

Days v I Peak C
y = 0.0173x + 1.1396
R² = 0.1392
Intensity R.U.
Days
0
1
2
3
4
5
6
0
50
100
150


Days v I Peak M
y = -0.0011x + 2.669
R² = 0.0004
Intensity R.U.
Days
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
0
50
100
150


Days v I CDOMEEM
y = 0.0059x + 1.1962
R² = 0.0475
Intensity R.U.
Days
0
0.5
1
1.5
2
2.5
3
3.5
0
50
100
150

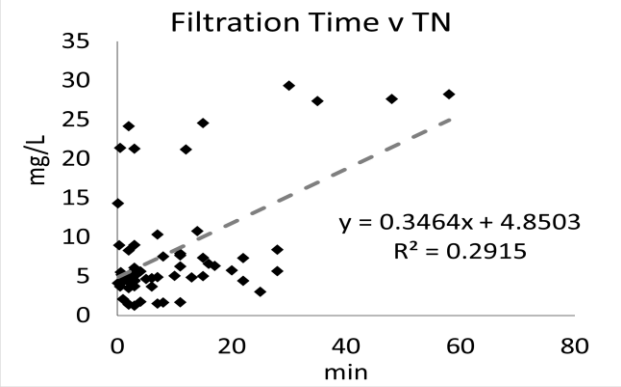


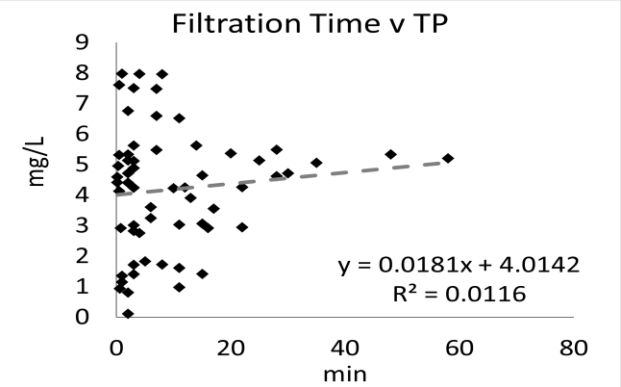


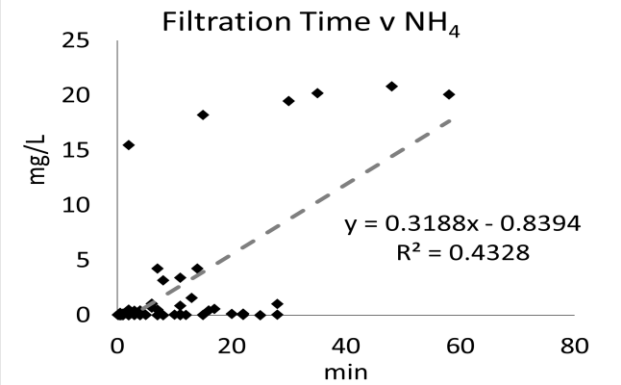


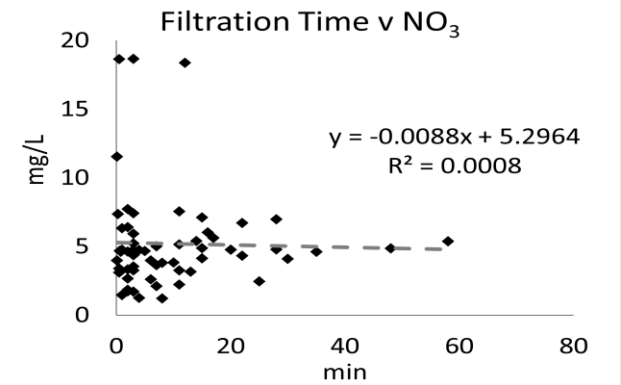
Filtration Time

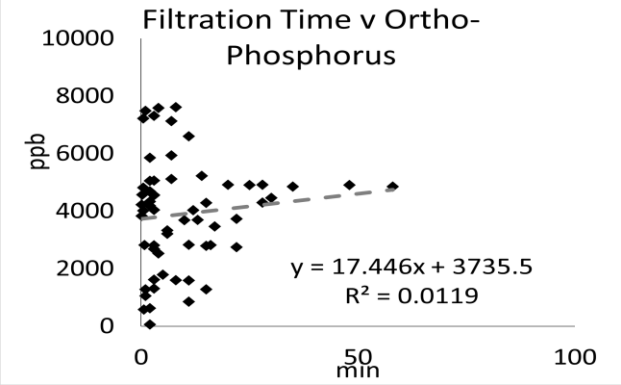
Effluent

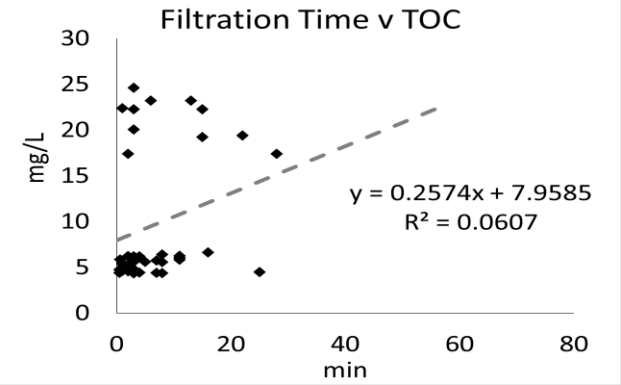

Filtration Time v TN
mg/L
min
y = 0.3464x + 4.8503
R² = 0.2915

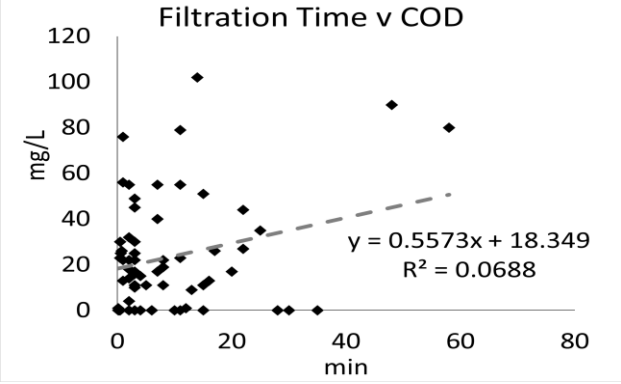

Filtration Time v TP
mg/L
min
y = 0.0181x + 4.0142
R² = 0.0116

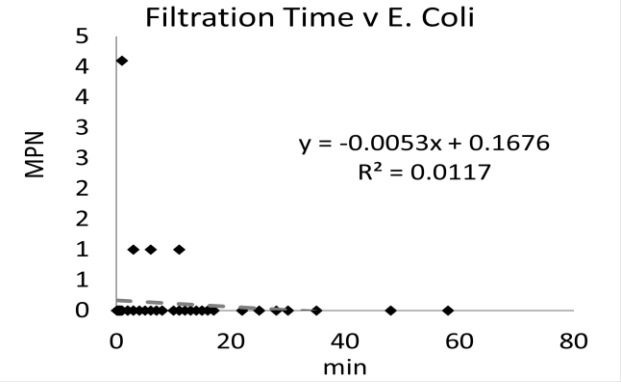

Filtration Time v NH4
mg/L
min
y = 0.3188x - 0.8394
R² = 0.4328

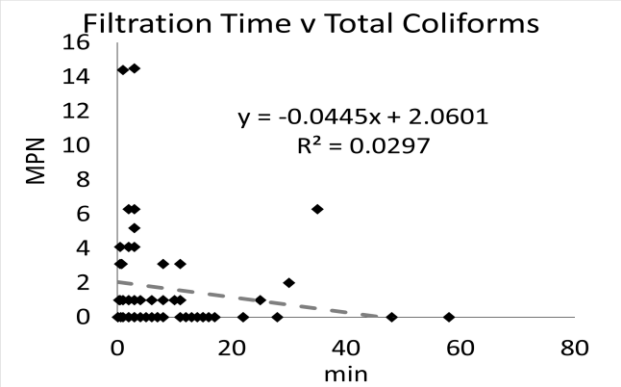

Filtration Time v NO3
mg/L
min
y = -0.0088x + 5.2964
R² = 0.0008

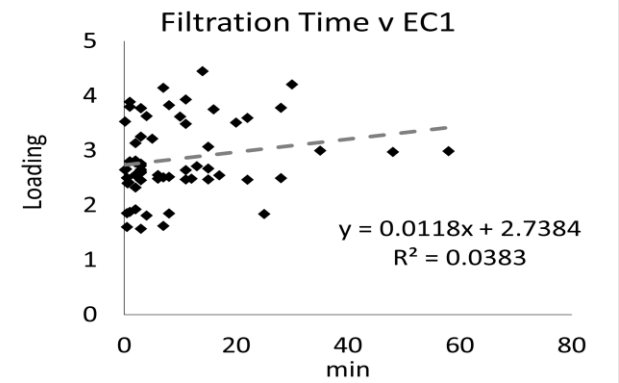

Filtration Time v Ortho-Phosphorus
ppb
min
y = 17.446x + 3735.5
R² = 0.0119

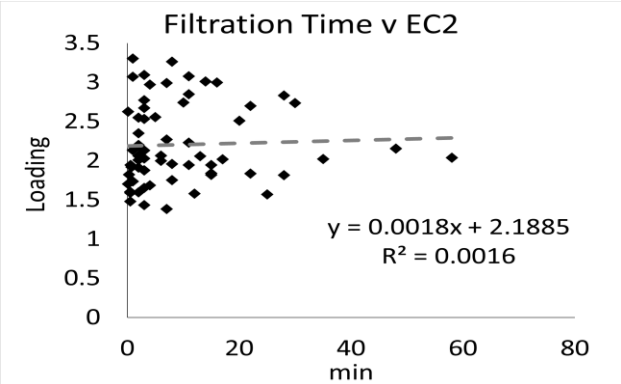

Filtration Time v TOC
mg/L
min
y = 0.2574x + 7.9585
R² = 0.0607

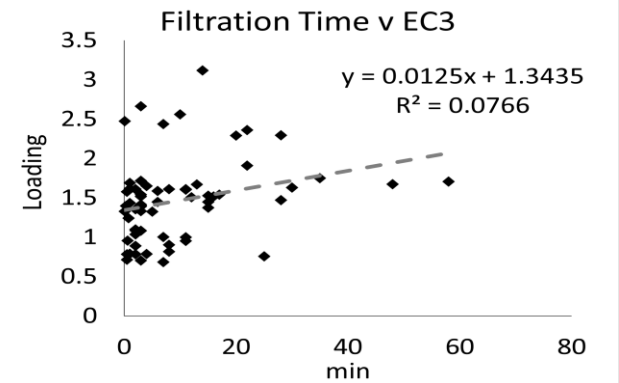

Filtration Time v COD
mg/L
min
y = 0.5573x + 18.349
R² = 0.0688

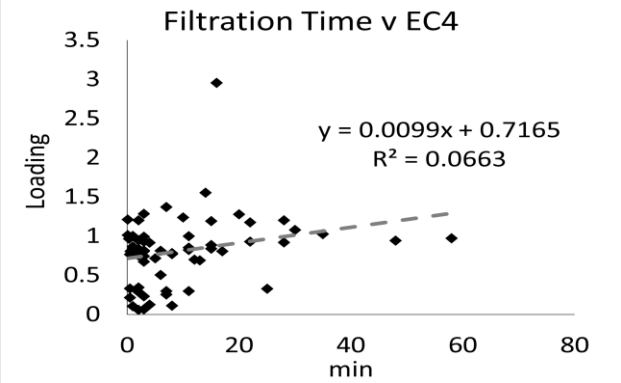

Filtration Time v E. Coli
MPN
min
y = -0.0053x + 0.1676
R² = 0.0117

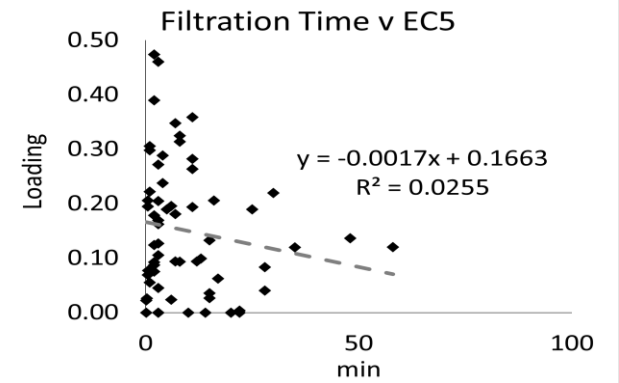

Filtration Time v Total Coliforms
MPN
min
y = -0.0445x + 2.0601
R² = 0.0297

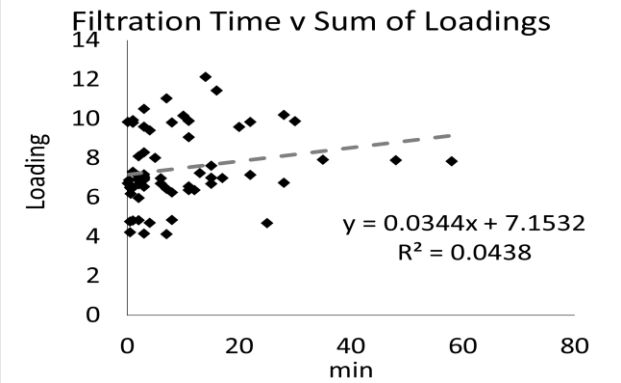

Filtration Time v EC1
Loading
min
y = 0.0118x + 2.7384
R² = 0.0383

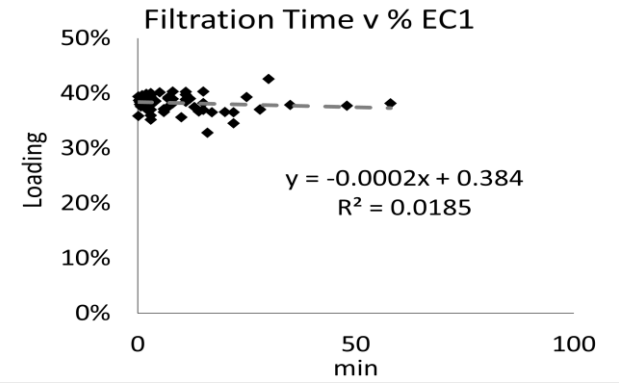

Filtration Time v EC2
Loading
min
y = 0.0018x + 2.1885
R² = 0.0016

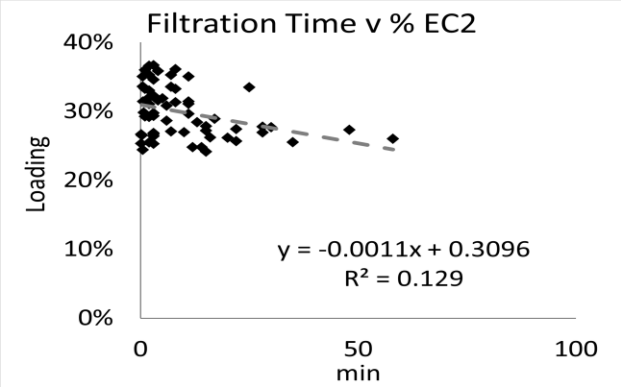

Filtration Time v EC3
Loading
min
y = 0.0125x + 1.3435
R² = 0.0766

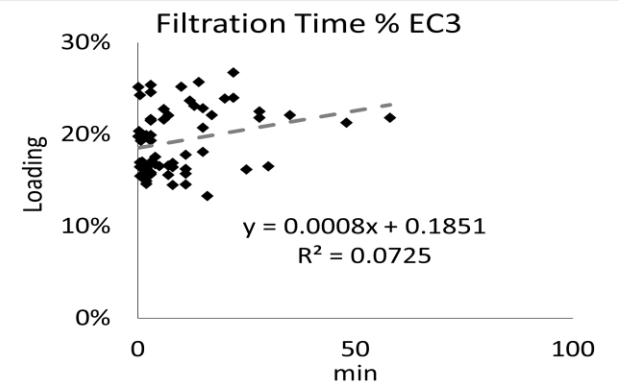

Filtration Time v EC4
Loading
min
y = 0.0099x + 0.7165
R² = 0.0663

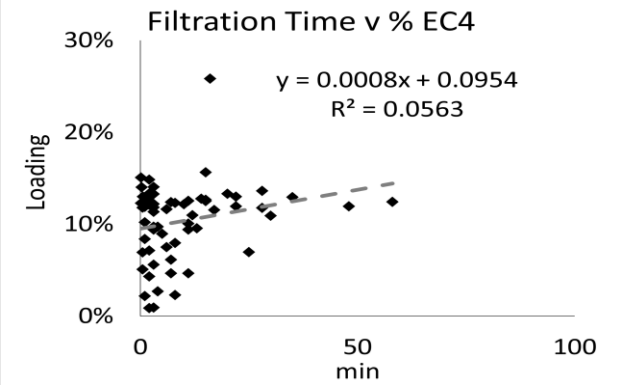

Filtration Time v EC5
Loading
min
y = -0.0017x + 0.1663
R² = 0.0255

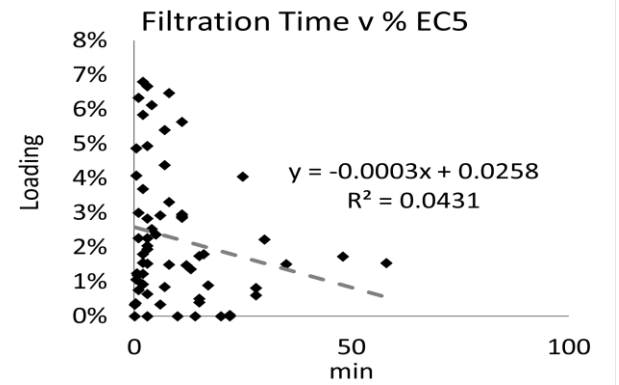

Filtration Time v Sum of Loadings
Loading
min
y = 0.0344x + 7.1532
R² = 0.0438

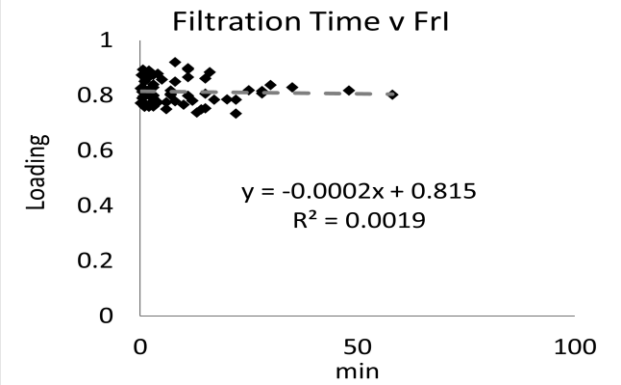

Filtration Time v % EC1
Loading
min
y = -0.0002x + 0.384
R² = 0.0185

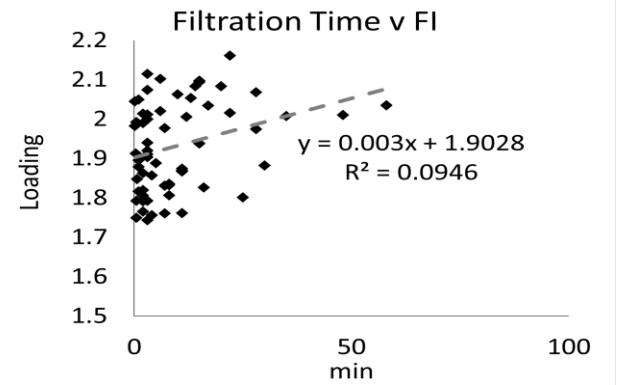

Filtration Time v % EC2
Loading
40%
30%
20%
10%
0%
y = -0.0011x + 0.3096
R² = 0.129
0
50
100
min

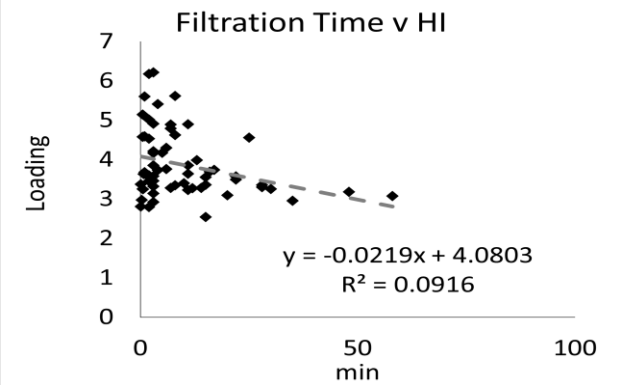

Filtration Time % EC3
Loading
30%
20%
10%
0%
y = 0.0008x + 0.1851
R² = 0.0725
0
50
100
min

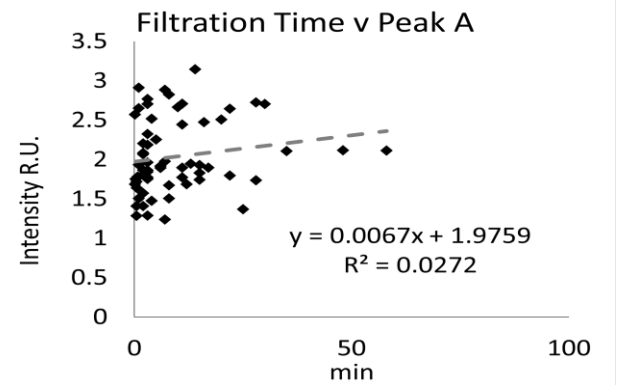

Filtration Time v % EC4
Loading
30%
20%
10%
0%
y = 0.0008x + 0.0954
R² = 0.0563
0
50
100
min

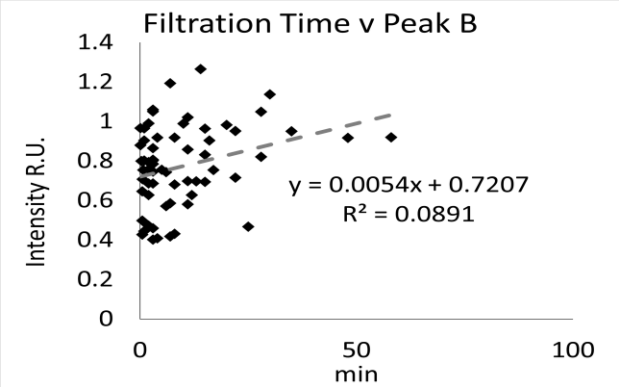

Filtration Time v % EC5
Loading
8%
7%
6%
5%
4%
3%
2%
1%
0%
y = -0.0003x + 0.0258
R² = 0.0431
0
50
100
min

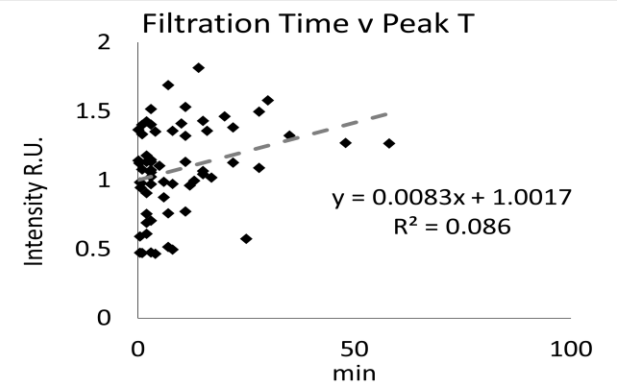

Filtration Time v FrI
Loading
1
0.8
0.6
0.4
0.2
0
y = -0.0002x + 0.815
R² = 0.0019
0
50
100
min

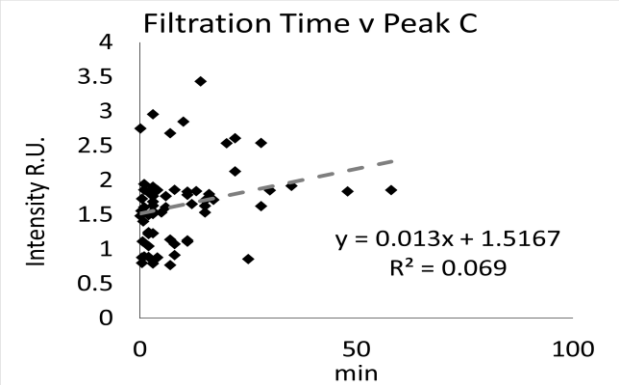

Filtration Time v FI
Loading
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
y = 0.003x + 1.9028
R² = 0.0946
0
50
100
min

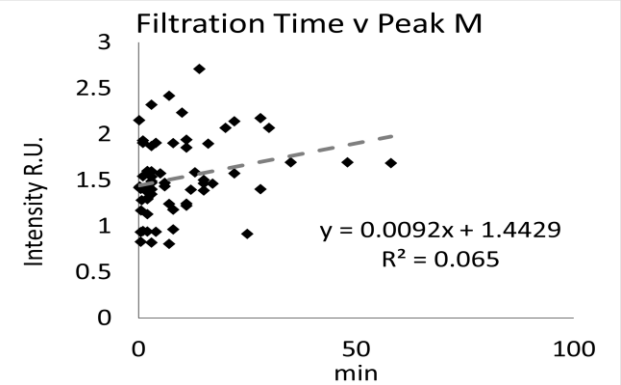

Filtration Time v HI
Loading
7
6
5
4
3
2
1
0
y = -0.0219x + 4.0803
R² = 0.0916
0
50
100
min

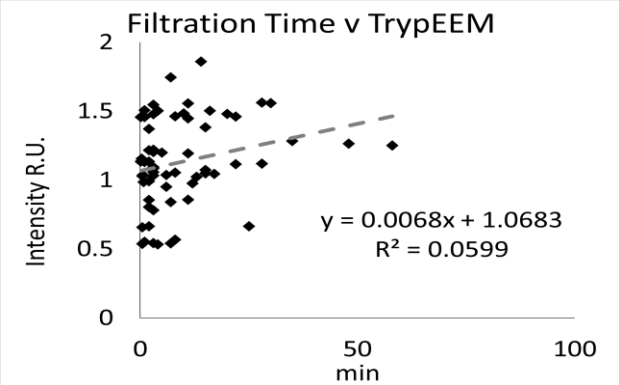

Filtration Time v Peak A
Intensity R.U.
3.5
3
2.5
2
1.5
1
0.5
0
y = 0.0067x + 1.9759
R² = 0.0272
0
50
100
min

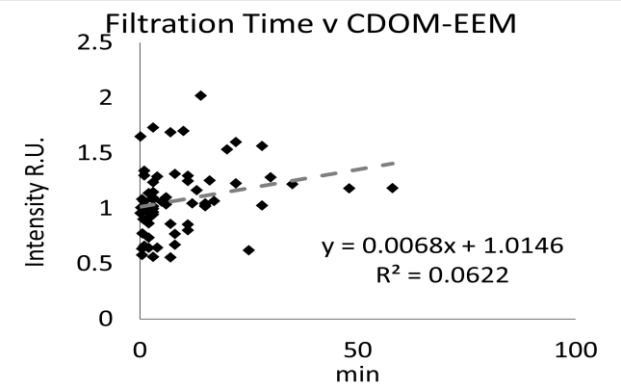

Filtration Time v Peak B
Intensity R.U.
y = 0.0054x + 0.7207
R² = 0.0891
min

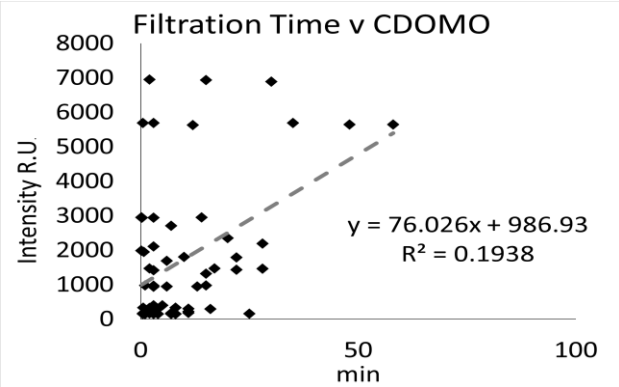

Filtration Time v Peak T
Intensity R.U.
y = 0.0083x + 1.0017
R² = 0.086
min

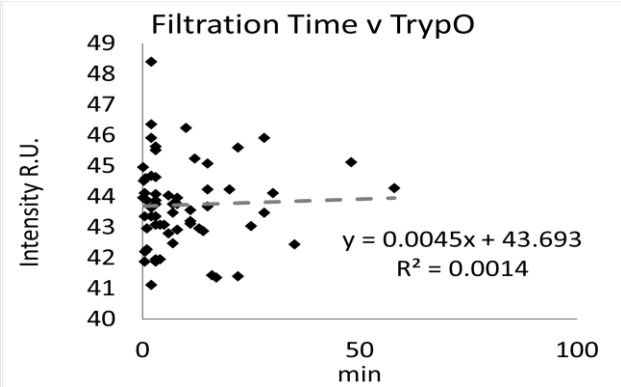

Filtration Time v Peak C
Intensity R.U.
y = 0.013x + 1.5167
R² = 0.069
min

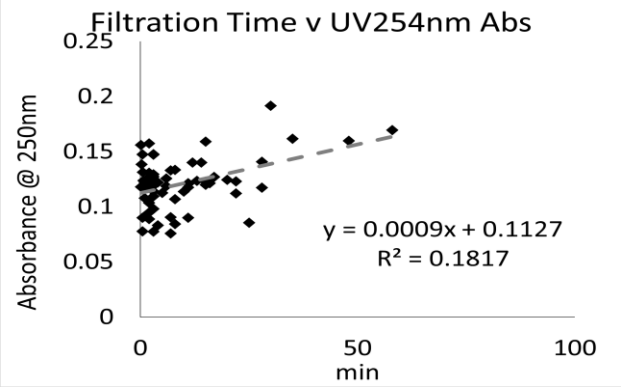

Filtration Time v Peak M
Intensity R.U.
y = 0.0092x + 1.4429
R² = 0.065
min

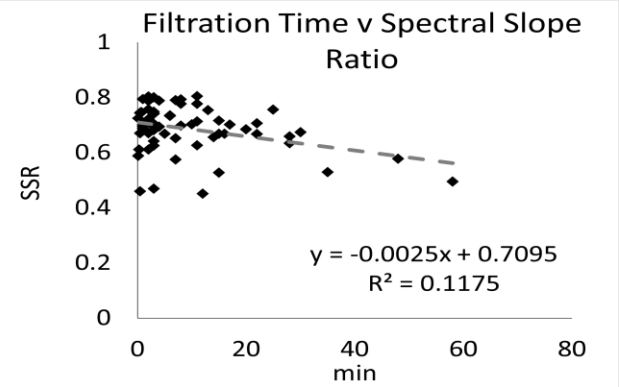

Filtration Time v TrypEEM
Intensity R.U.
y = 0.0068x + 1.0683
R² = 0.0599
min


Filtration Time v CDOM-EEM
Intensity R.U.
y = 0.0068x + 1.0146
R² = 0.0622
min


Filtration Time v CDOMO
Intensity R.U.
y = 76.026x + 986.93
R² = 0.1938
min

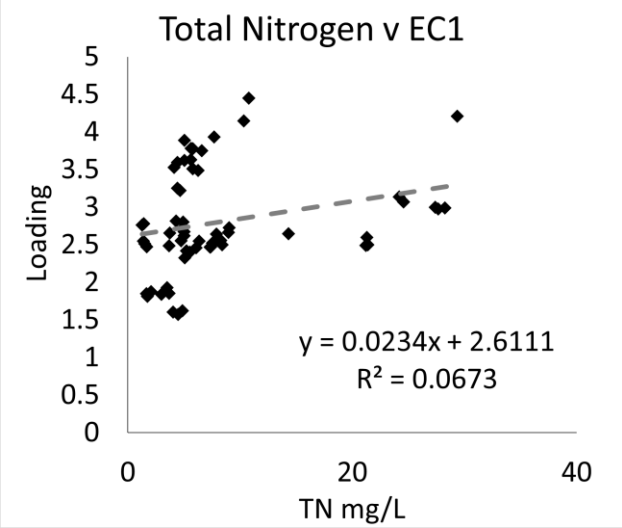

Filtration Time v TrypO
Intensity R.U.
y = 0.0045x + 43.693
R² = 0.0014
min

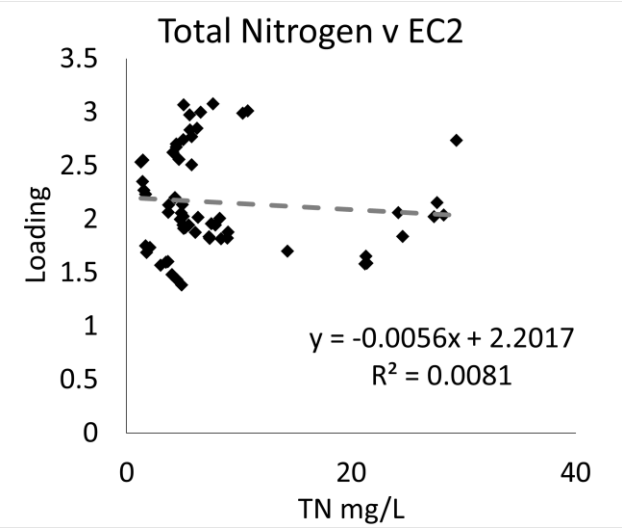

Filtration Time v UV254nm Abs
Absorbance @ 250nm
0.25
0.2
0.15
0.1
0.05
0
0
50
100
min
y = 0.0009x + 0.1127
R² = 0.1817

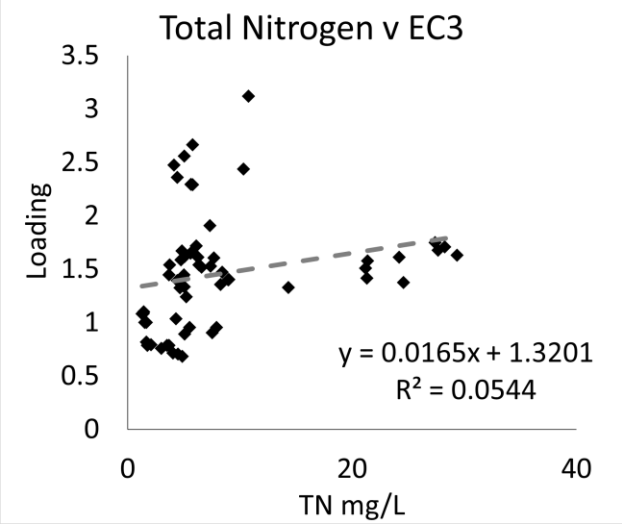

Filtration Time v Spectral Slope Ratio
SSR
1
0.8
0.6
0.4
0.2
0
0
20
40
60
80
min
y = -0.0025x + 0.7095
R² = 0.1175

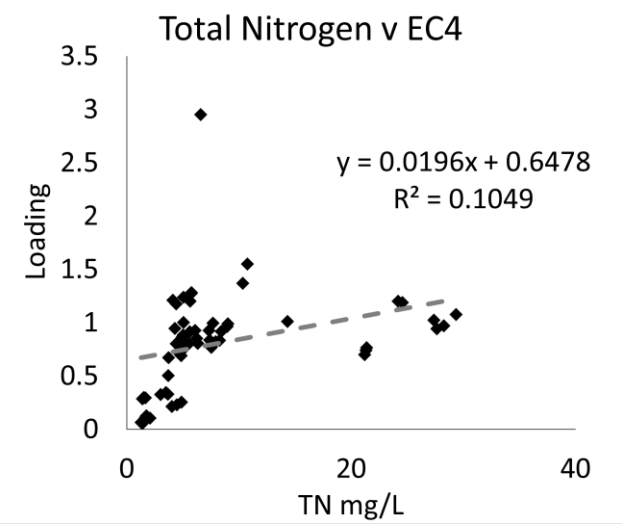
Total Nitrogen

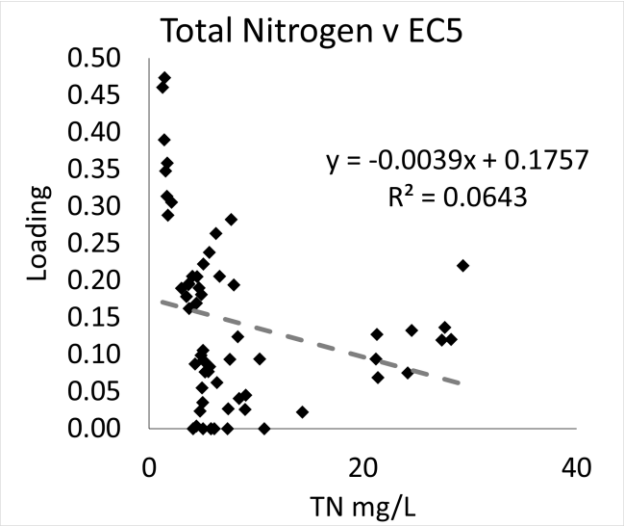
Effluent

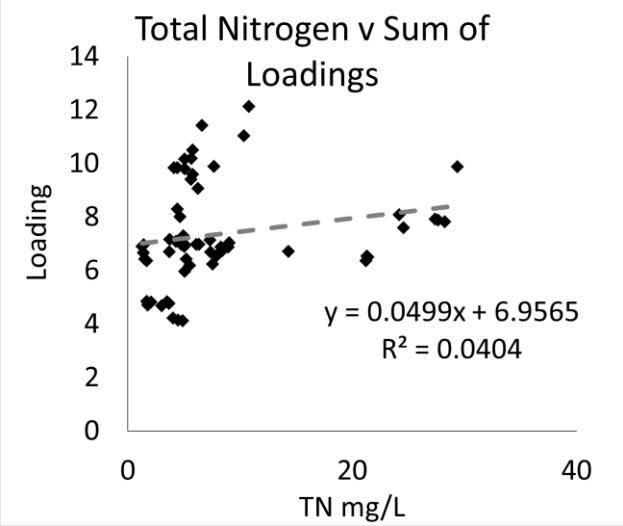


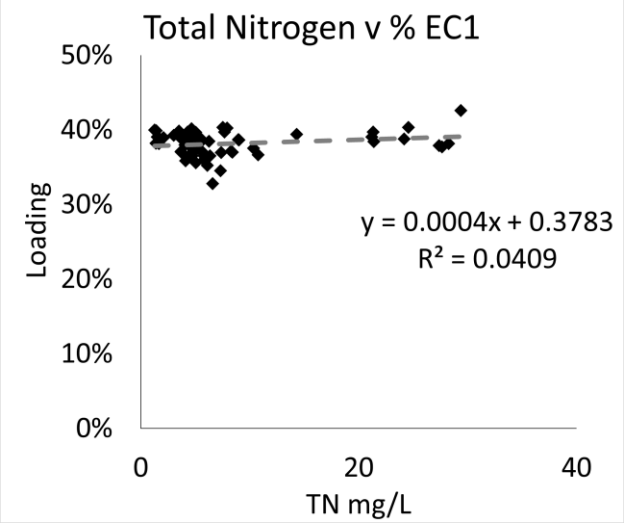


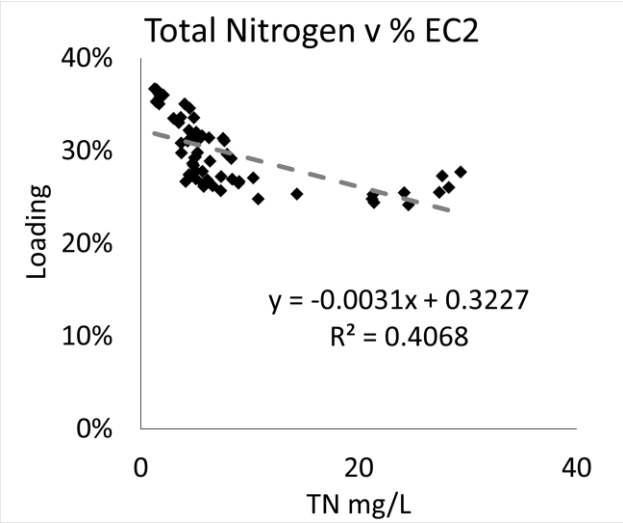


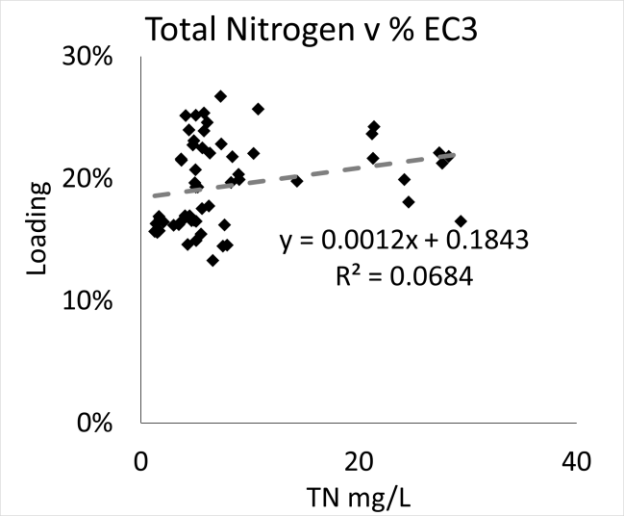


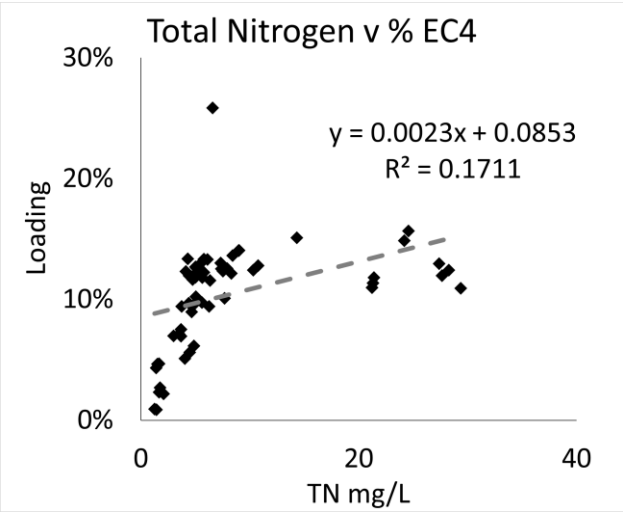

Total Nitrogen v EC5
y = -0.0039x + 0.1757
R² = 0.0643
Loading
TN mg/L
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
20
40

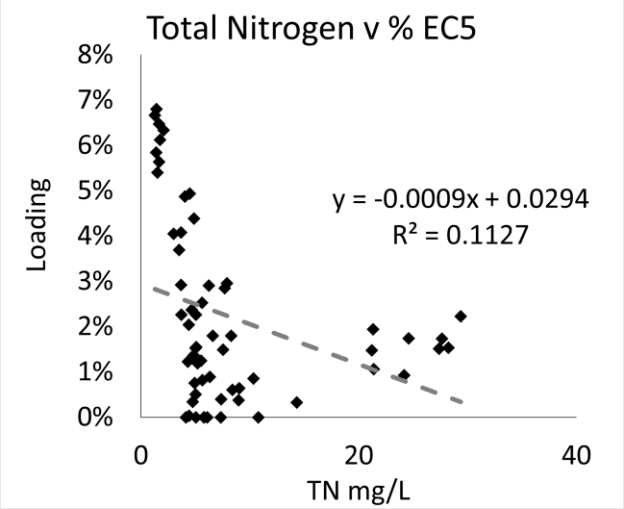

Total Nitrogen v Sum of Loadings
y = 0.0499x + 6.9565
R² = 0.0404
Loading
TN mg/L
14
12
10
8
6
4
2
0
0
20
40

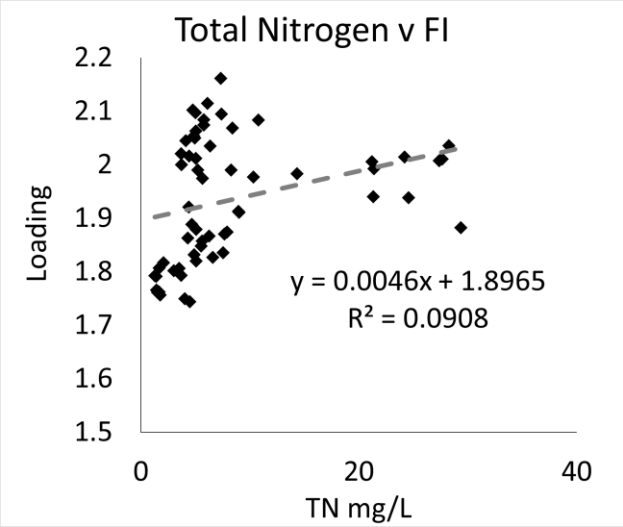

Total Nitrogen v % EC1
y = 0.0004x + 0.3783
R² = 0.0409
Loading
TN mg/L
50%
40%
30%
20%
10%
0%
0
20
40

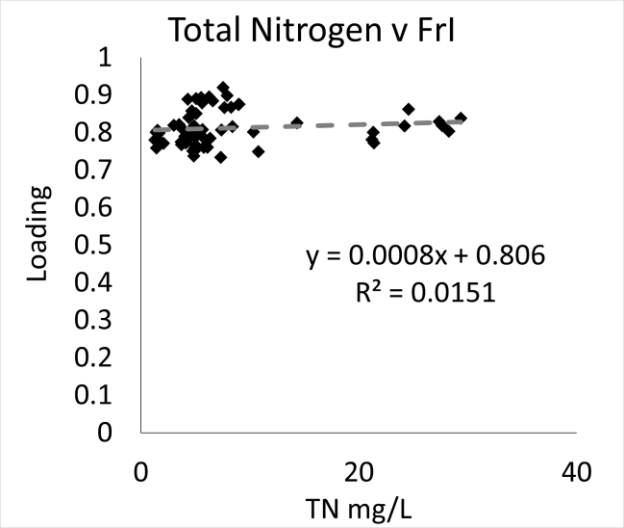

Total Nitrogen v % EC2
y = -0.0031x + 0.3227
R² = 0.4068
Loading
TN mg/L
40%
30%
20%
10%
0%
0
20
40

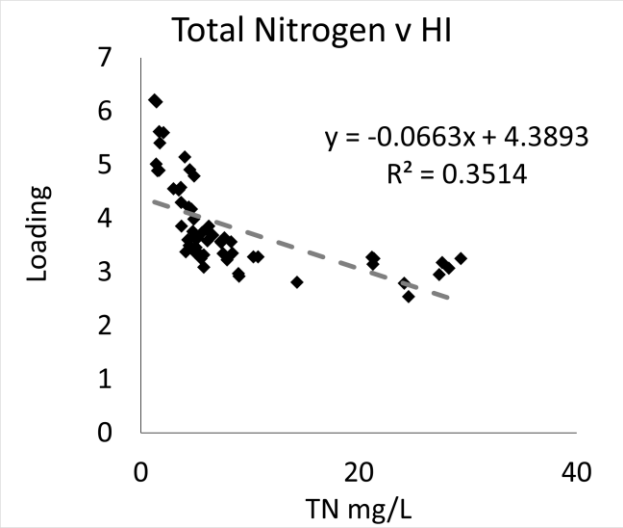

Total Nitrogen v % EC3
y = 0.0012x + 0.1843
R² = 0.0684
Loading
TN mg/L
30%
20%
10%
0%
0
20
40

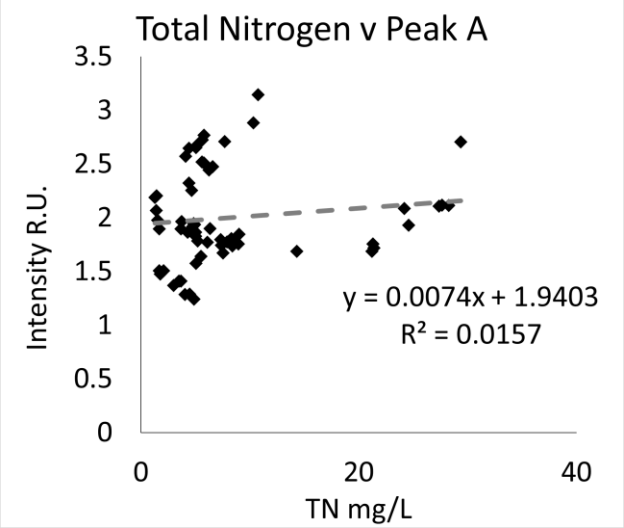

Total Nitrogen v % EC4
y = 0.0023x + 0.0853
R² = 0.1711
Loading
TN mg/L
30%
20%
10%
0%
0
20
40

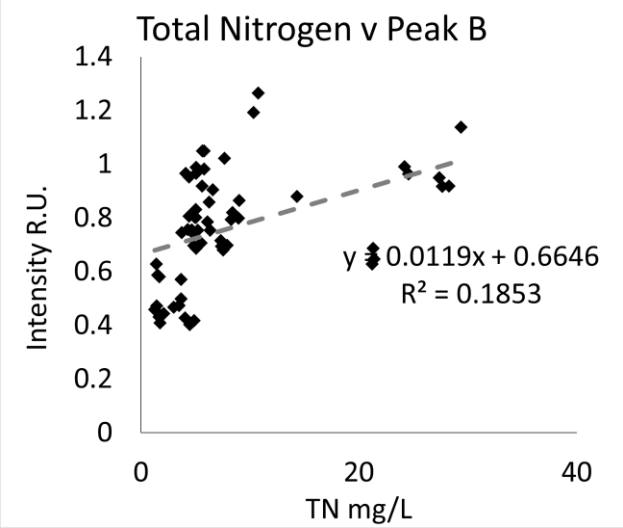

Total Nitrogen v % EC5
Loading
8%
7%
6%
5%
4%
3%
2%
1%
0%
y = -0.0009x + 0.0294
R² = 0.1127
0
20
40
TN mg/L

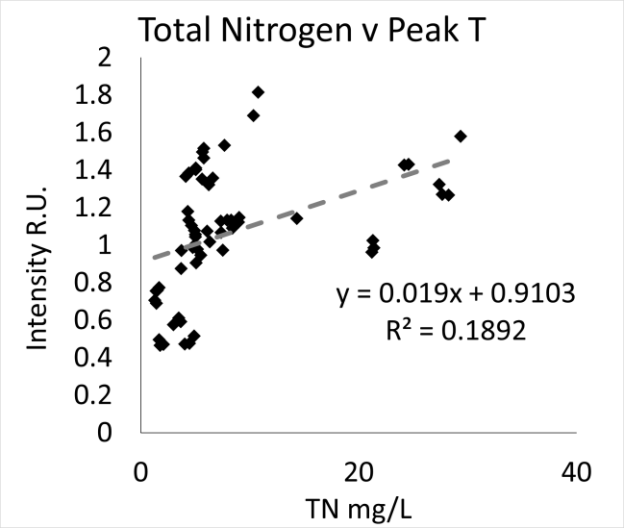

Total Nitrogen v FI
Loading
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
y = 0.0046x + 1.8965
R² = 0.0908
0
20
40
TN mg/L

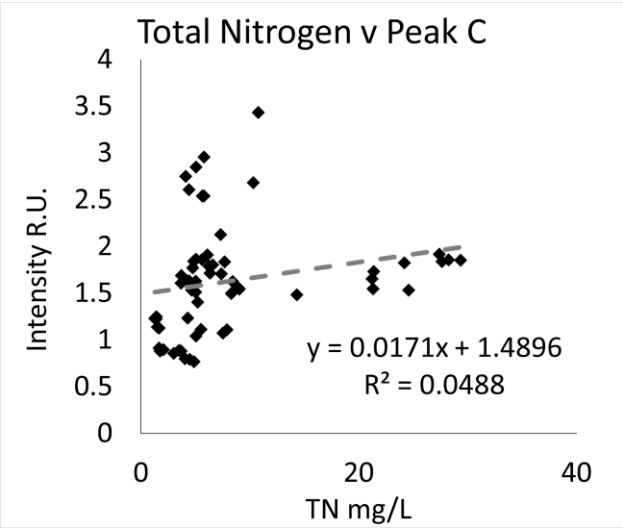

Total Nitrogen v FrI
Loading
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
y = 0.0008x + 0.806
R² = 0.0151
0
20
40
TN mg/L

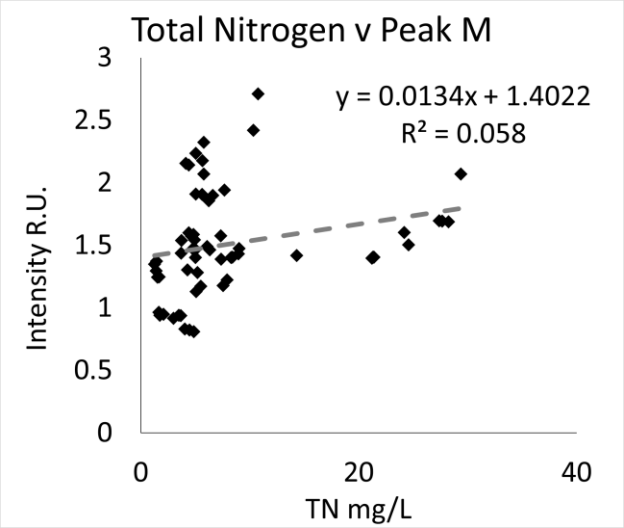

Total Nitrogen v HI
Loading
7
6
5
4
3
2
1
0
y = -0.0663x + 4.3893
R² = 0.3514
0
20
40
TN mg/L

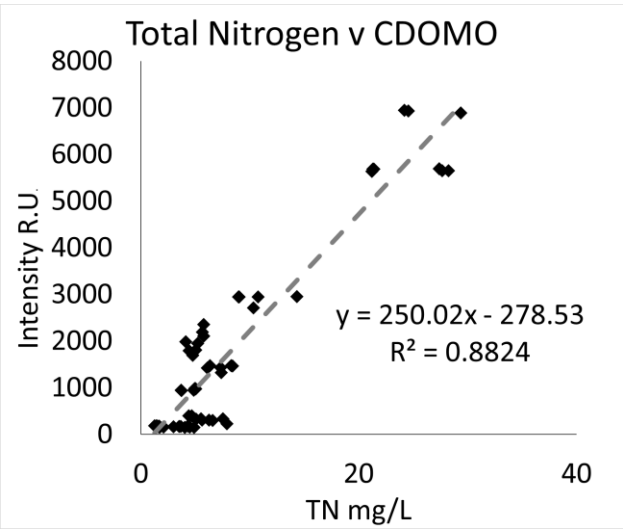

Total Nitrogen v Peak A
Intensity R.U.
3.5
3
2.5
2
1.5
1
0.5
0
y = 0.0074x + 1.9403
R² = 0.0157
0
20
40
TN mg/L

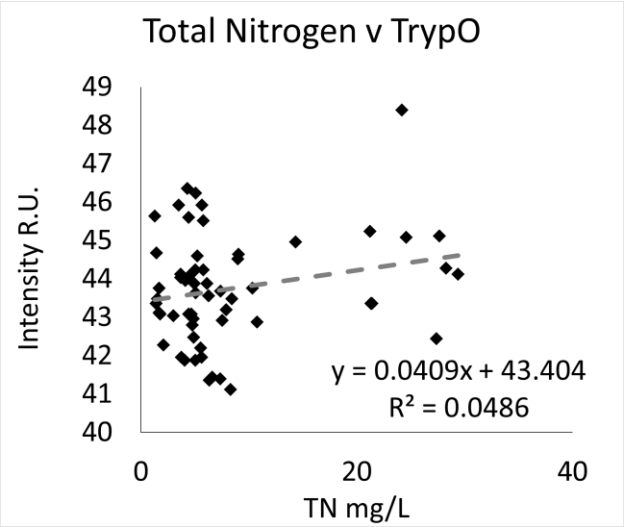

Total Nitrogen v Peak B
Intensity R.U.
1.4
1.2
1
0.8
0.6
0.4
0.2
0
y = 0.0119x + 0.6646
R² = 0.1853
0
20
40
TN mg/L

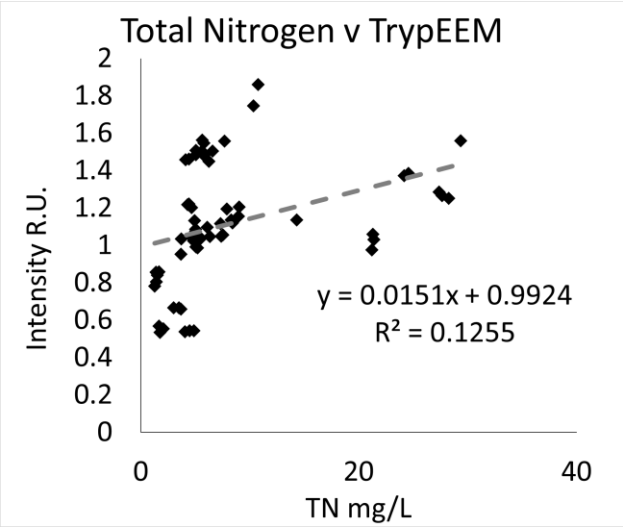

Total Nitrogen v Peak T
Intensity R.U.
TN mg/L
y = 0.019x + 0.9103
R² = 0.1892

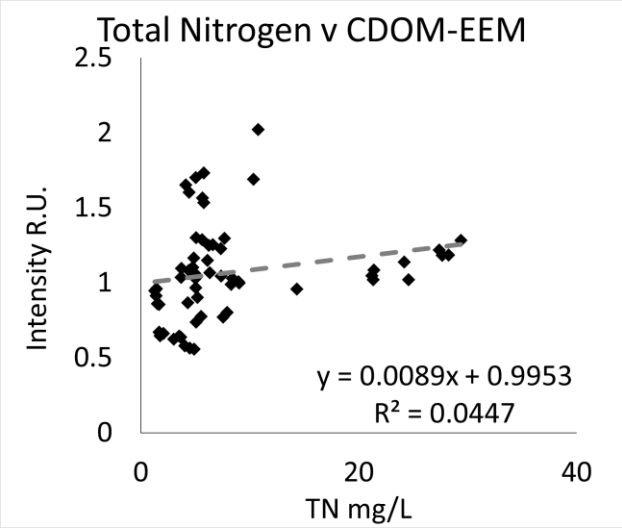

Total Nitrogen v Peak C
Intensity R.U.
TN mg/L
y = 0.0171x + 1.4896
R² = 0.0488

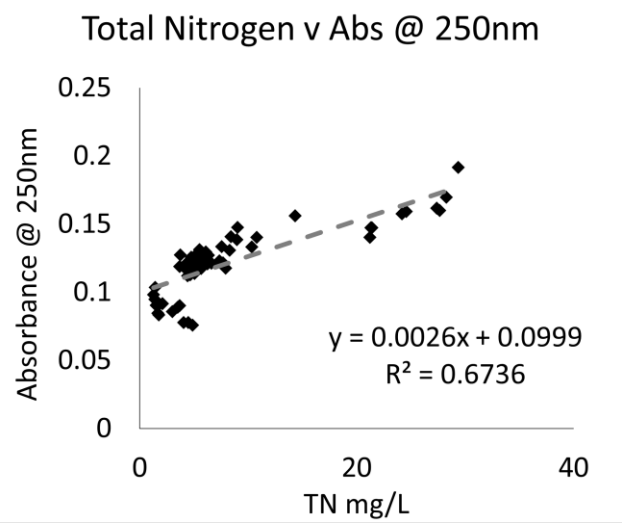

Total Nitrogen v Peak M
Intensity R.U.
TN mg/L
y = 0.0134x + 1.4022
R² = 0.058

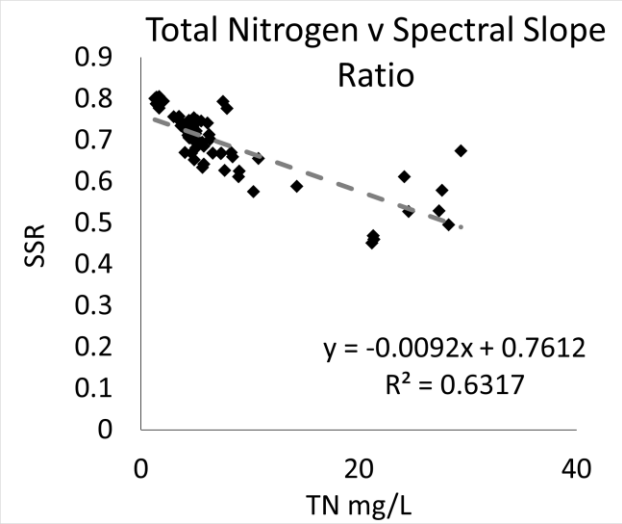

Total Nitrogen v CDOMO
Intensity R.U
TN mg/L
y = 250.02x - 278.53
R² = 0.8824


Total Nitrogen v TrypO
Intensity R.U.
TN mg/L
y = 0.0409x + 43.404
R² = 0.0486

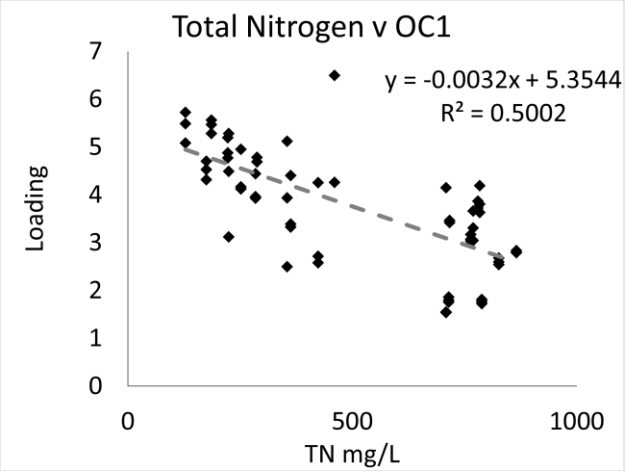

Total Nitrogen v TrypEEM
Intensity R.U.
TN mg/L
y = 0.0151x + 0.9924
R² = 0.1255

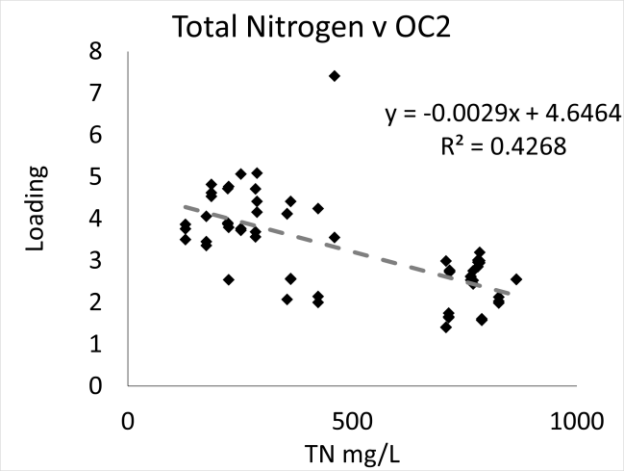

Total Nitrogen v CDOM-EEM
Intensity R.U.
TN mg/L
y = 0.0089x + 0.9953
R² = 0.0447
0
0.5
1
1.5
2
2.5
0
20
40

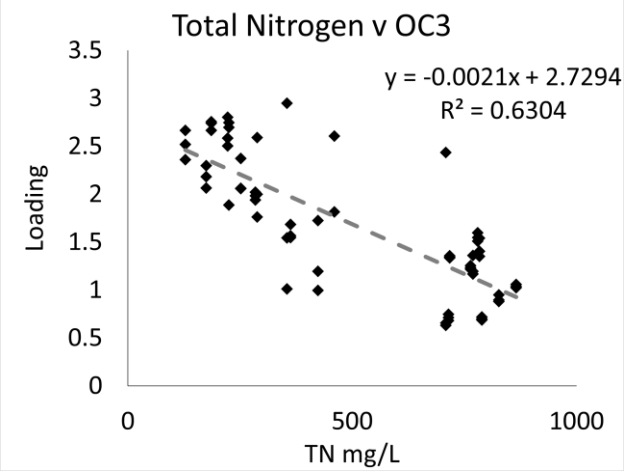

Total Nitrogen v Abs @ 250nm
Absorbance @ 250nm
TN mg/L
y = 0.0026x + 0.0999
R² = 0.6736
0
0.05
0.1
0.15
0.2
0.25
0
20
40

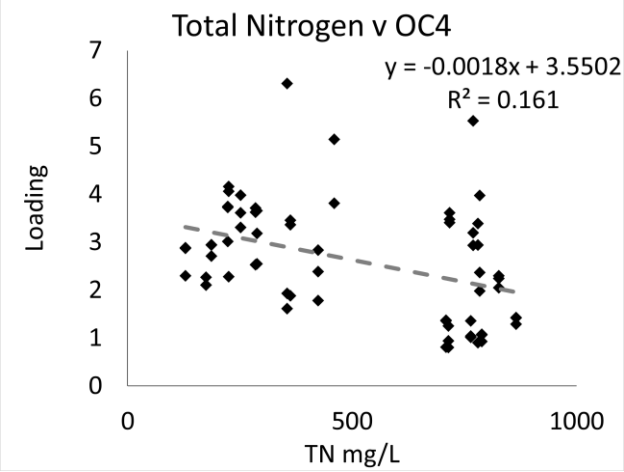

Total Nitrogen v Spectral Slope Ratio
SSR
TN mg/L
y = -0.0092x + 0.7612
R² = 0.6317
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0
20
40

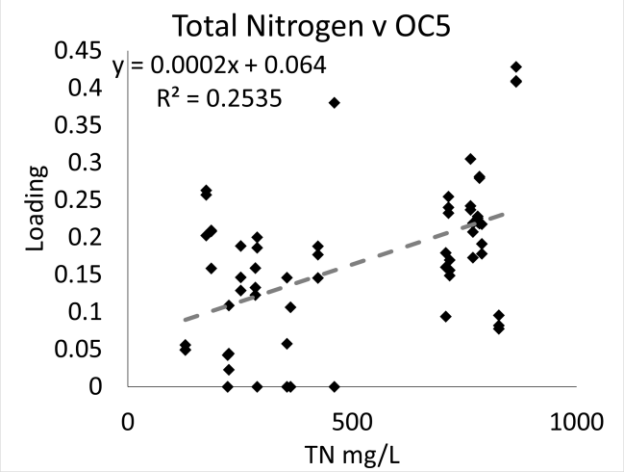
Oxic Tank

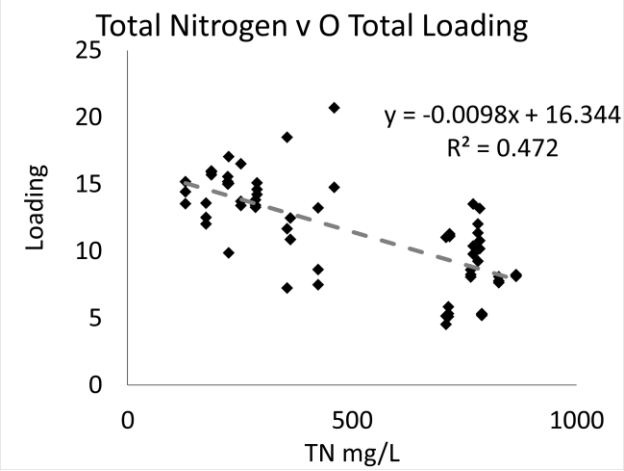

Total Nitrogen v OC1
y = -0.0032x + 5.3544
R² = 0.5002
Loading
TN mg/L
0
1
2
3
4
5
6
7
0
500
1000

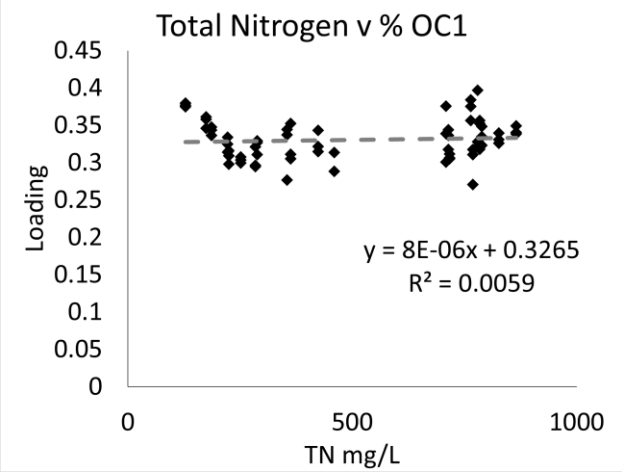

Total Nitrogen v OC2
y = -0.0029x + 4.6464
R² = 0.4268
Loading
TN mg/L
0
1
2
3
4
5
6
7
8
0
500
1000

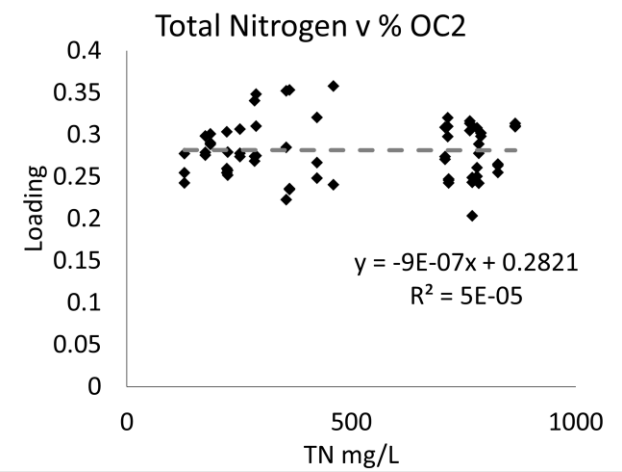

Total Nitrogen v OC3
y = -0.0021x + 2.7294
R² = 0.6304
Loading
TN mg/L
0
0.5
1
1.5
2
2.5
3
3.5
0
500
1000

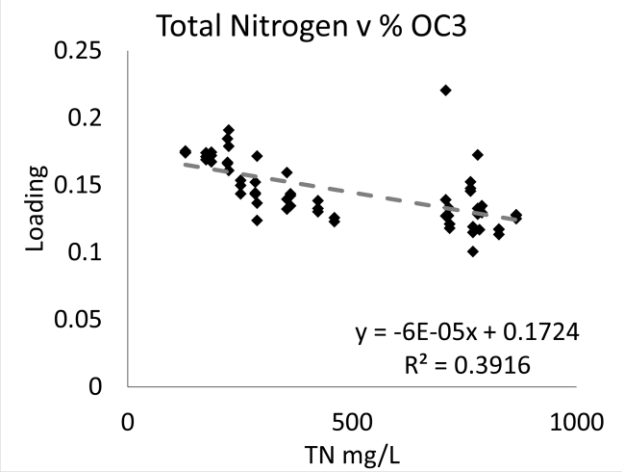

Total Nitrogen v OC4
y = -0.0018x + 3.5502
R² = 0.161
Loading
TN mg/L
0
1
2
3
4
5
6
7
0
500
1000

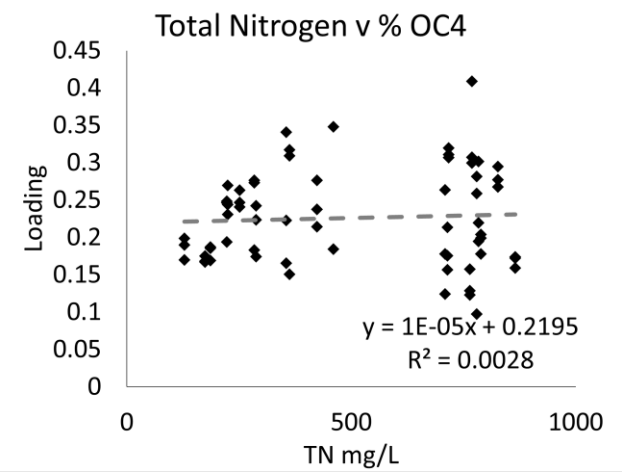

Total Nitrogen v OC5
y = 0.0002x + 0.064
R² = 0.2535
Loading
TN mg/L
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0
500
1000

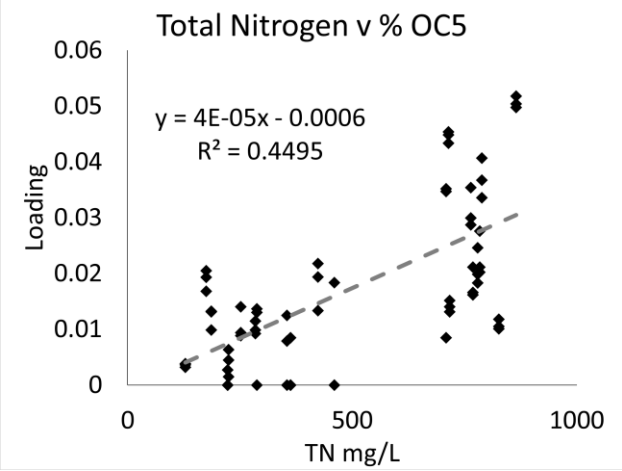

Total Nitrogen v O Total Loading
y = -0.0098x + 16.344
R² = 0.472
Loading
TN mg/L
0
5
10
15
20
25
0
500
1000

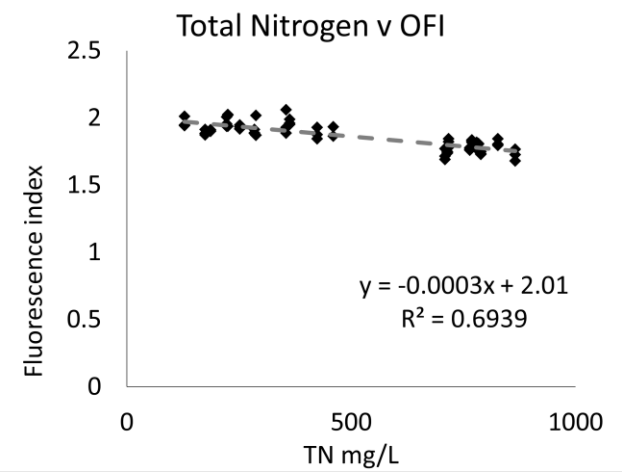

Total Nitrogen v % OC1
Loading
TN mg/L
y = 8E-06x + 0.3265
R² = 0.0059
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
500
1000

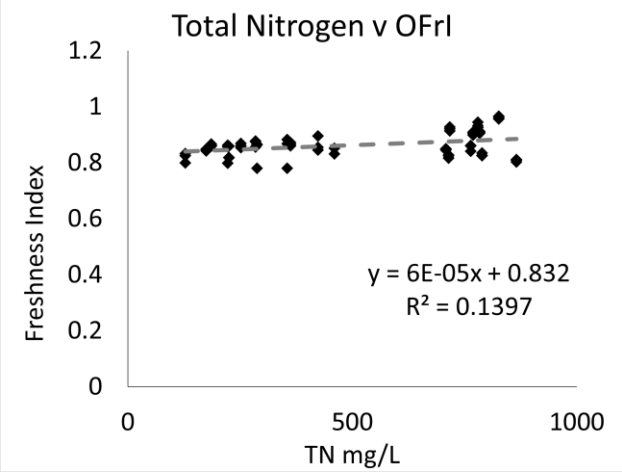

Total Nitrogen v % OC2
Loading
TN mg/L
y = -9E-07x + 0.2821
R² = 5E-05
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
500
1000

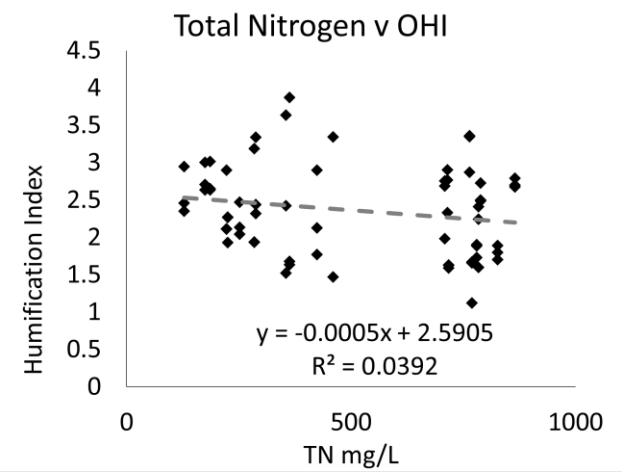

Total Nitrogen v % OC3
Loading
TN mg/L
y = -6E-05x + 0.1724
R² = 0.3916
0.25
0.2
0.15
0.1
0.05
0
0
500
1000

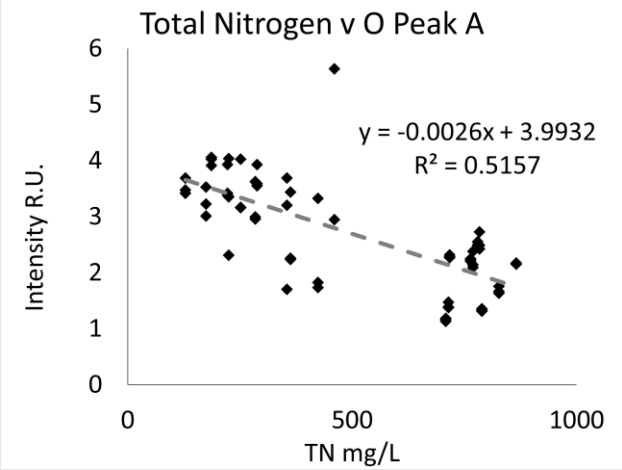

Total Nitrogen v % OC4
Loading
TN mg/L
y = 1E-05x + 0.2195
R² = 0.0028
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
500
1000

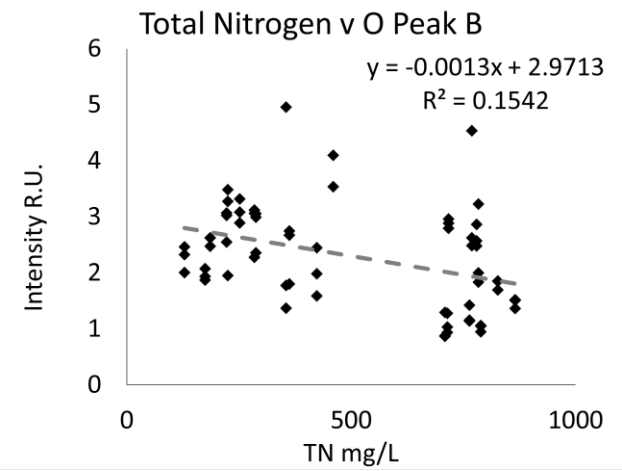

Total Nitrogen v % OC5
Loading
TN mg/L
y = 4E-05x - 0.0006
R² = 0.4495
0.06
0.05
0.04
0.03
0.02
0.01
0
0
500
1000

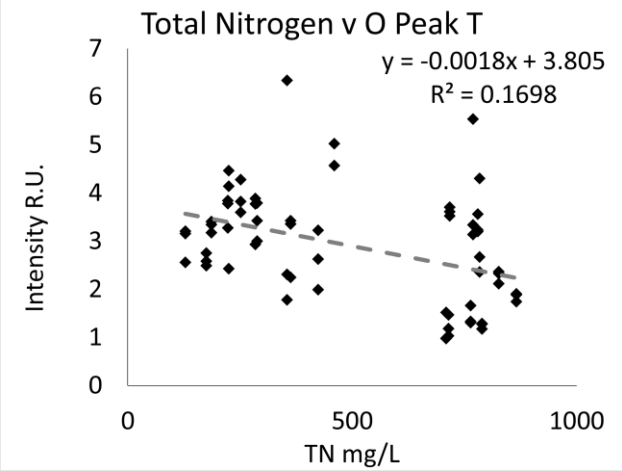

Total Nitrogen v OFI
Fluorescence index
TN mg/L
y = -0.0003x + 2.01
R² = 0.6939
2.5
2
1.5
1
0.5
0
0
500
1000

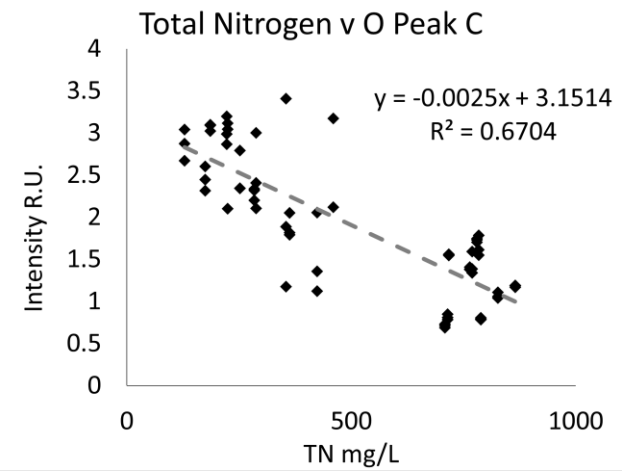

Total Nitrogen v OFrI
Freshness Index
TN mg/L
y = 6E-05x + 0.832
R² = 0.1397
0
0.2
0.4
0.6
0.8
1
1.2
0
500
1000

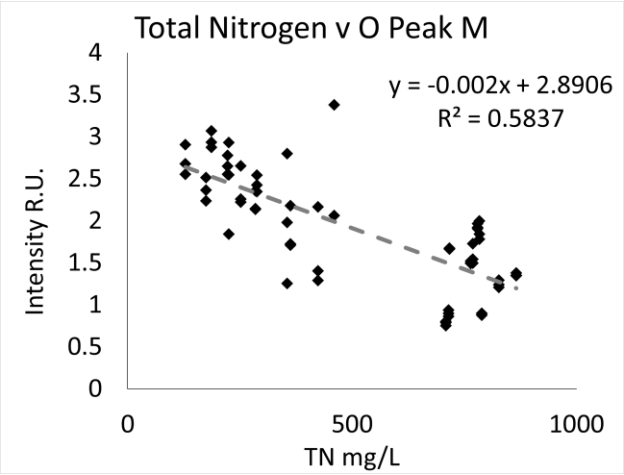

Total Nitrogen v OHI
Humification Index
TN mg/L
y = -0.0005x + 2.5905
R² = 0.0392
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
0
500
1000

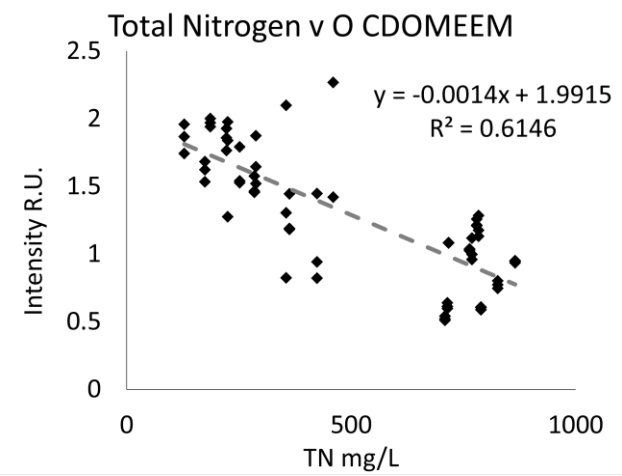

Total Nitrogen v O Peak A
Intensity R.U.
TN mg/L
y = -0.0026x + 3.9932
R² = 0.5157
0
1
2
3
4
5
6
0
500
1000

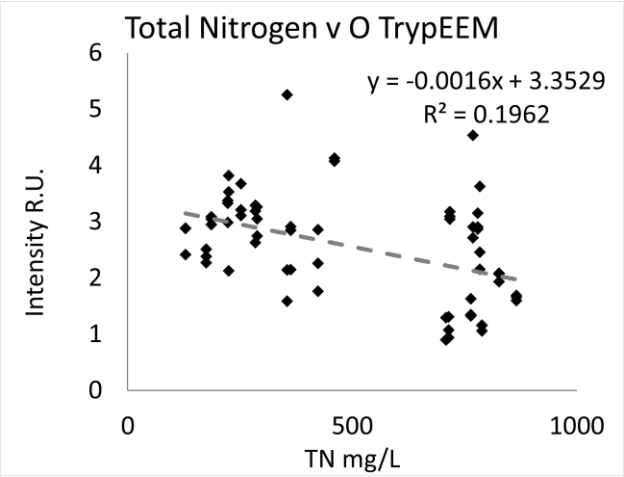

Total Nitrogen v O Peak B
Intensity R.U.
TN mg/L
y = -0.0013x + 2.9713
R² = 0.1542
0
1
2
3
4
5
6
0
500
1000

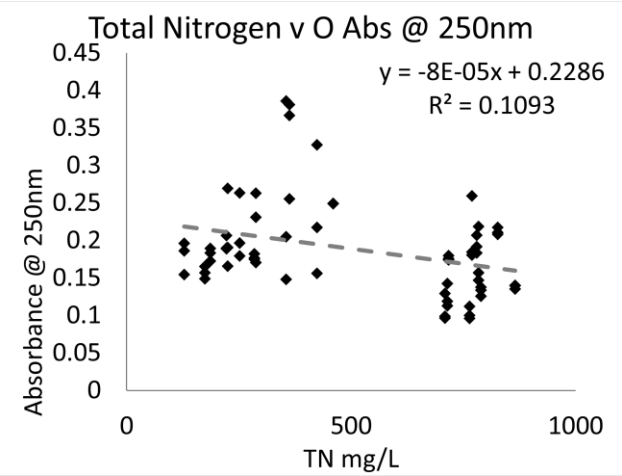

Total Nitrogen v O Peak T
Intensity R.U.
TN mg/L
y = -0.0018x + 3.805
R² = 0.1698
0
1
2
3
4
5
6
7
0
500
1000

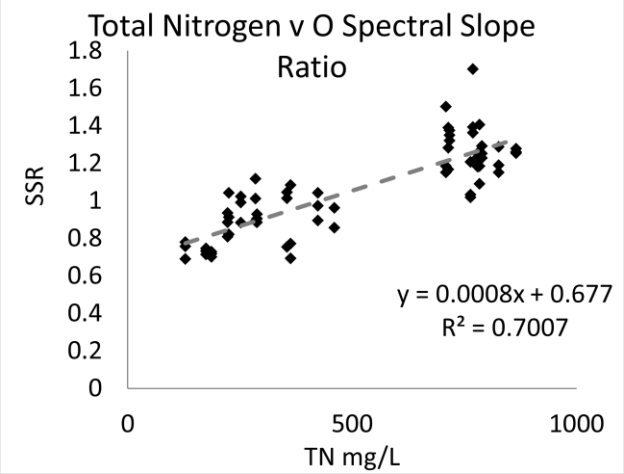

Total Nitrogen v O Peak C
Intensity R.U.
TN mg/L
y = -0.0025x + 3.1514
R² = 0.6704
0
0.5
1
1.5
2
2.5
3
3.5
4
0
500
1000


Total Nitrogen v O Peak M
y = -0.002x + 2.8906
R² = 0.5837
Intensity R.U.
TN mg/L
0
0.5
1
1.5
2
2.5
3
3.5
4
0
500
1000

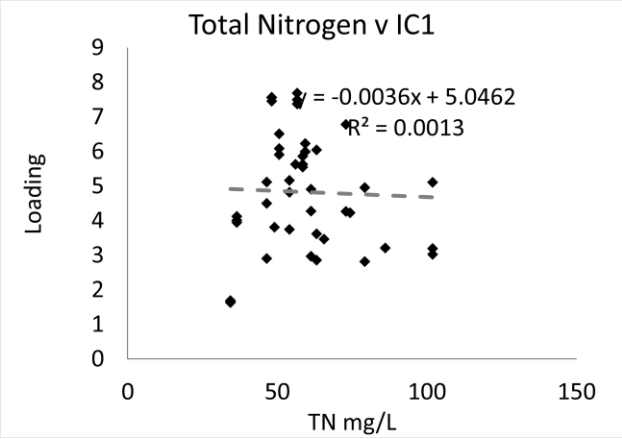

Total Nitrogen v O CDOMEEM
y = -0.0014x + 1.9915
R² = 0.6146
Intensity R.U.
TN mg/L
0
0.5
1
1.5
2
2.5
0
500
1000

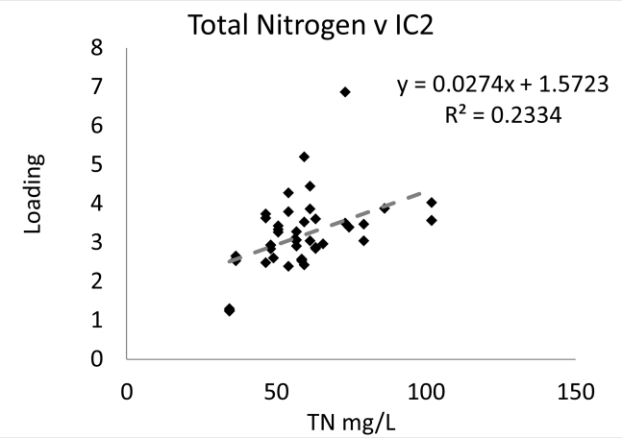

Total Nitrogen v O TrypEEM
y = -0.0016x + 3.3529
R² = 0.1962
Intensity R.U.
TN mg/L
0
1
2
3
4
5
6
0
500
1000

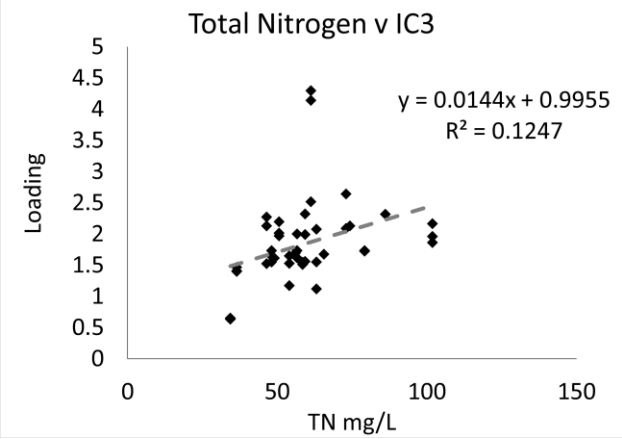

Total Nitrogen v O Abs @ 250nm
y = -8E-05x + 0.2286
R² = 0.1093
Absorbance @ 250nm
TN mg/L
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0
500
1000

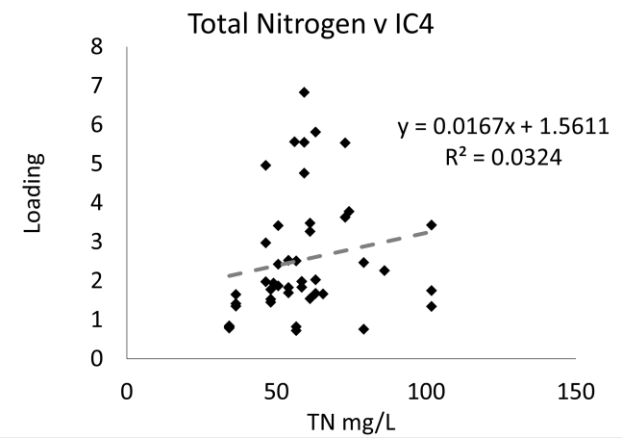

Total Nitrogen v O Spectral Slope Ratio
y = 0.0008x + 0.677
R² = 0.7007
SSR
TN mg/L
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
0
500
1000

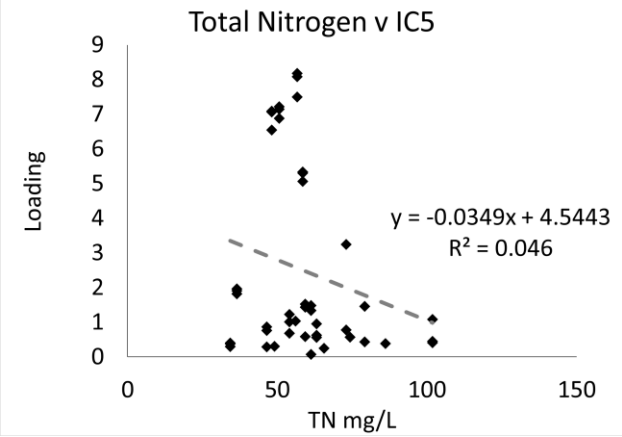
Influent

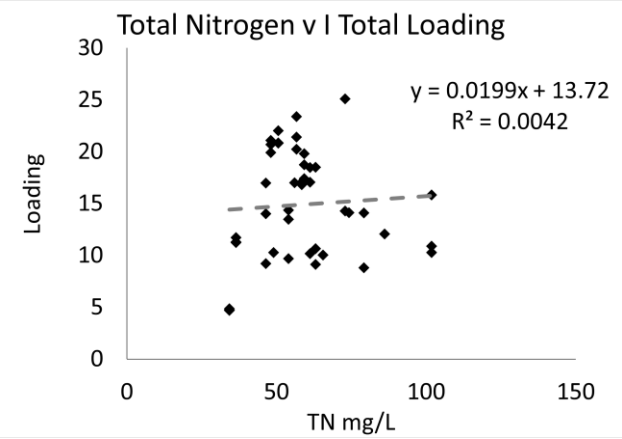

Total Nitrogen v IC1
y = -0.0036x + 5.0462
R² = 0.0013
Loading
TN mg/L

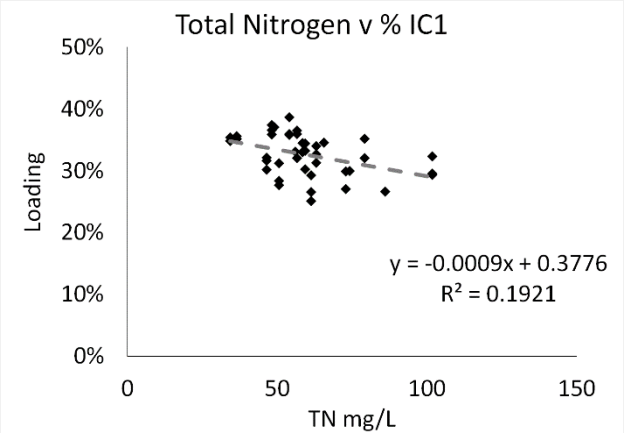

Total Nitrogen v IC2
y = 0.0274x + 1.5723
R² = 0.2334
Loading
TN mg/L

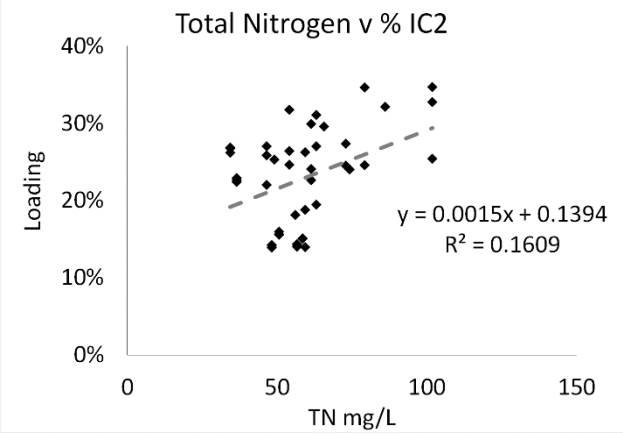

Total Nitrogen v IC3
y = 0.0144x + 0.9955
R² = 0.1247
Loading
TN mg/L

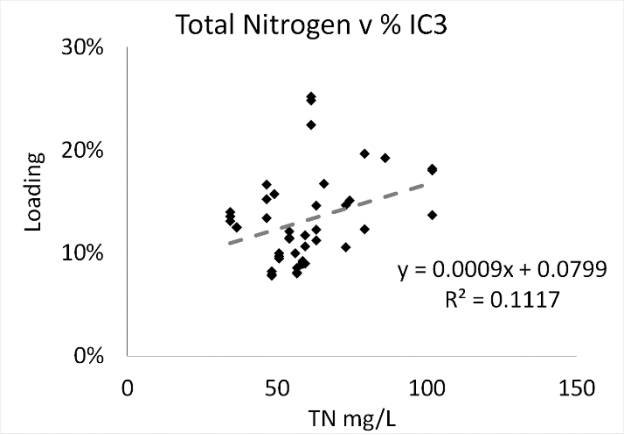

Total Nitrogen v IC4
y = 0.0167x + 1.5611
R² = 0.0324
Loading
TN mg/L

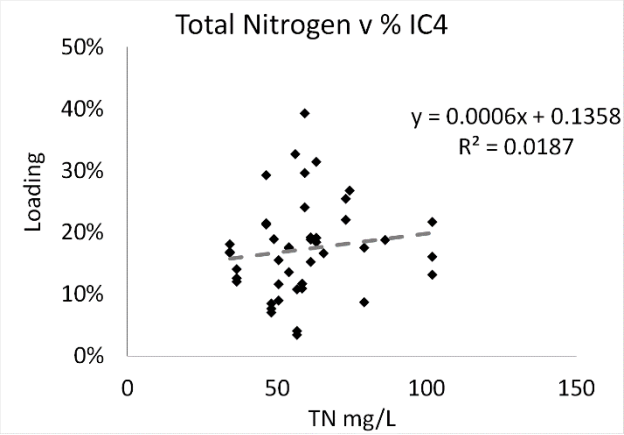

Total Nitrogen v IC5
y = -0.0349x + 4.5443
R² = 0.046
Loading
TN mg/L

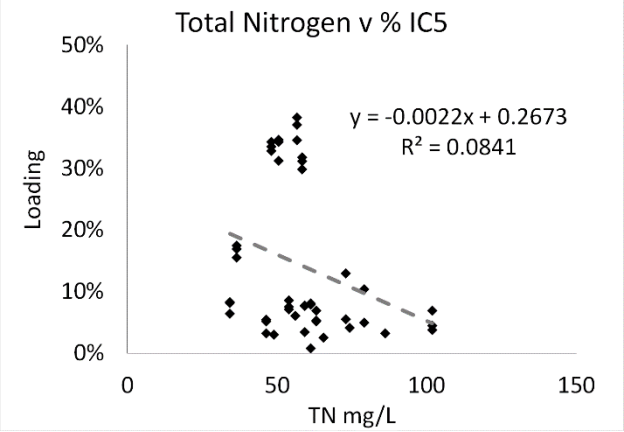

Total Nitrogen v I Total Loading
y = 0.0199x + 13.72
R² = 0.0042
Loading
TN mg/L

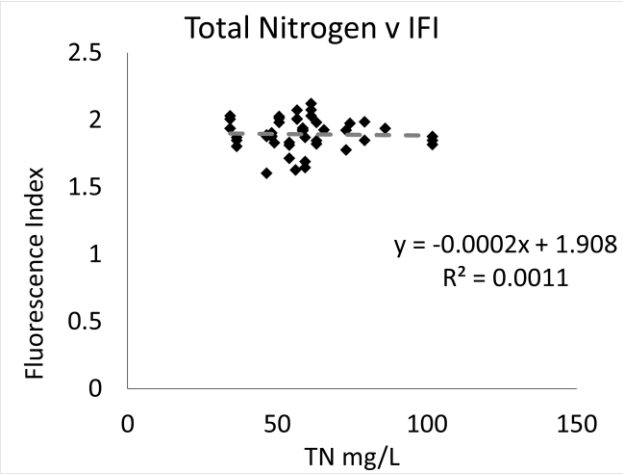

Total Nitrogen v % IC1
Loading
50%
40%
30%
20%
10%
0%
0
50
100
150
TN mg/L
y = -0.0009x + 0.3776
R² = 0.1921

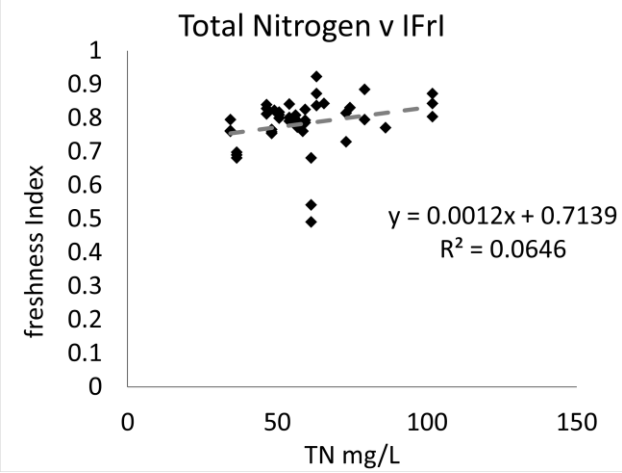

Total Nitrogen v % IC2
Loading
40%
30%
20%
10%
0%
0
50
100
150
TN mg/L
y = 0.0015x + 0.1394
R² = 0.1609

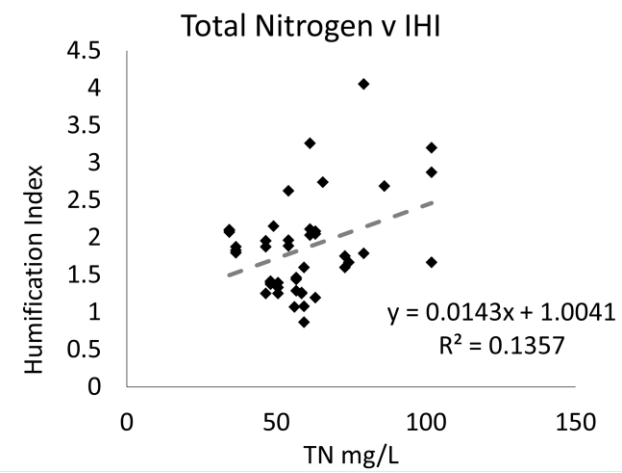

Total Nitrogen v % IC3
Loading
30%
20%
10%
0%
0
50
100
150
TN mg/L
y = 0.0009x + 0.0799
R² = 0.1117

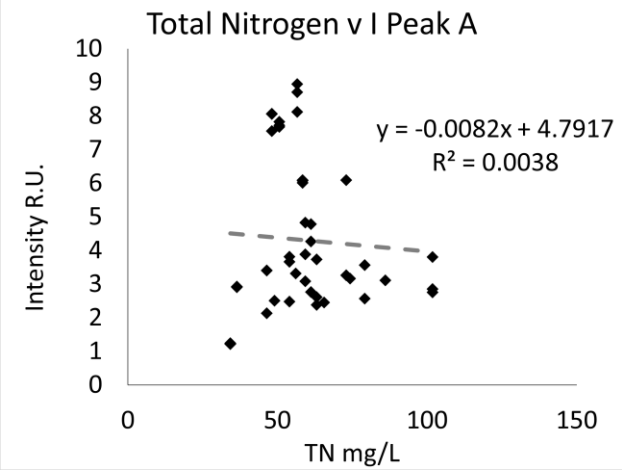

Total Nitrogen v % IC4
Loading
50%
40%
30%
20%
10%
0%
0
50
100
150
TN mg/L
y = 0.0006x + 0.1358
R² = 0.0187

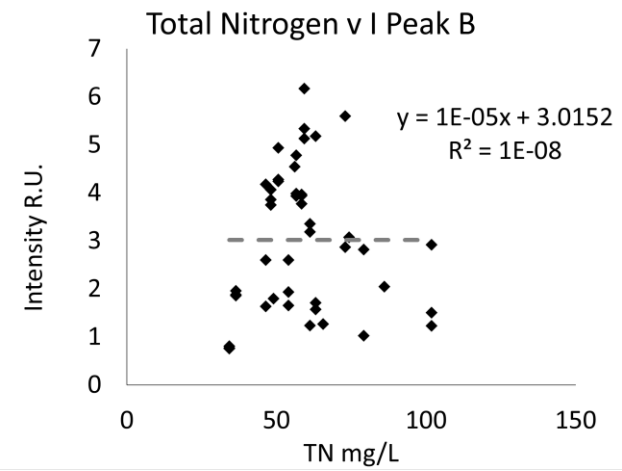

Total Nitrogen v % IC5
Loading
50%
40%
30%
20%
10%
0%
0
50
100
150
TN mg/L
y = -0.0022x + 0.2673
R² = 0.0841

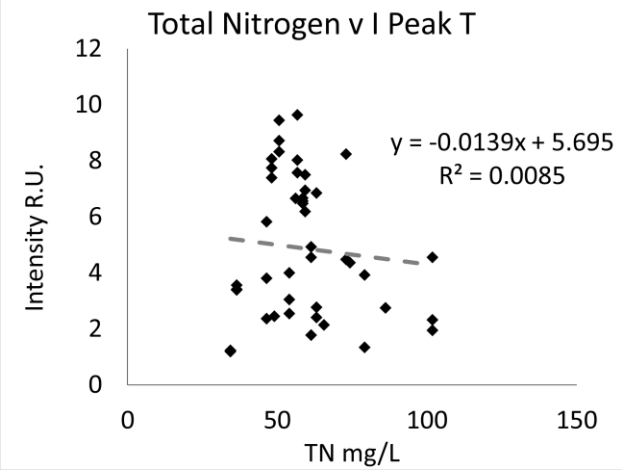

Total Nitrogen v IFI
Fluorescence Index
2.5
2
1.5
1
0.5
0
0
50
100
150
TN mg/L
y = -0.0002x + 1.908
R² = 0.0011

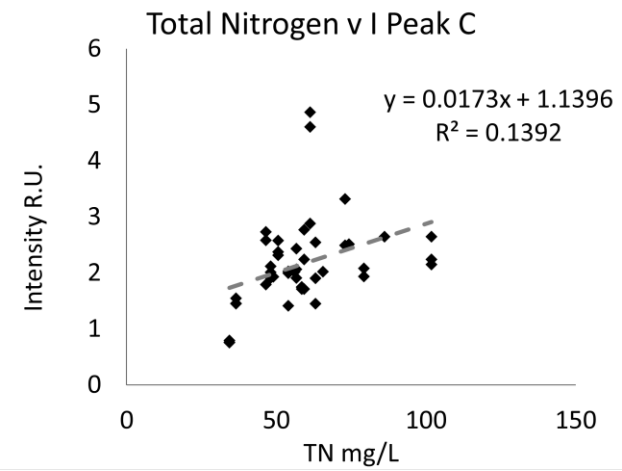

Total Nitrogen v IFrI
freshness Index
y = 0.0012x + 0.7139
R² = 0.0646
TN mg/L

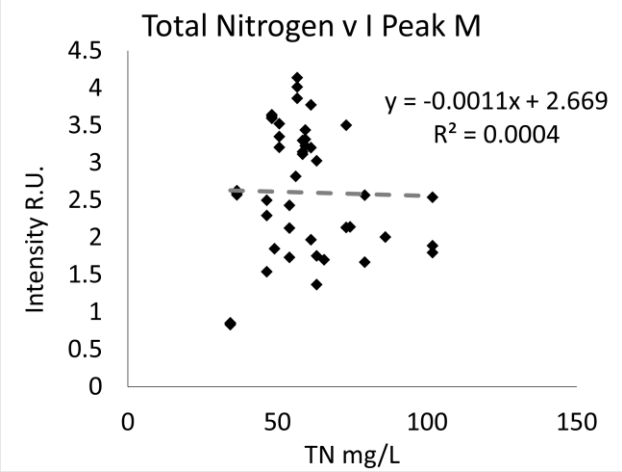

Total Nitrogen v IHI
Humification Index
y = 0.0143x + 1.0041
R² = 0.1357
TN mg/L

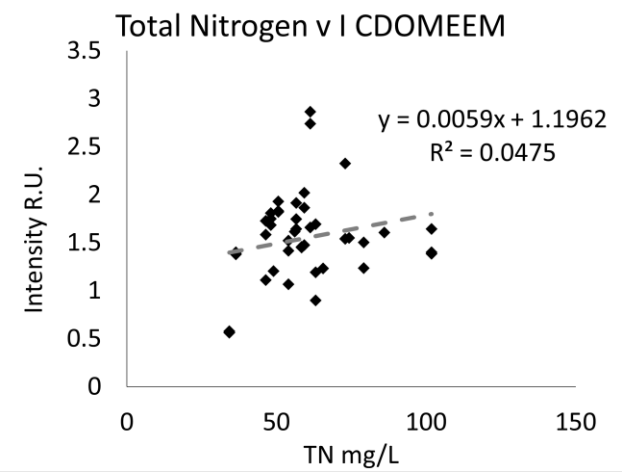

Total Nitrogen v I Peak A
Intensity R.U.
y = -0.0082x + 4.7917
R² = 0.0038
TN mg/L

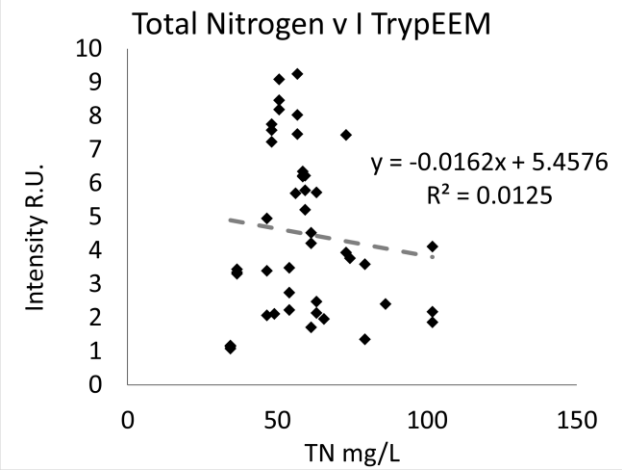

Total Nitrogen v I Peak B
Intensity R.U.
y = 1E-05x + 3.0152
R² = 1E-08
TN mg/L

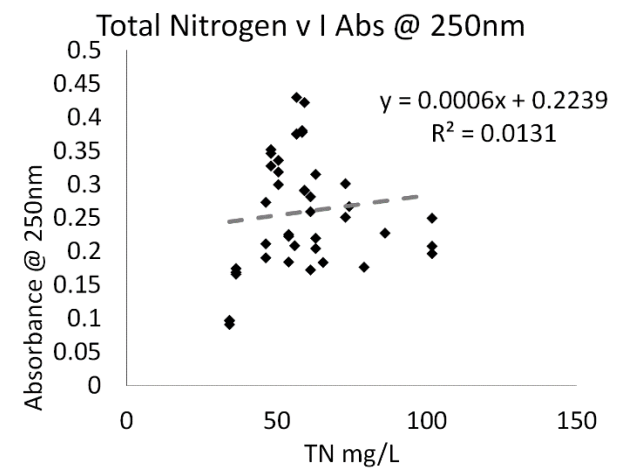

Total Nitrogen v I Peak T
Intensity R.U.
y = -0.0139x + 5.695
R² = 0.0085
TN mg/L

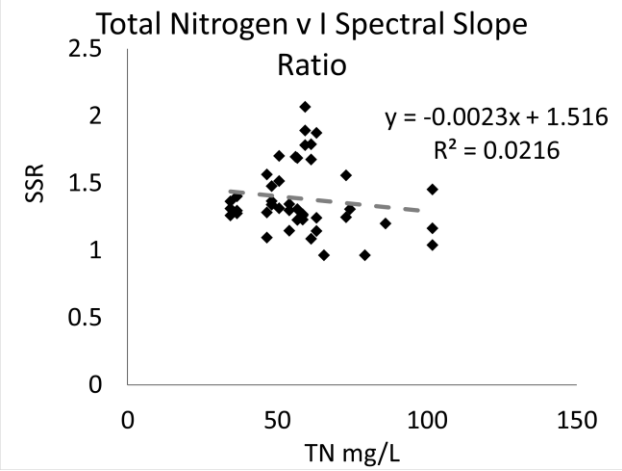

Total Nitrogen v I Peak C
Intensity R.U.
y = 0.0173x + 1.1396
R² = 0.1392
TN mg/L





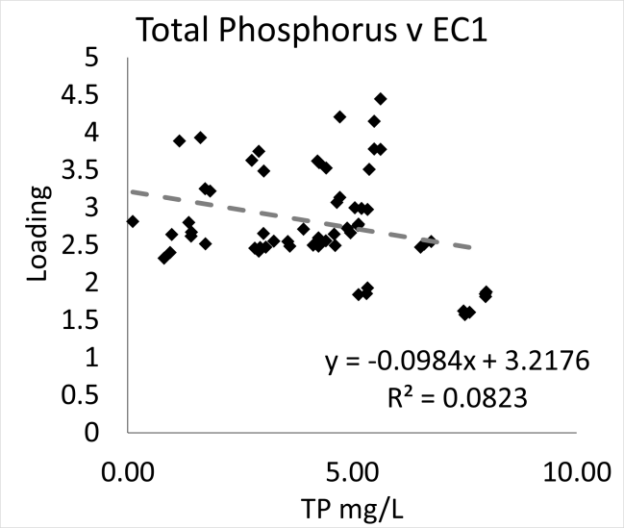


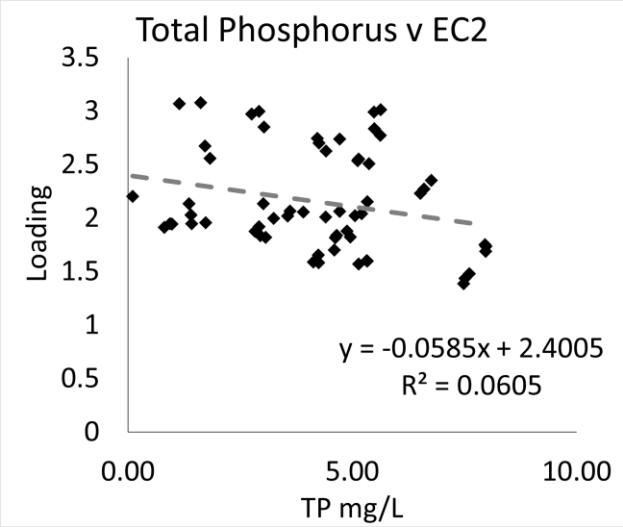


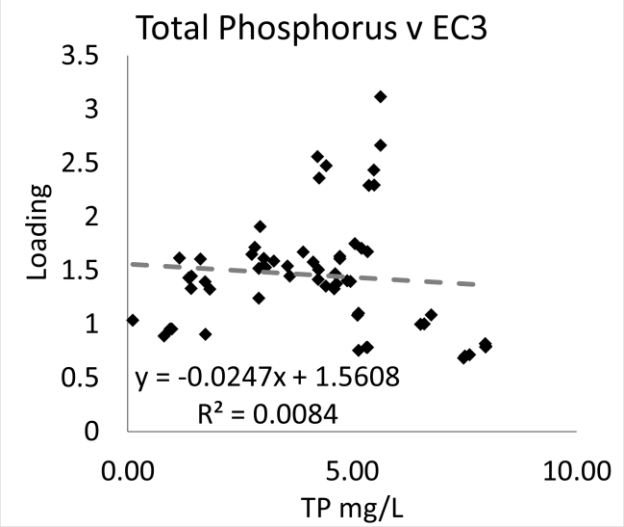


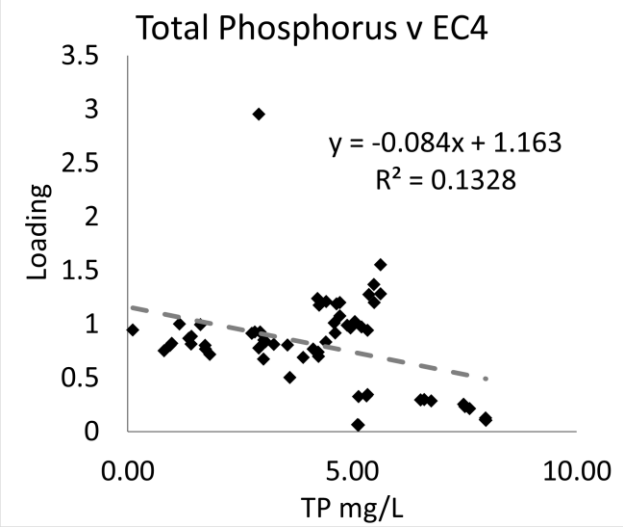
Total phosphorus

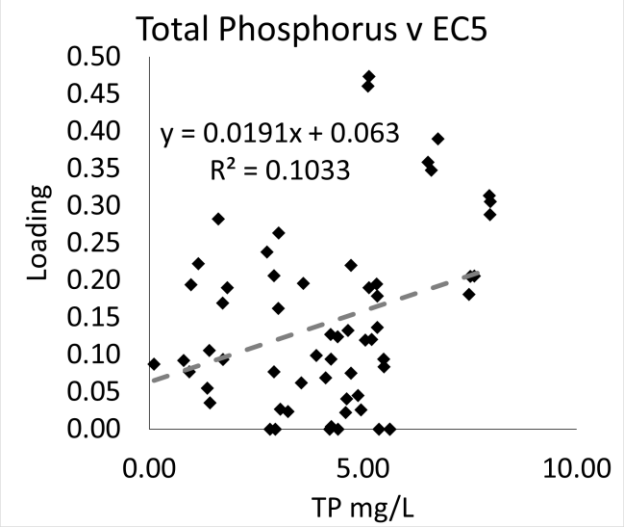
Effluent

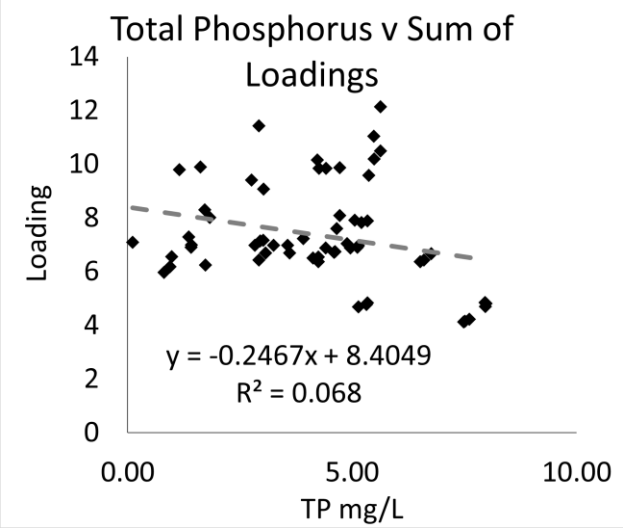

Total Phosphorus v EC1
Loading
TP mg/L
y = -0.0984x + 3.2176
R² = 0.0823
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
0.00
5.00
10.00

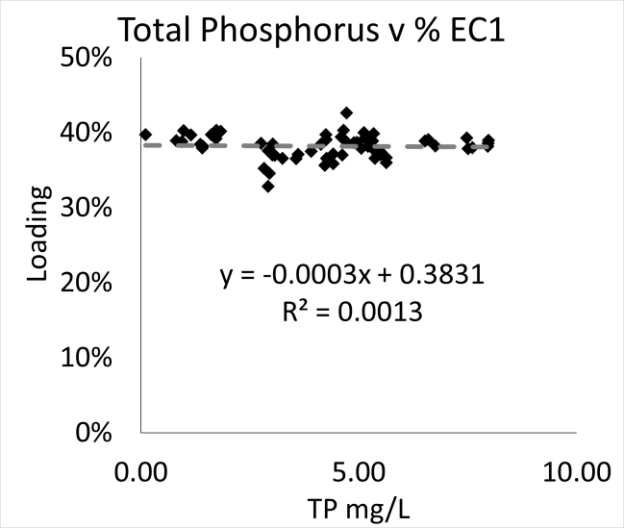

Total Phosphorus v EC2
Loading
TP mg/L
y = -0.0585x + 2.4005
R² = 0.0605
0
0.5
1
1.5
2
2.5
3
3.5
0.00
5.00
10.00

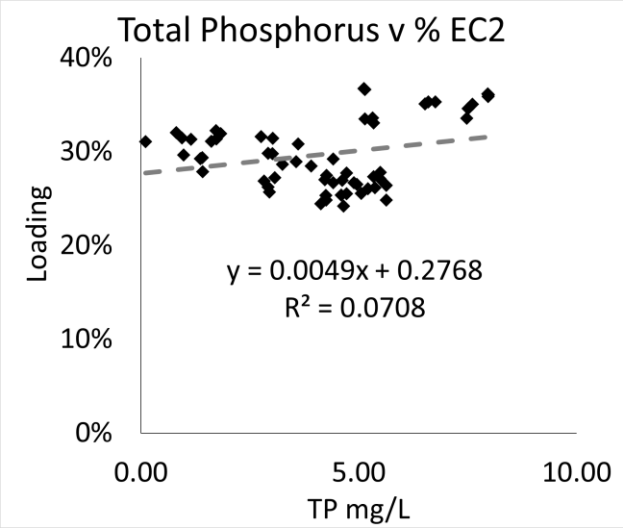

Total Phosphorus v EC3
Loading
TP mg/L
y = -0.0247x + 1.5608
R² = 0.0084
0
0.5
1
1.5
2
2.5
3
3.5
0.00
5.00
10.00

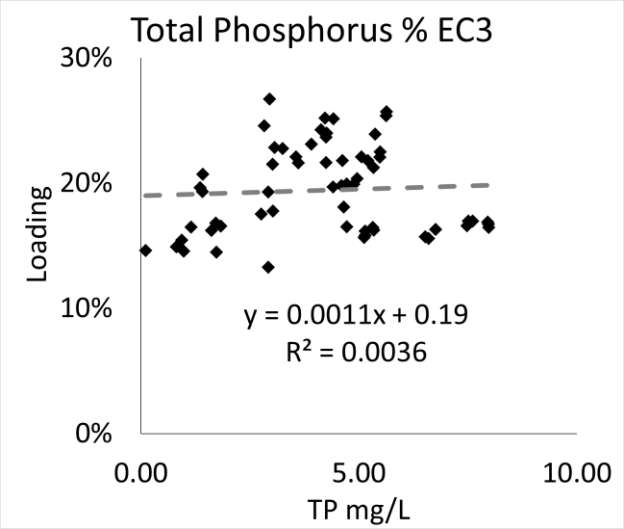

Total Phosphorus v EC4
Loading
TP mg/L
y = -0.084x + 1.163
R² = 0.1328
0
0.5
1
1.5
2
2.5
3
3.5
0.00
5.00
10.00

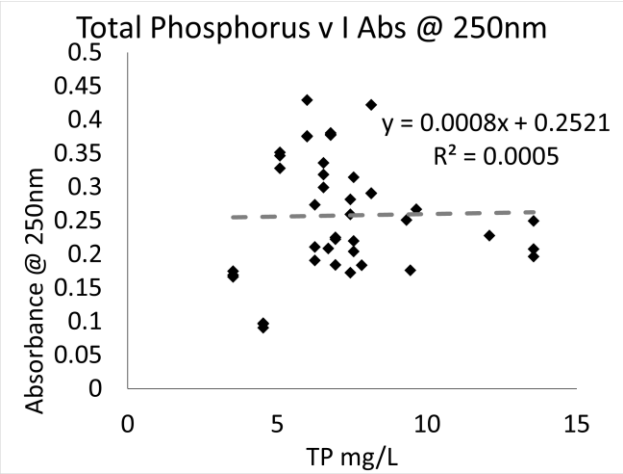

Total Phosphorus v EC5
Loading
TP mg/L
y = 0.0191x + 0.063
R² = 0.1033
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0.45
0.50
0.00
5.00
10.00

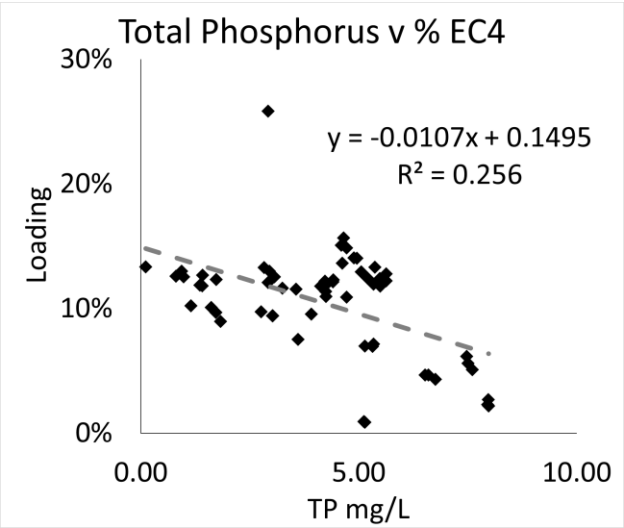

Total Phosphorus v Sum of Loadings
Loading
TP mg/L
y = -0.2467x + 8.4049
R² = 0.068
0
2
4
6
8
10
12
14
0.00
5.00
10.00

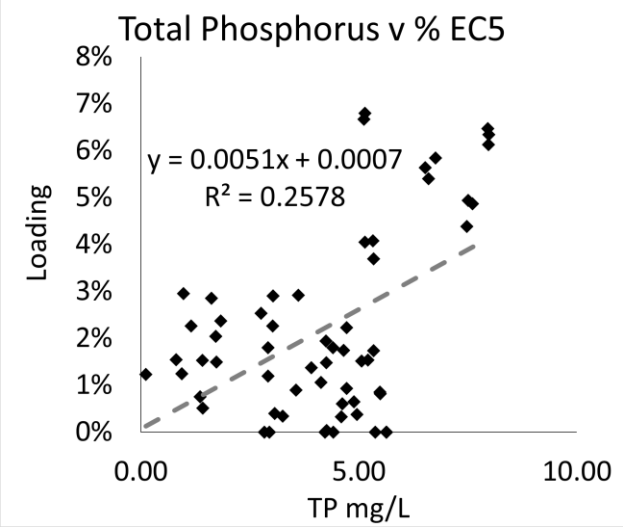

Total Phosphorus v % EC1
50%
40%
30%
20%
10%
0%
Loading
y = -0.0003x + 0.3831
R² = 0.0013
0.00
5.00
10.00
TP mg/L

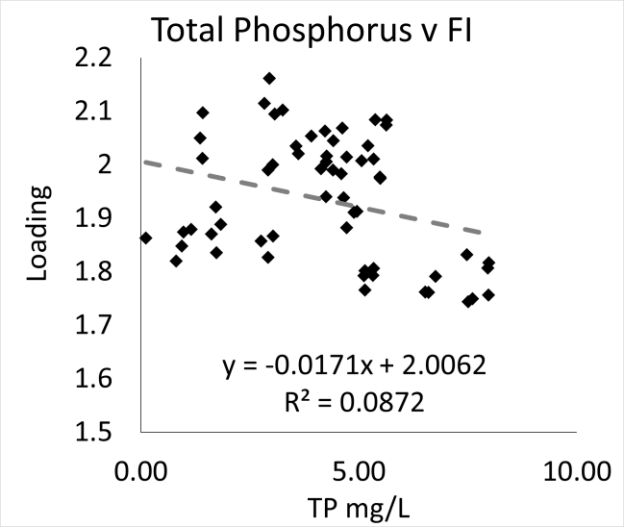

Total Phosphorus v % EC2
40%
30%
20%
10%
0%
Loading
y = 0.0049x + 0.2768
R² = 0.0708
0.00
5.00
10.00
TP mg/L

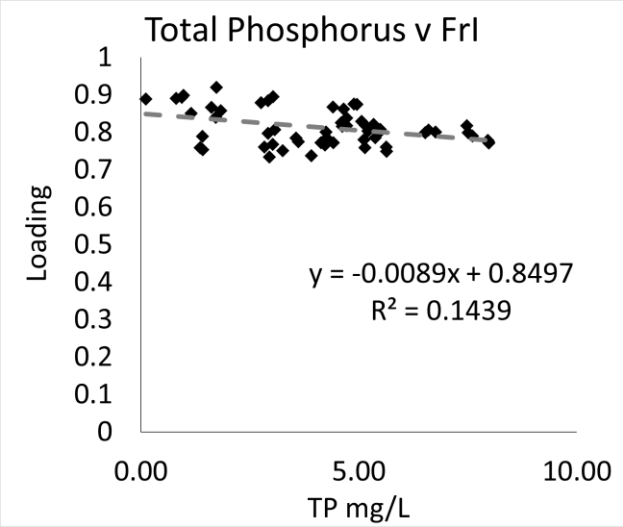

Total Phosphorus % EC3
30%
20%
10%
0%
Loading
y = 0.0011x + 0.19
R² = 0.0036
0.00
5.00
10.00
TP mg/L

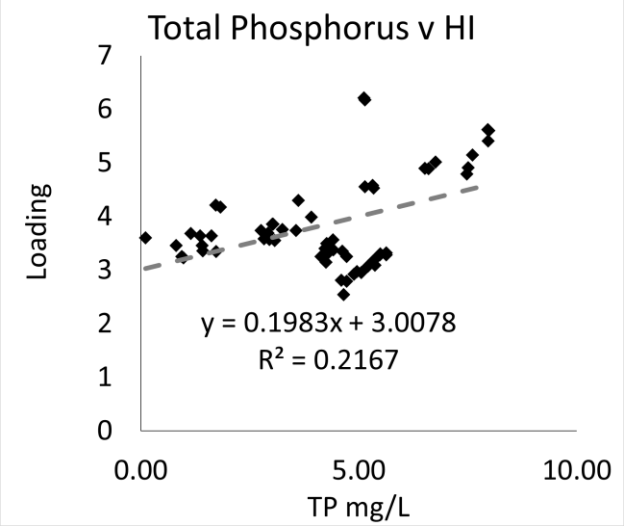

Total Phosphorus v I Abs @ 250nm
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
Absorbance @ 250nm
y = 0.0008x + 0.2521
R² = 0.0005
0
5
10
15
TP mg/L

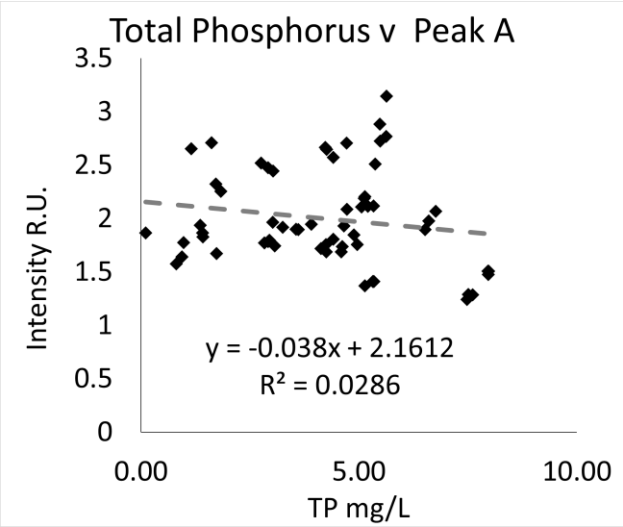

Total Phosphorus v % EC4
30%
20%
10%
0%
Loading
y = -0.0107x + 0.1495
R² = 0.256
0.00
5.00
10.00
TP mg/L

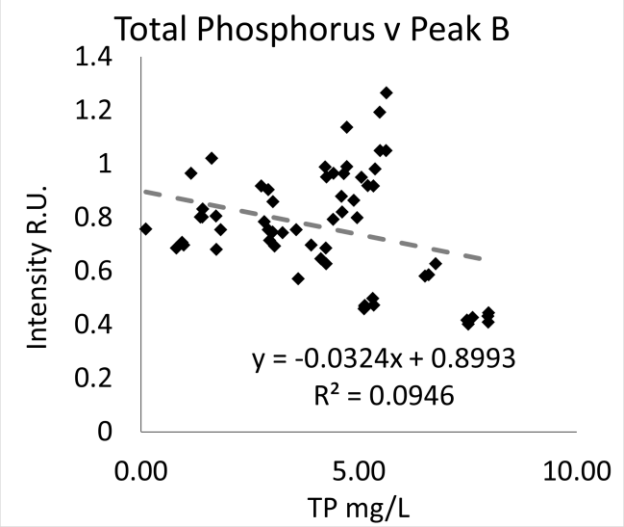

Total Phosphorus v % EC5
8%
7%
6%
5%
4%
3%
2%
1%
0%
Loading
y = 0.0051x + 0.0007
R² = 0.2578
0.00
5.00
10.00
TP mg/L

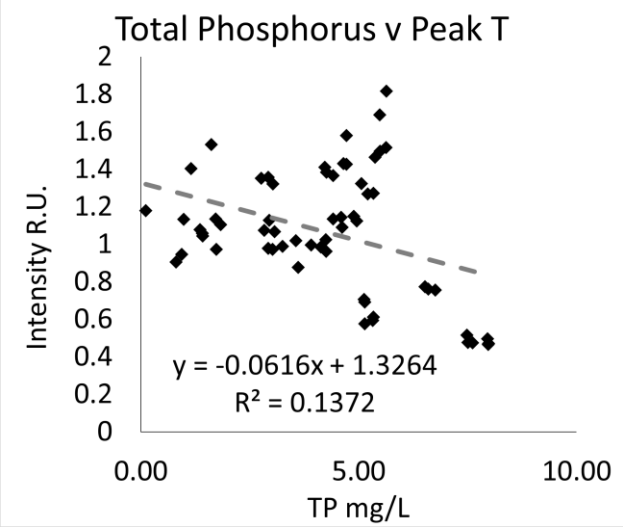

Total Phosphorus v FI
Loading
TP mg/L
y = -0.0171x + 2.0062
R² = 0.0872
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
0.00
5.00
10.00

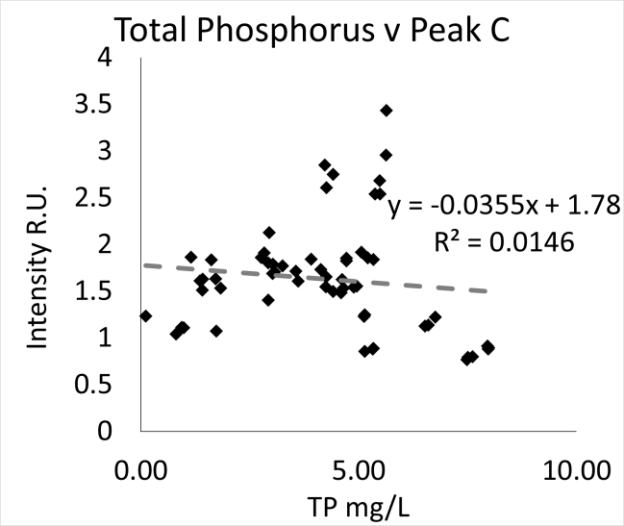

Total Phosphorus v FrI
Loading
TP mg/L
y = -0.0089x + 0.8497
R² = 0.1439
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.00
5.00
10.00

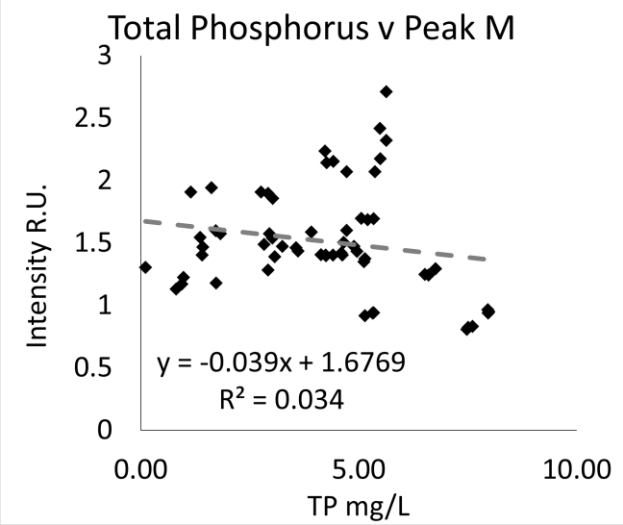

Total Phosphorus v HI
Loading
TP mg/L
y = 0.1983x + 3.0078
R² = 0.2167
7
6
5
4
3
2
1
0
0.00
5.00
10.00

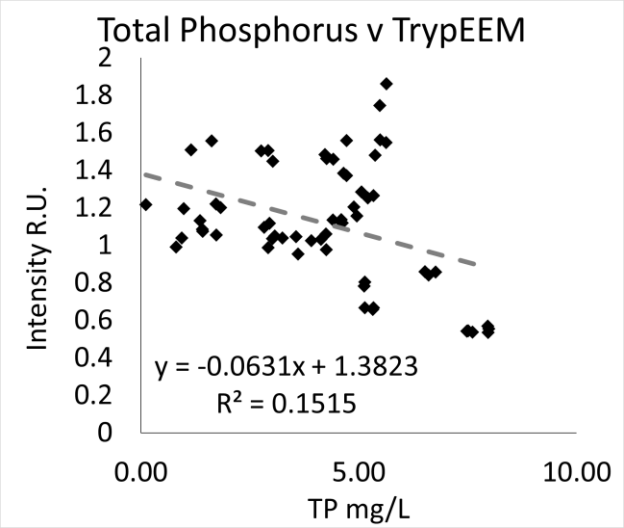

Total Phosphorus v Peak A
Intensity R.U.
TP mg/L
y = -0.038x + 2.1612
R² = 0.0286
3.5
3
2.5
2
1.5
1
0.5
0
0.00
5.00
10.00

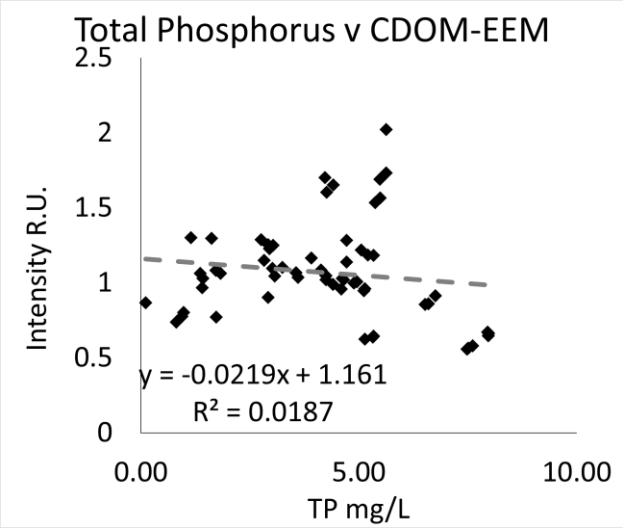

Total Phosphorus v Peak B
Intensity R.U.
TP mg/L
y = -0.0324x + 0.8993
R² = 0.0946
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0.00
5.00
10.00

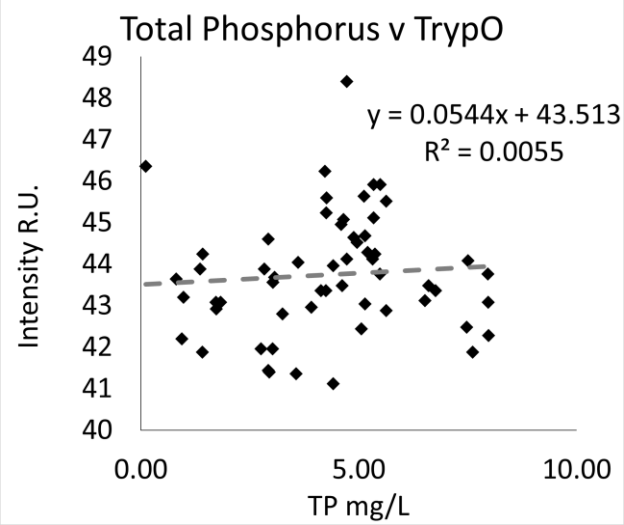

Total Phosphorus v Peak T
Intensity R.U.
TP mg/L
y = -0.0616x + 1.3264
R² = 0.1372
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0.00
5.00
10.00

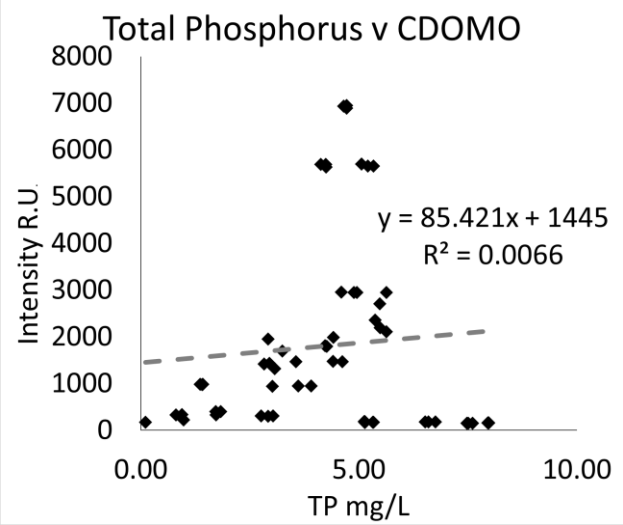

Total Phosphorus v Peak C
Intensity R.U.
TP mg/L
y = -0.0355x + 1.78
R² = 0.0146
0
0.5
1
1.5
2
2.5
3
3.5
4
0.00
5.00
10.00

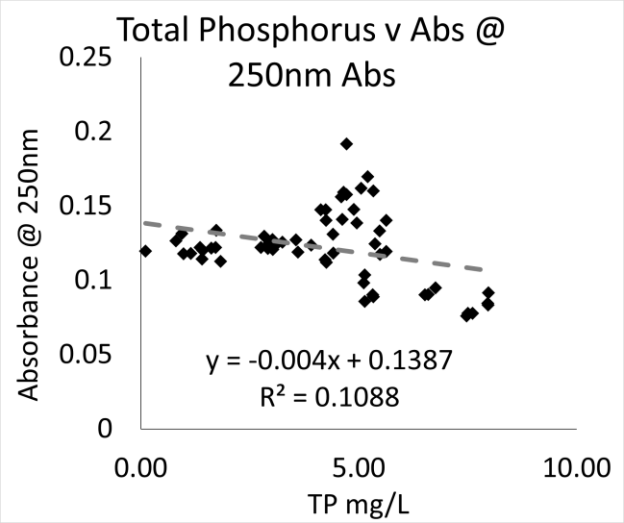

Total Phosphorus v Peak M
Intensity R.U.
TP mg/L
y = -0.039x + 1.6769
R² = 0.034
0
0.5
1
1.5
2
2.5
3
0.00
5.00
10.00

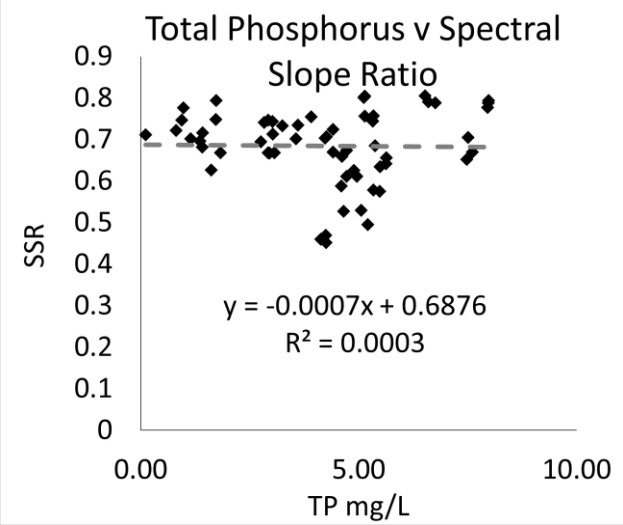

Total Phosphorus v TrypEEM
Intensity R.U.
TP mg/L
y = -0.0631x + 1.3823
R² = 0.1515
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0.00
5.00
10.00


Total Phosphorus v CDOM-EEM
Intensity R.U.
TP mg/L
y = -0.0219x + 1.161
R² = 0.0187
0
0.5
1
1.5
2
2.5
0.00
5.00
10.00

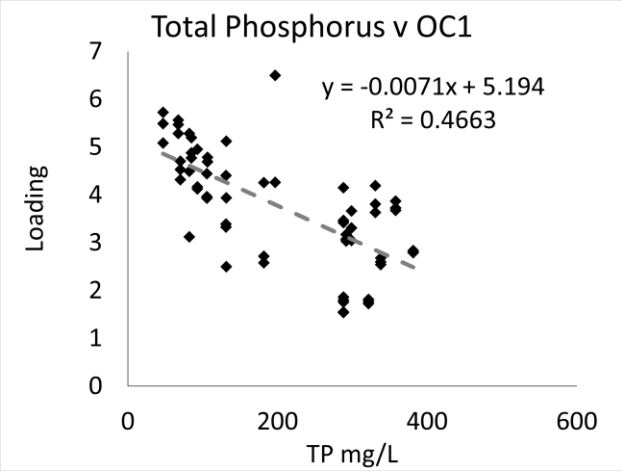

Total Phosphorus v TrypO
y = 0.0544x + 43.513
R² = 0.0055
Intensity R.U.
TP mg/L
49
48
47
46
45
44
43
42
41
40
0.00
5.00
10.00

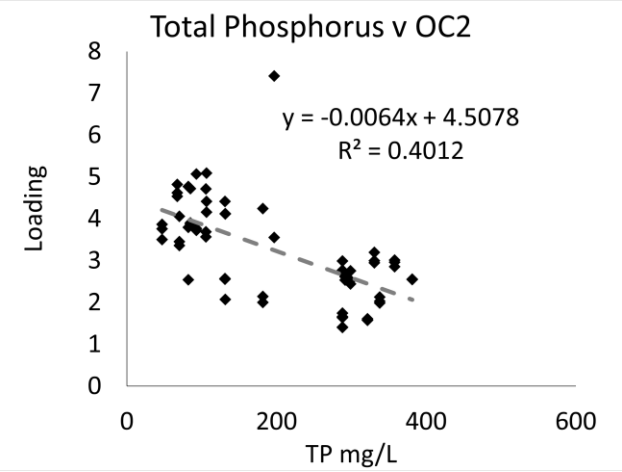

Total Phosphorus v CDOMO
y = 85.421x + 1445
R² = 0.0066
Intensity R.U.
TP mg/L
8000
7000
6000
5000
4000
3000
2000
1000
0
0.00
5.00
10.00

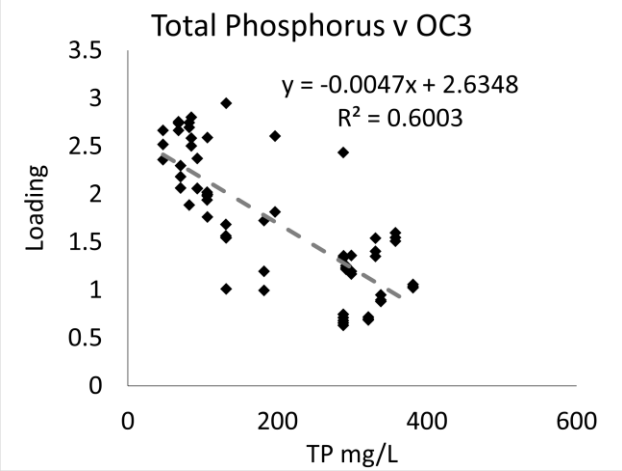

Total Phosphorus v Abs @ 250nm Abs
y = -0.004x + 0.1387
R² = 0.1088
Absorbance @ 250nm
TP mg/L
0.25
0.2
0.15
0.1
0.05
0
0.00
5.00
10.00

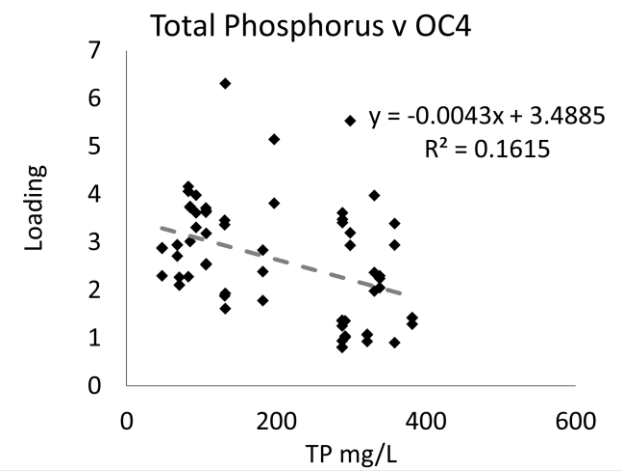

Total Phosphorus v Spectral Slope Ratio
y = -0.0007x + 0.6876
R² = 0.0003
SSR
TP mg/L
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.00
5.00
10.00

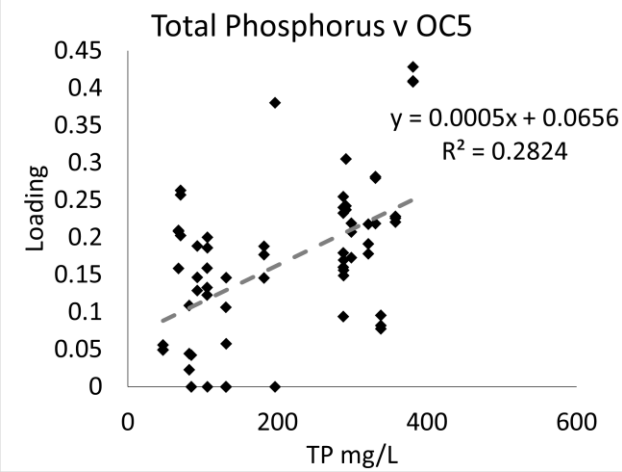
Oxic Tank

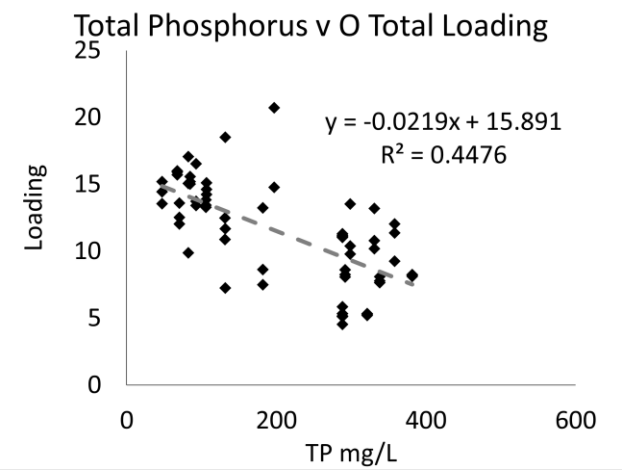

Total Phosphorus v OC1
y = -0.0071x + 5.194
R² = 0.4663
Loading
TP mg/L
0
1
2
3
4
5
6
7
0
200
400
600

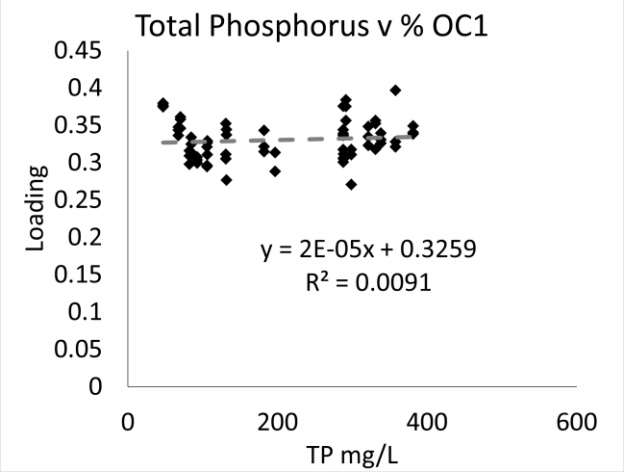

Total Phosphorus v OC2
y = -0.0064x + 4.5078
R² = 0.4012
Loading
TP mg/L
0
1
2
3
4
5
6
7
8
0
200
400
600

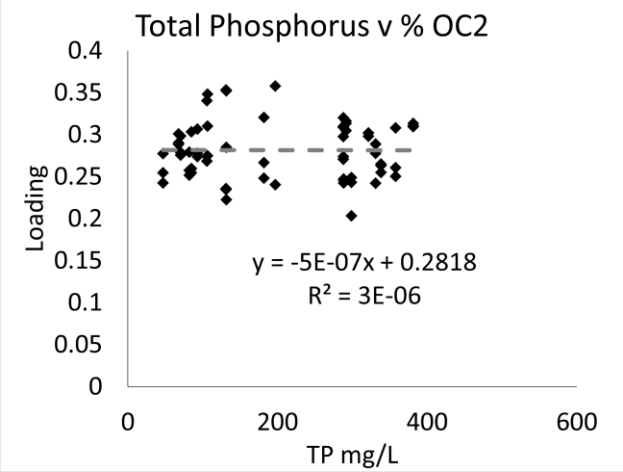

Total Phosphorus v OC3
y = -0.0047x + 2.6348
R² = 0.6003
Loading
TP mg/L
0
0.5
1
1.5
2
2.5
3
3.5
0
200
400
600

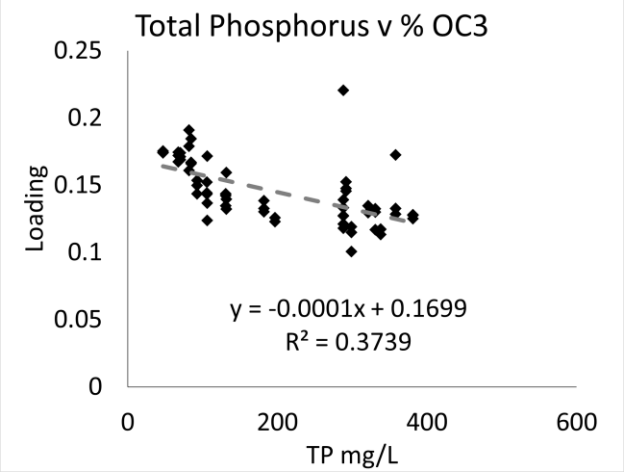

Total Phosphorus v OC4
y = -0.0043x + 3.4885
R² = 0.1615
Loading
TP mg/L
0
1
2
3
4
5
6
7
0
200
400
600

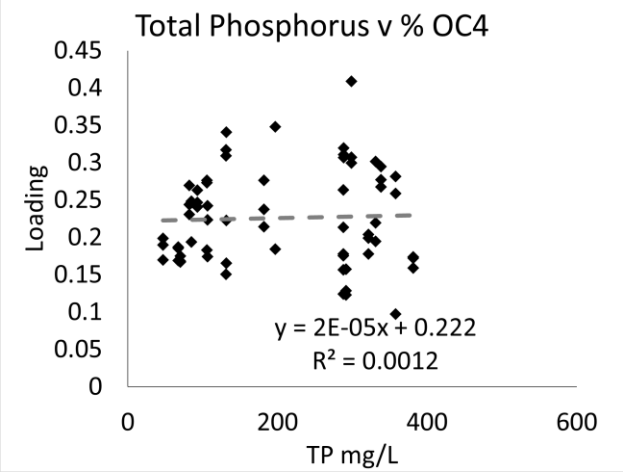

Total Phosphorus v OC5
y = 0.0005x + 0.0656
R² = 0.2824
Loading
TP mg/L
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0
200
400
600

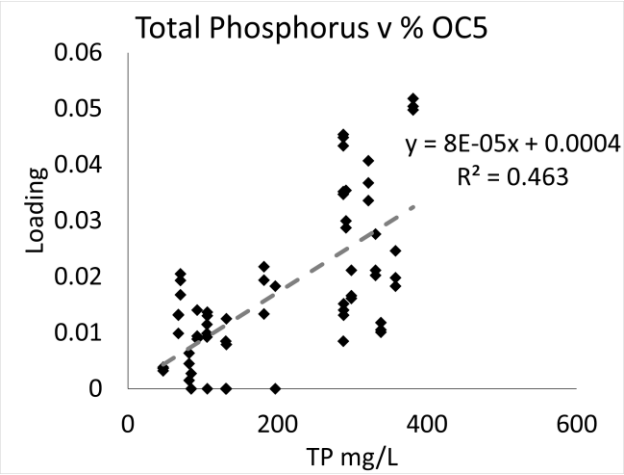

Total Phosphorus v O Total Loading
y = -0.0219x + 15.891
R² = 0.4476
Loading
TP mg/L
0
5
10
15
20
25
0
200
400
600

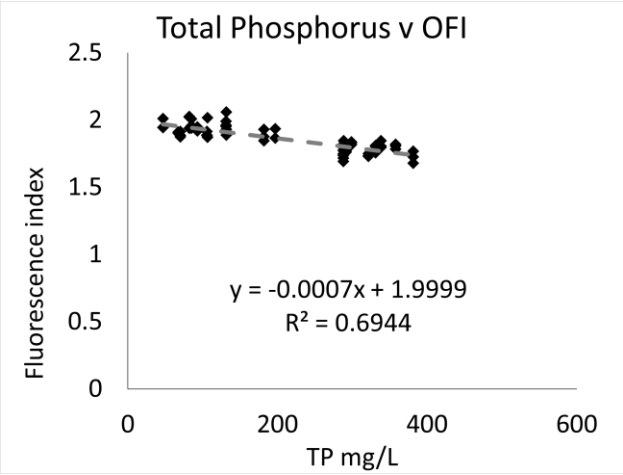

Total Phosphorus v % OC1
Loading
TP mg/L
y = 2E-05x + 0.3259
R² = 0.0091
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
200
400
600

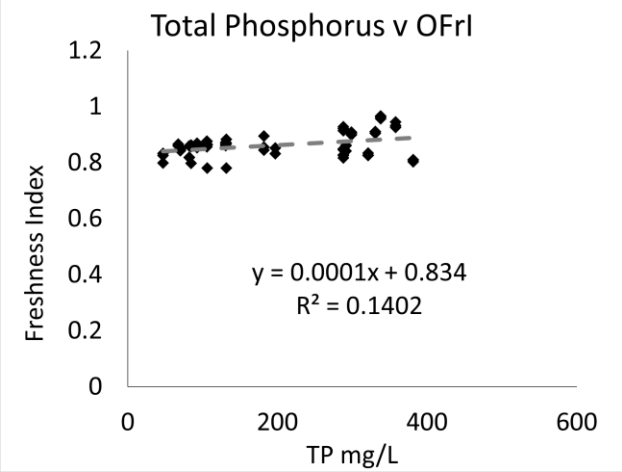

Total Phosphorus v % OC2
Loading
TP mg/L
y = -5E-07x + 0.2818
R² = 3E-06
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
200
400
600

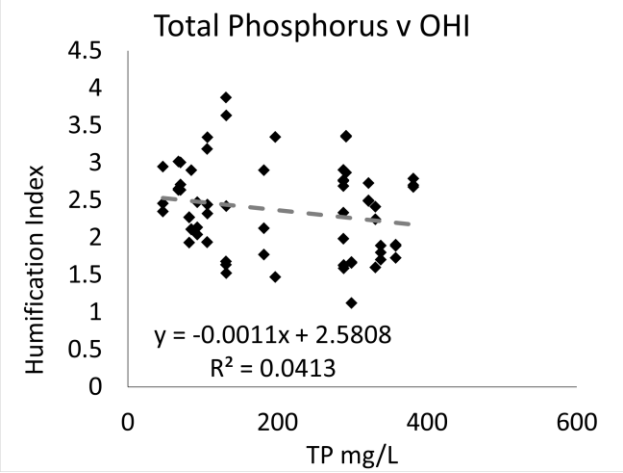

Total Phosphorus v % OC3
Loading
TP mg/L
y = -0.0001x + 0.1699
R² = 0.3739
0.25
0.2
0.15
0.1
0.05
0
0
200
400
600

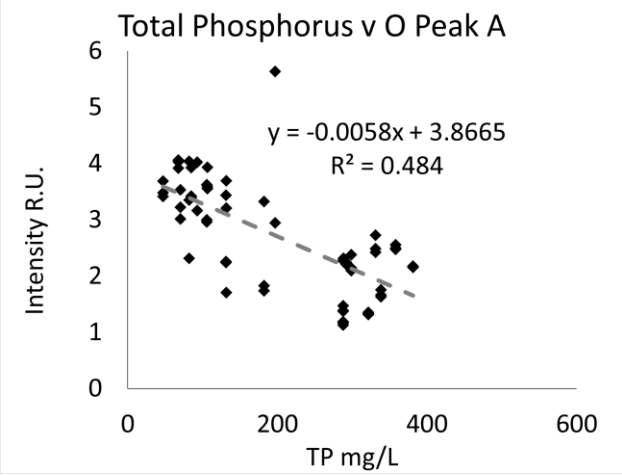

Total Phosphorus v % OC4
Loading
TP mg/L
y = 2E-05x + 0.222
R² = 0.0012
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
200
400
600

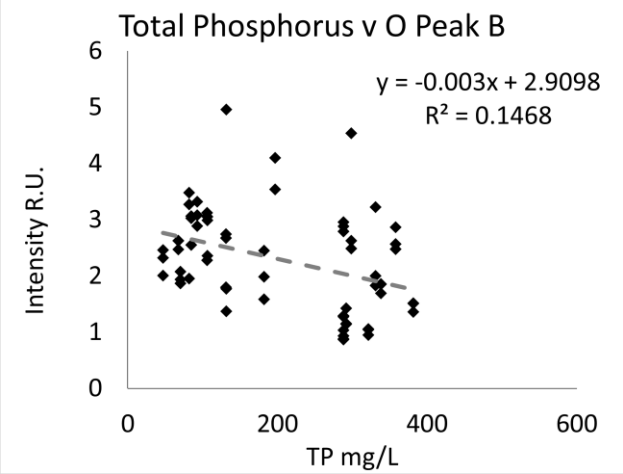

Total Phosphorus v % OC5
Loading
TP mg/L
y = 8E-05x + 0.0004
R² = 0.463
0.06
0.05
0.04
0.03
0.02
0.01
0
0
200
400
600

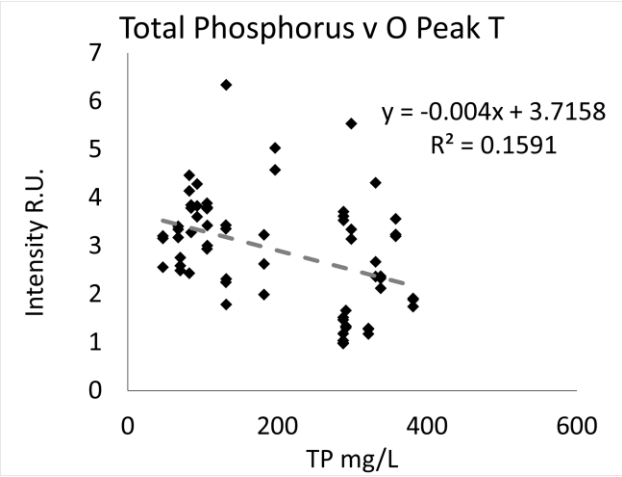

Total Phosphorus v OFI
Fluorescence index
TP mg/L
y = -0.0007x + 1.9999
R² = 0.6944
2.5
2
1.5
1
0.5
0
0
200
400
600

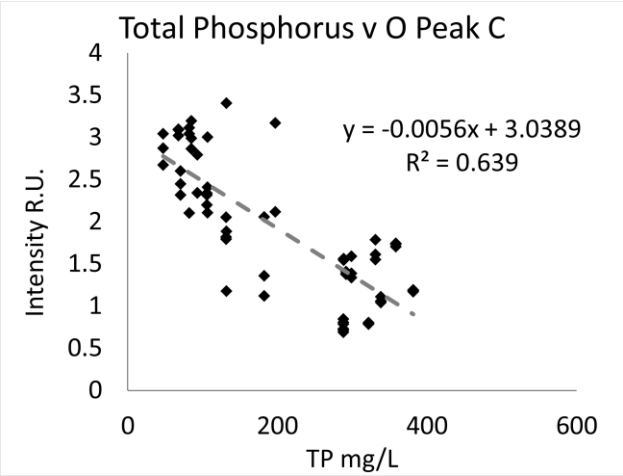

Total Phosphorus v OFrI
Freshness Index
TP mg/L
y = 0.0001x + 0.834
R² = 0.1402
0
0.2
0.4
0.6
0.8
1
1.2
0
200
400
600

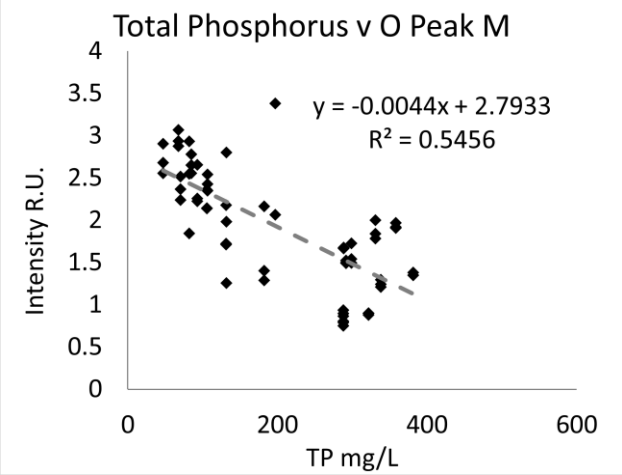

Total Phosphorus v OHI
Humification Index
TP mg/L
y = -0.0011x + 2.5808
R² = 0.0413
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
0
200
400
600

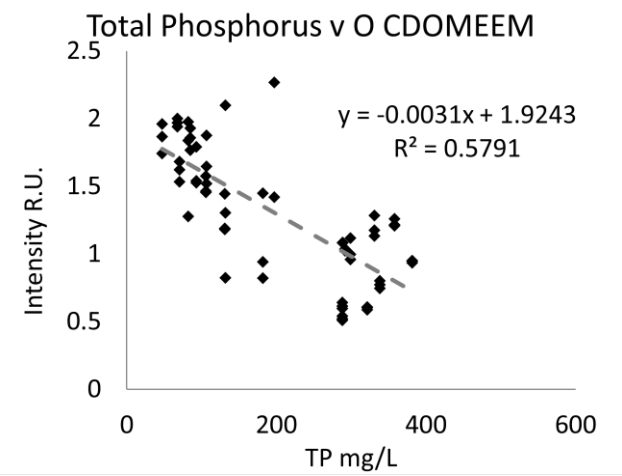

Total Phosphorus v O Peak A
Intensity R.U.
TP mg/L
y = -0.0058x + 3.8665
R² = 0.484
0
1
2
3
4
5
6
0
200
400
600

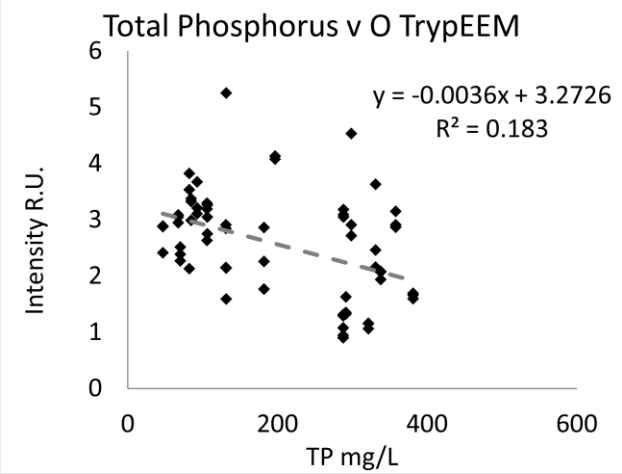

Total Phosphorus v O Peak B
Intensity R.U.
TP mg/L
y = -0.003x + 2.9098
R² = 0.1468
0
1
2
3
4
5
6
0
200
400
600

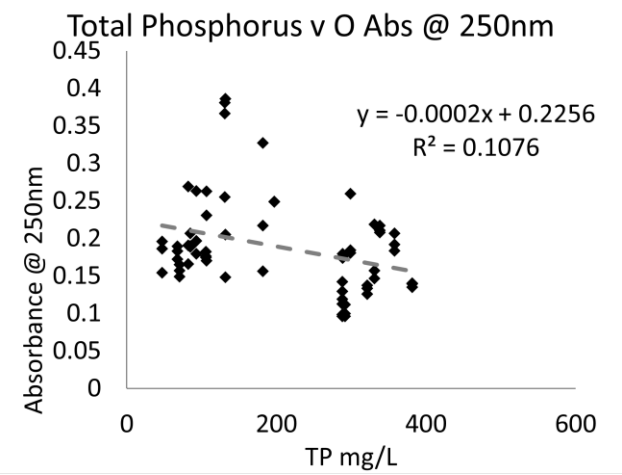

Total Phosphorus v O Peak T
Intensity R.U.
TP mg/L
y = -0.004x + 3.7158
R² = 0.1591
0
1
2
3
4
5
6
7
0
200
400
600

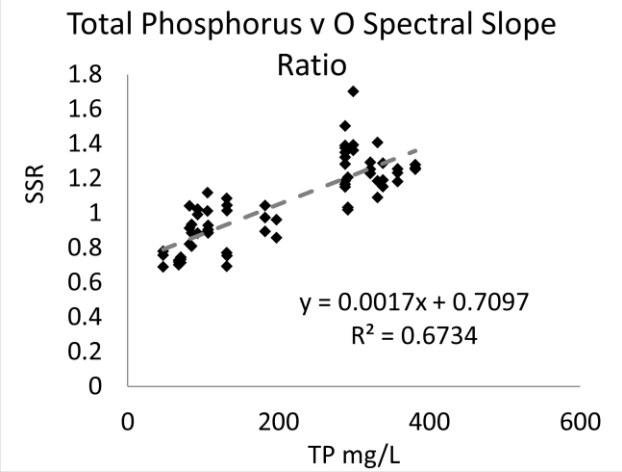

Total Phosphorus v O Peak C
Intensity R.U.
TP mg/L
y = -0.0056x + 3.0389
R² = 0.639
0
0.5
1
1.5
2
2.5
3
3.5
4
0
200
400
600


Total Phosphorus v O Peak M
y = -0.0044x + 2.7933
R² = 0.5456
Intensity R.U.
TP mg/L

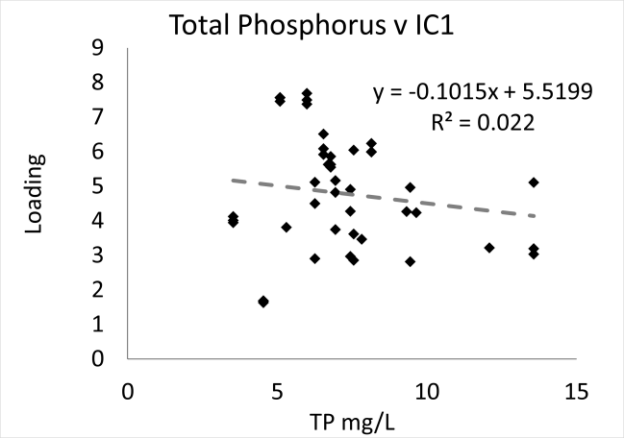

Total Phosphorus v O CDOMEEM
y = -0.0031x + 1.9243
R² = 0.5791
Intensity R.U.
TP mg/L

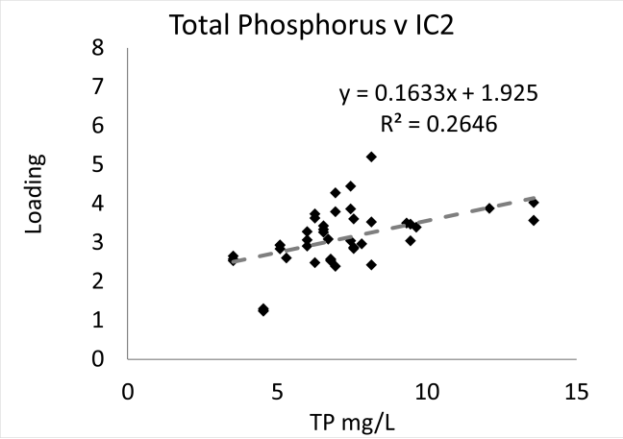

Total Phosphorus v O TrypEEM
y = -0.0036x + 3.2726
R² = 0.183
Intensity R.U.
TP mg/L

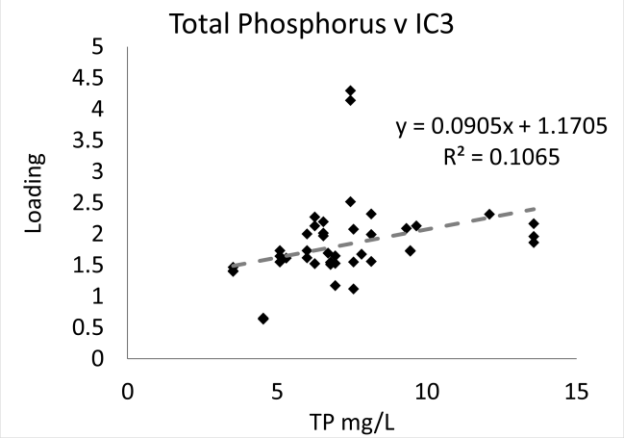

Total Phosphorus v O Abs @ 250nm
y = -0.0002x + 0.2256
R² = 0.1076
Absorbance @ 250nm
TP mg/L

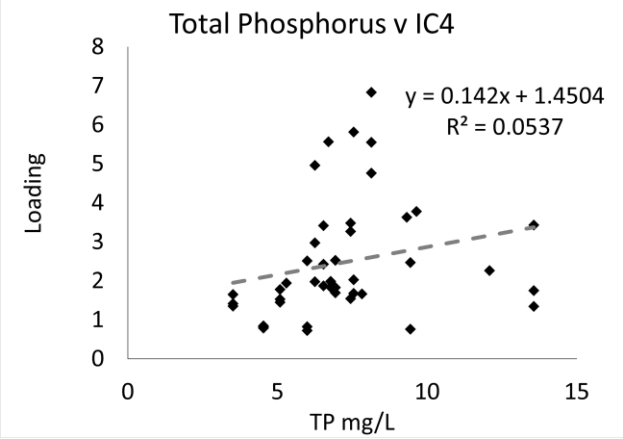

Total Phosphorus v O Spectral Slope Ratio
y = 0.0017x + 0.7097
R² = 0.6734
SSR
TP mg/L

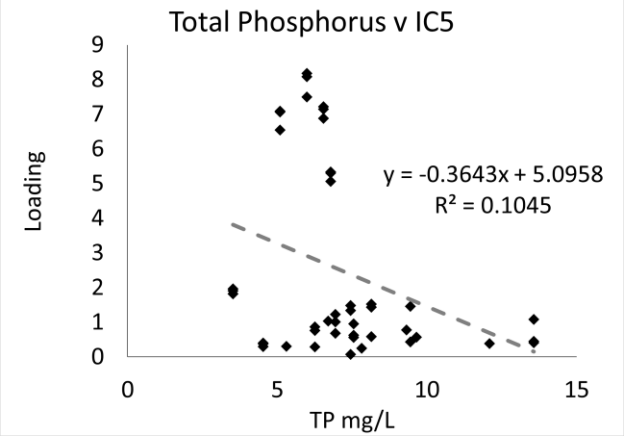
Influent

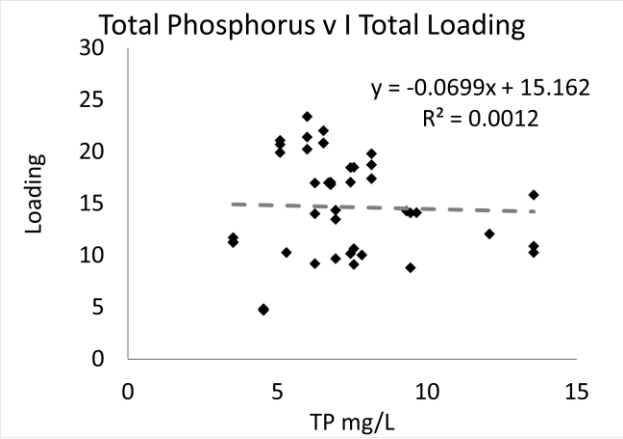

Total Phosphorus v IC1
y = -0.1015x + 5.5199
R² = 0.022
Loading
TP mg/L

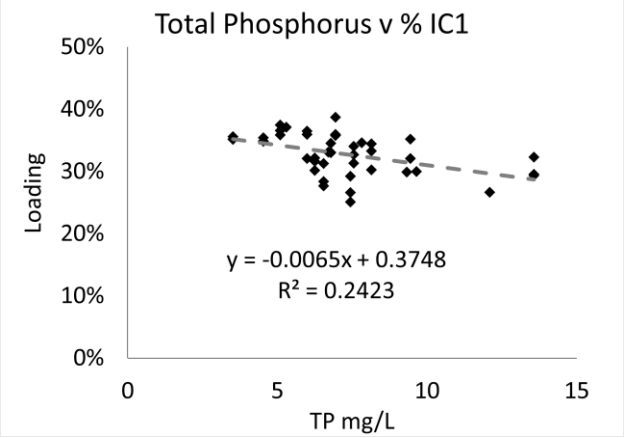

Total Phosphorus v IC2
y = 0.1633x + 1.925
R² = 0.2646
Loading
TP mg/L

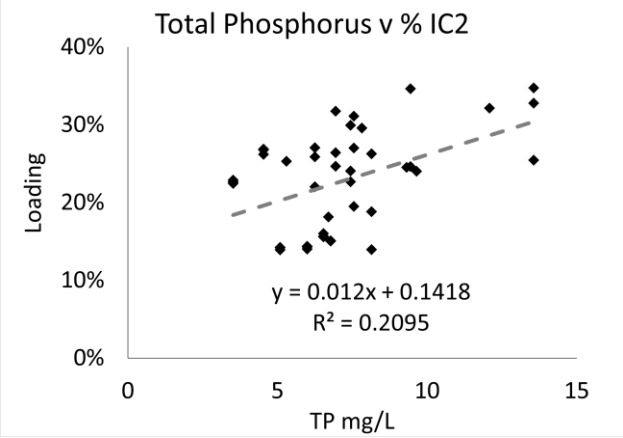

Total Phosphorus v IC3
y = 0.0905x + 1.1705
R² = 0.1065
Loading
TP mg/L

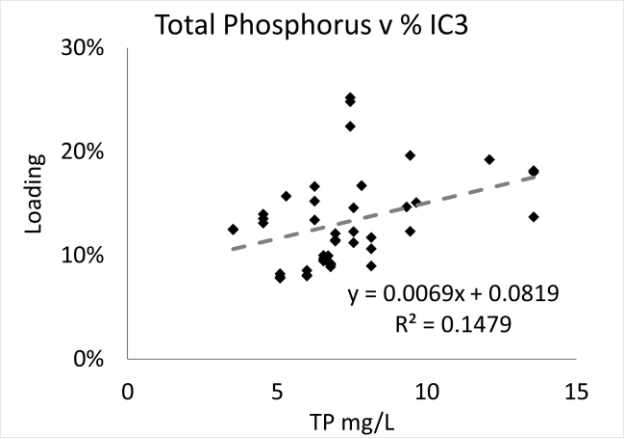

Total Phosphorus v IC4
y = 0.142x + 1.4504
R² = 0.0537
Loading
TP mg/L

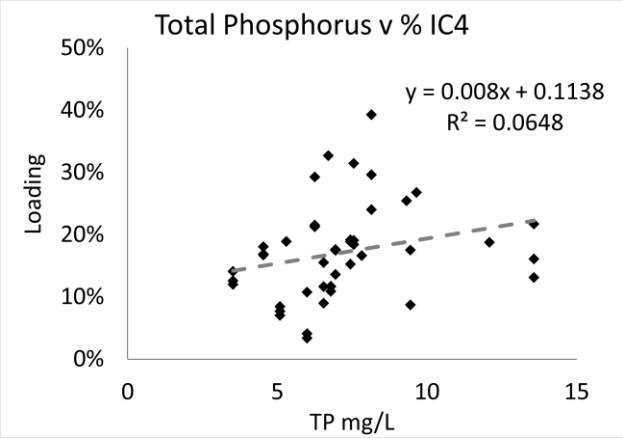

Total Phosphorus v IC5
y = -0.3643x + 5.0958
R² = 0.1045
Loading
TP mg/L

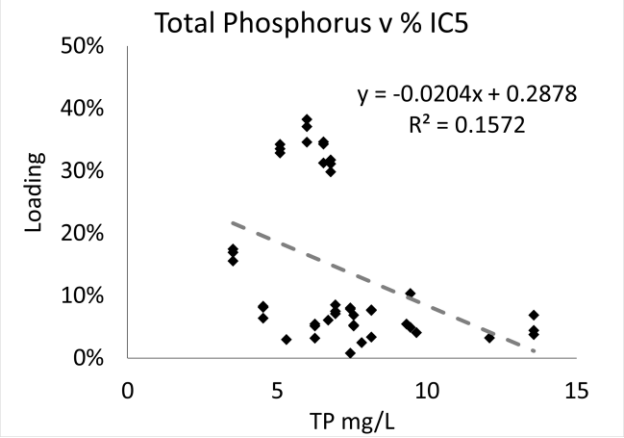

Total Phosphorus v I Total Loading
y = -0.0699x + 15.162
R² = 0.0012
Loading
TP mg/L

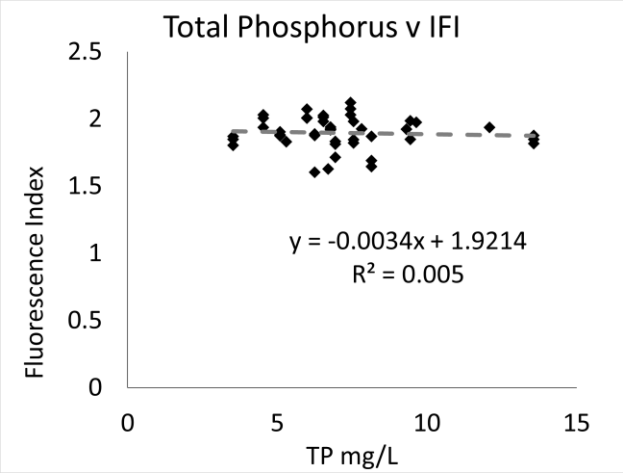

Total Phosphorus v % IC1
Loading
50%
40%
30%
20%
10%
0%
0
5
10
15
TP mg/L
y = -0.0065x + 0.3748
R² = 0.2423

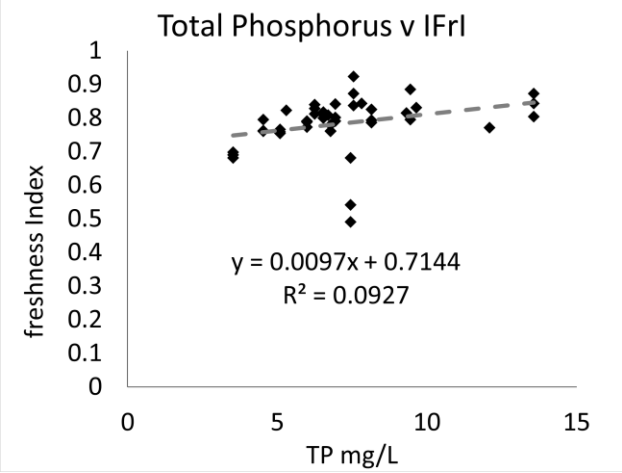

Total Phosphorus v % IC2
Loading
40%
30%
20%
10%
0%
0
5
10
15
TP mg/L
y = 0.012x + 0.1418
R² = 0.2095

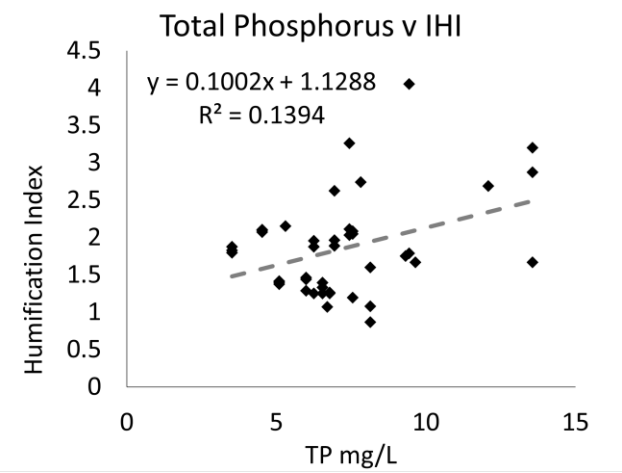

Total Phosphorus v % IC3
Loading
30%
20%
10%
0%
0
5
10
15
TP mg/L
y = 0.0069x + 0.0819
R² = 0.1479

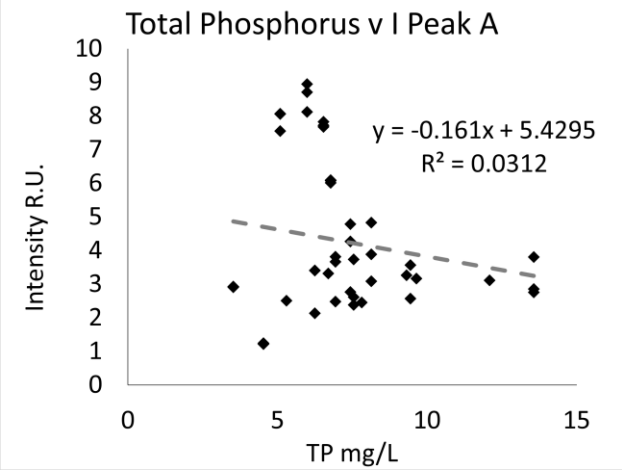

Total Phosphorus v % IC4
Loading
50%
40%
30%
20%
10%
0%
0
5
10
15
TP mg/L
y = 0.008x + 0.1138
R² = 0.0648

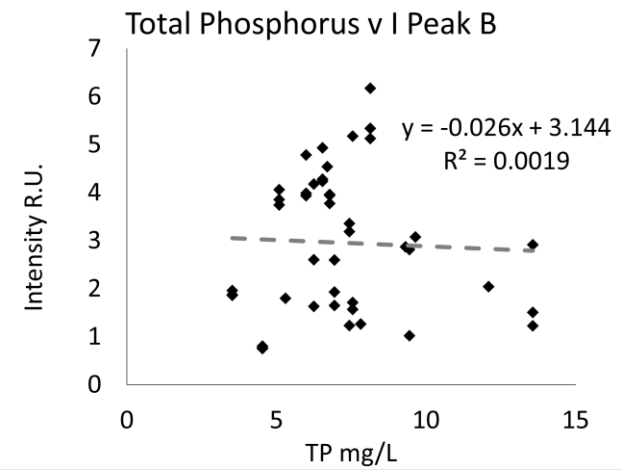

Total Phosphorus v % IC5
Loading
50%
40%
30%
20%
10%
0%
0
5
10
15
TP mg/L
y = -0.0204x + 0.2878
R² = 0.1572

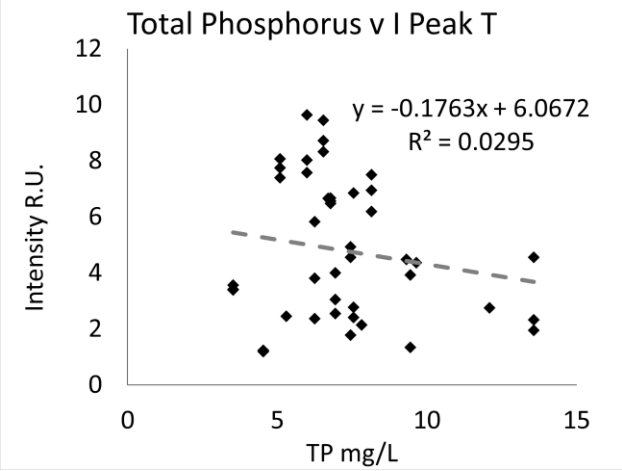

Total Phosphorus v IFI
Fluorescence Index
2.5
2
1.5
1
0.5
0
0
5
10
15
TP mg/L
y = -0.0034x + 1.9214
R² = 0.005

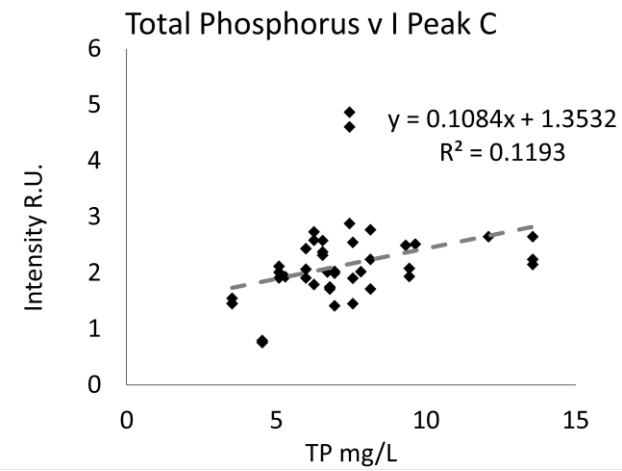

Total Phosphorus v IFrI
freshness Index
y = 0.0097x + 0.7144
R² = 0.0927
TP mg/L

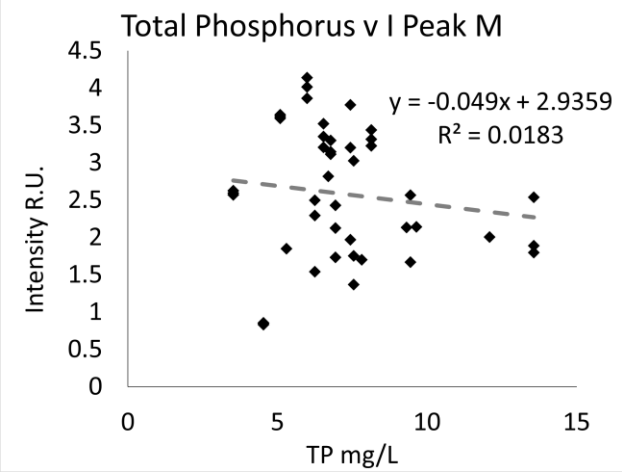

Total Phosphorus v IHI
Humification Index
y = 0.1002x + 1.1288
R² = 0.1394
TP mg/L

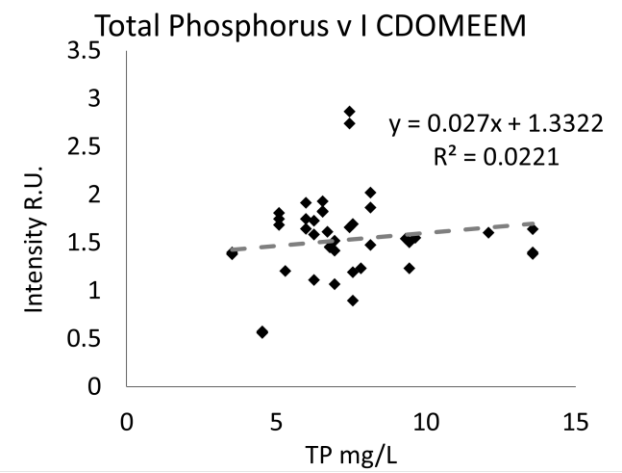

Total Phosphorus v I Peak A
Intensity R.U.
y = -0.161x + 5.4295
R² = 0.0312
TP mg/L

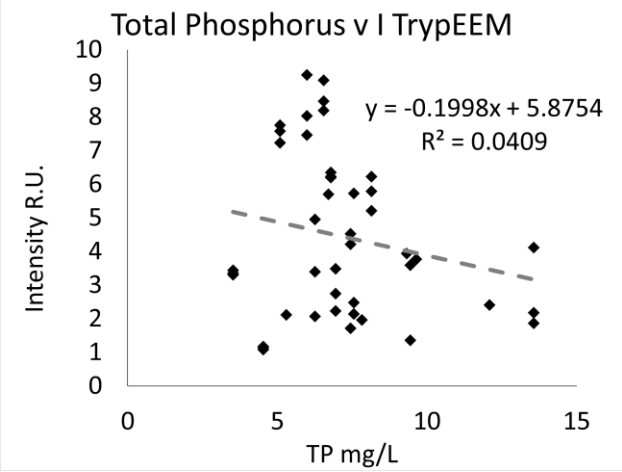

Total Phosphorus v I Peak B
Intensity R.U.
y = -0.026x + 3.144
R² = 0.0019
TP mg/L

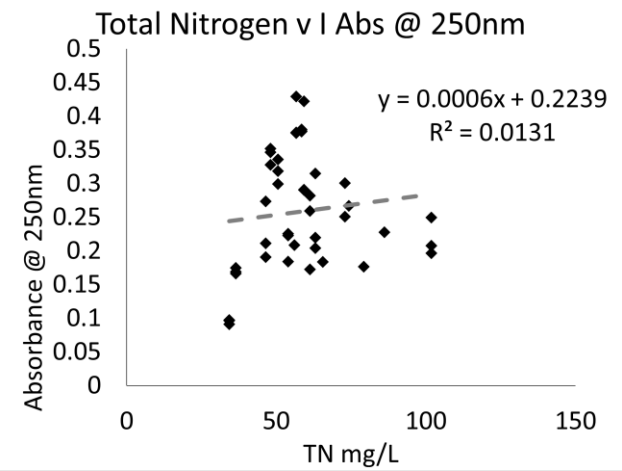

Total Phosphorus v I Peak T
Intensity R.U.
y = -0.1763x + 6.0672
R² = 0.0295
TP mg/L

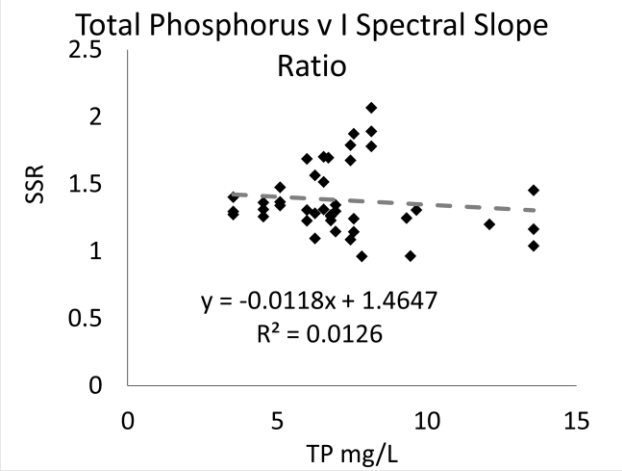

Total Phosphorus v I Peak C
Intensity R.U.
y = 0.1084x + 1.3532
R² = 0.1193
TP mg/L





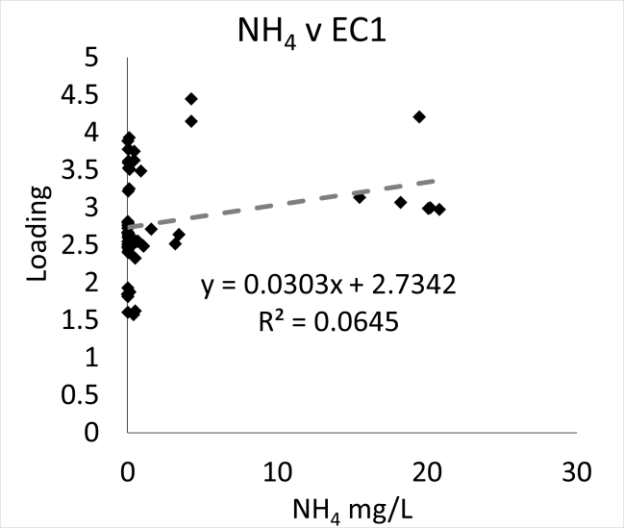


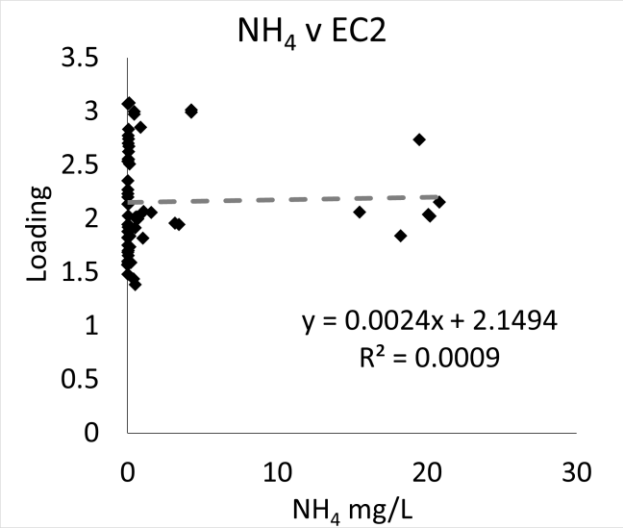


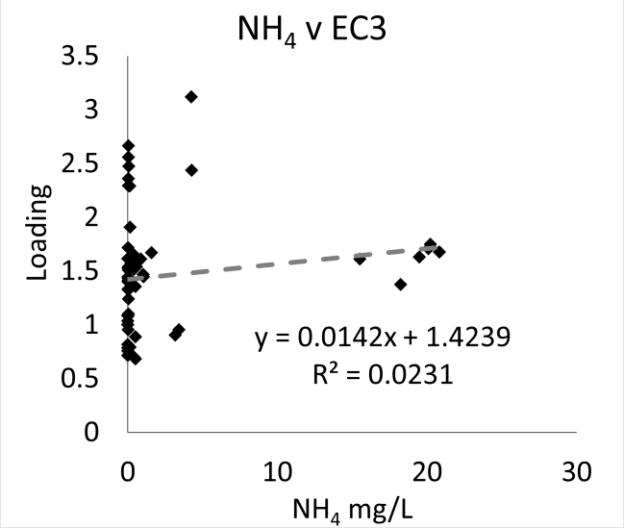


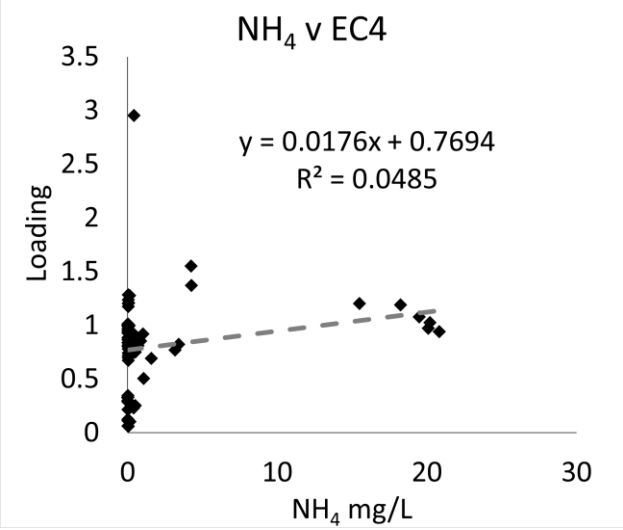
Ammonium

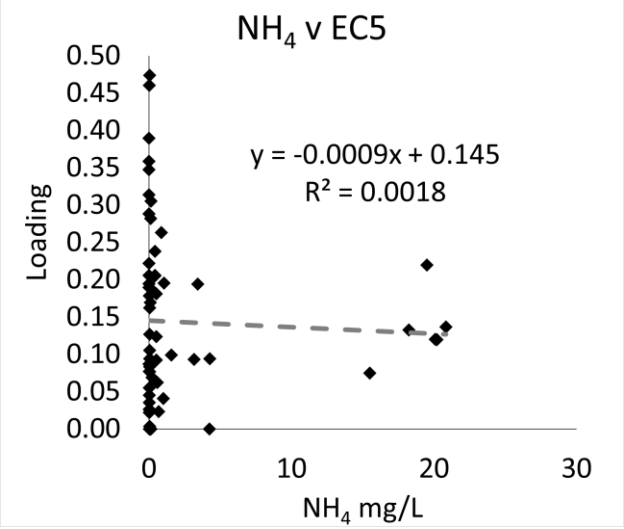
Effluent

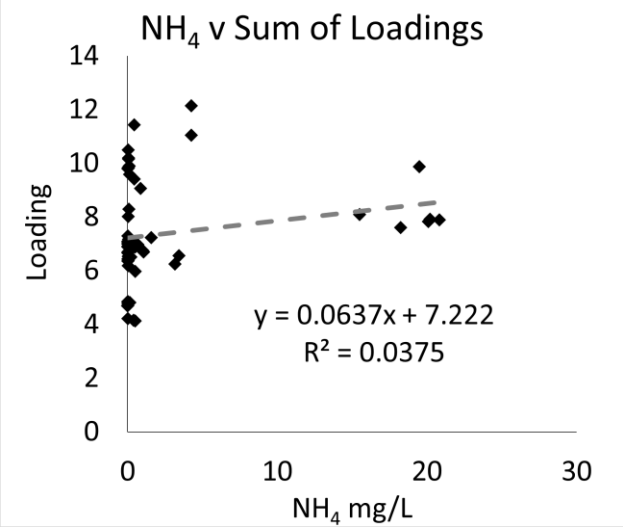

NH4 v EC1
Loading
NH4 mg/L
y = 0.0303x + 2.7342
R² = 0.0645

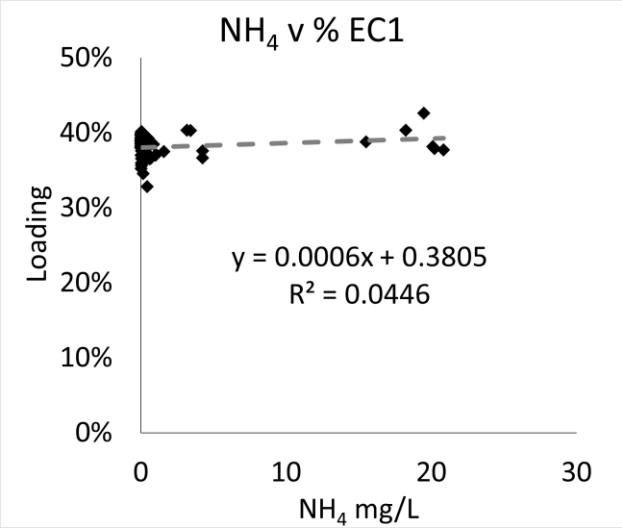

NH4 v EC2
Loading
NH4 mg/L
y = 0.0024x + 2.1494
R² = 0.0009

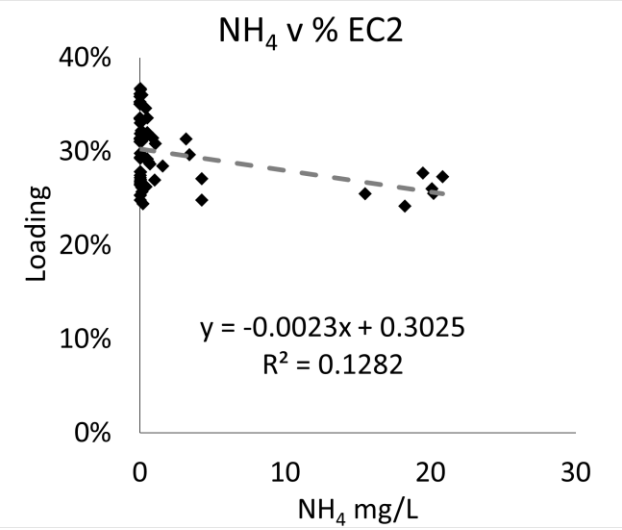

NH4 v EC3
Loading
NH4 mg/L
y = 0.0142x + 1.4239
R² = 0.0231

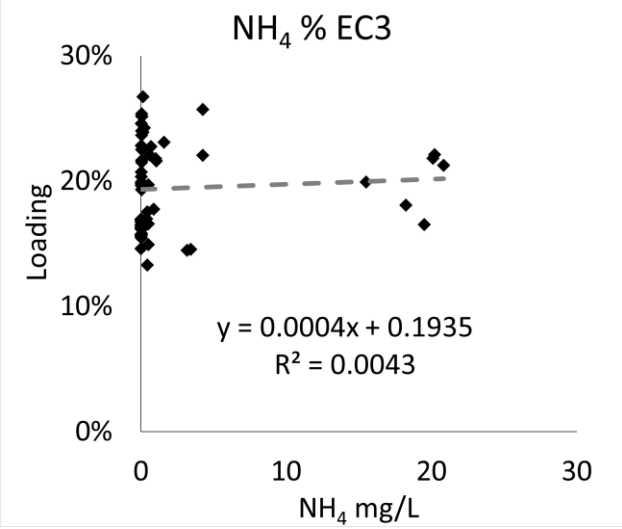

NH4 v EC4
Loading
NH4 mg/L
y = 0.0176x + 0.7694
R² = 0.0485

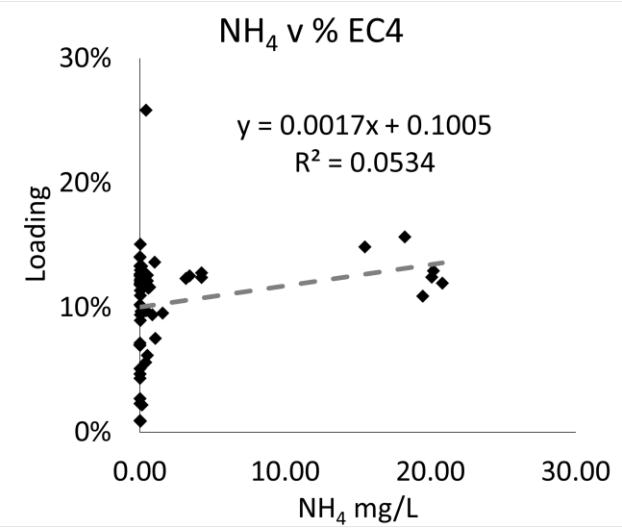

NH4 v EC5
Loading
NH4 mg/L
y = -0.0009x + 0.145
R² = 0.0018

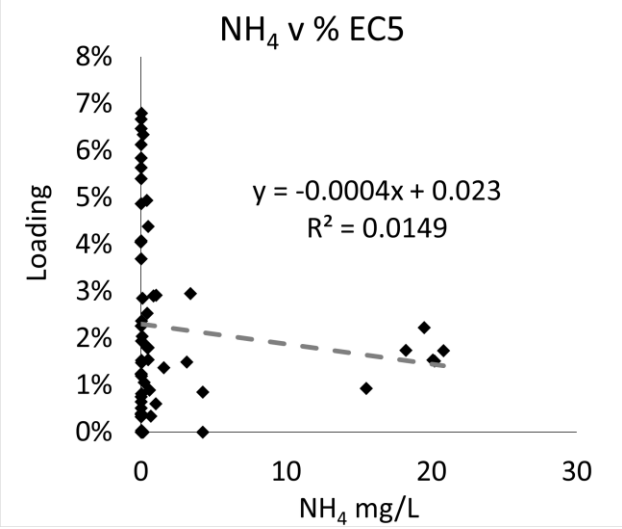

NH4 v Sum of Loadings
Loading
NH4 mg/L
y = 0.0637x + 7.222
R² = 0.0375

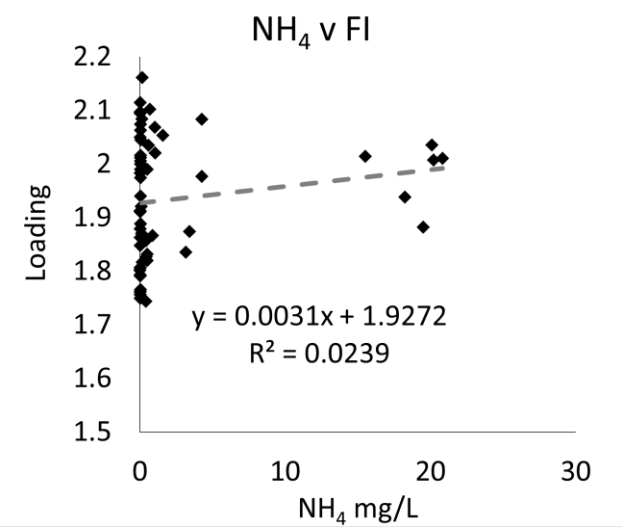

NH4 v % EC1
50%
40%
30%
20%
10%
0%
Loading
y = 0.0006x + 0.3805
R² = 0.0446
0
10
20
30
NH4 mg/L

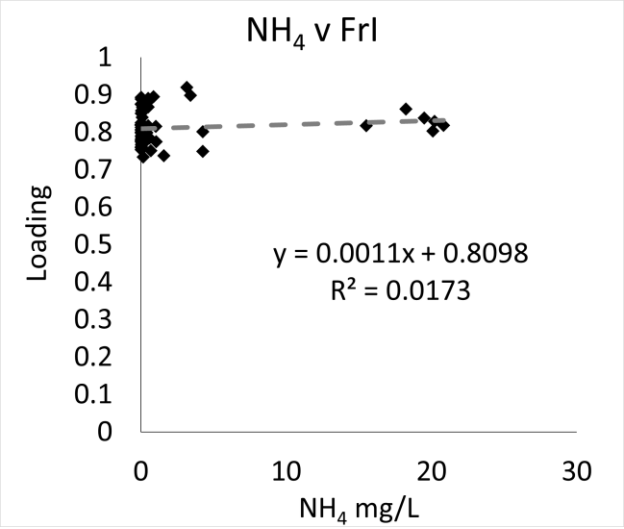

NH4 v % EC2
40%
30%
20%
10%
0%
Loading
y = -0.0023x + 0.3025
R² = 0.1282
0
10
20
30
NH4 mg/L

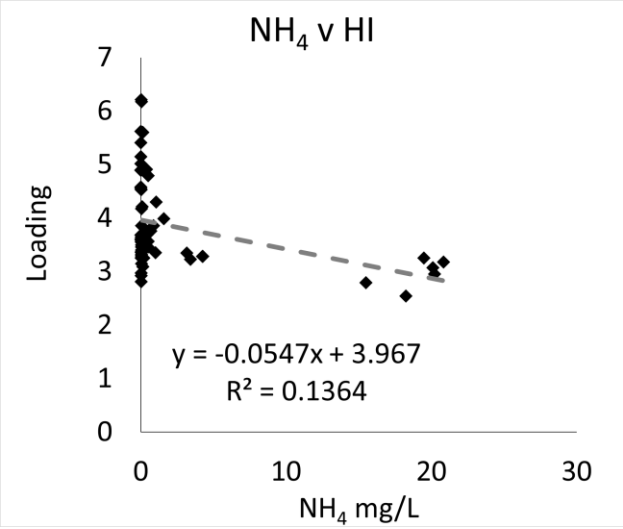

NH4 % EC3
30%
20%
10%
0%
Loading
y = 0.0004x + 0.1935
R² = 0.0043
0
10
20
30
NH4 mg/L

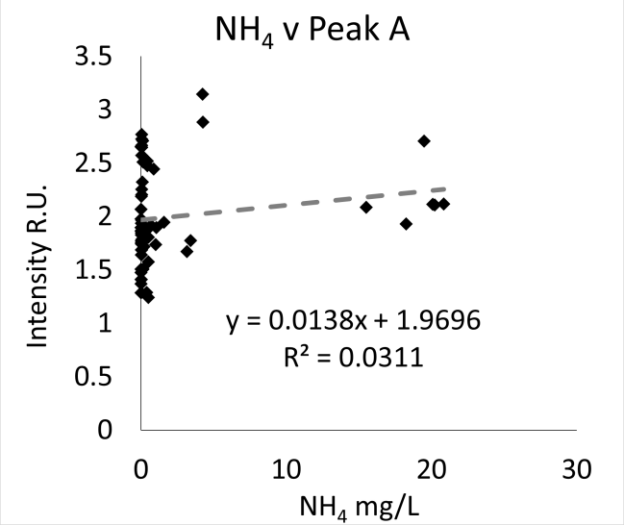

NH4 v % EC4
30%
20%
10%
0%
Loading
y = 0.0017x + 0.1005
R² = 0.0534
0.00
10.00
20.00
30.00
NH4 mg/L

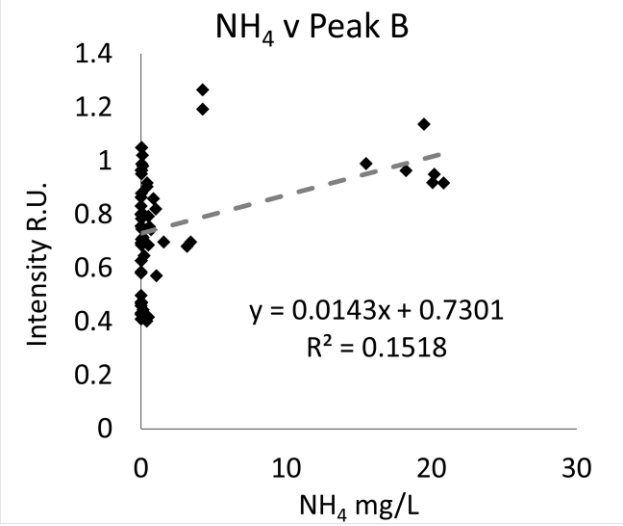

NH4 v % EC5
8%
7%
6%
5%
4%
3%
2%
1%
0%
Loading
y = -0.0004x + 0.023
R² = 0.0149
0
10
20
30
NH4 mg/L

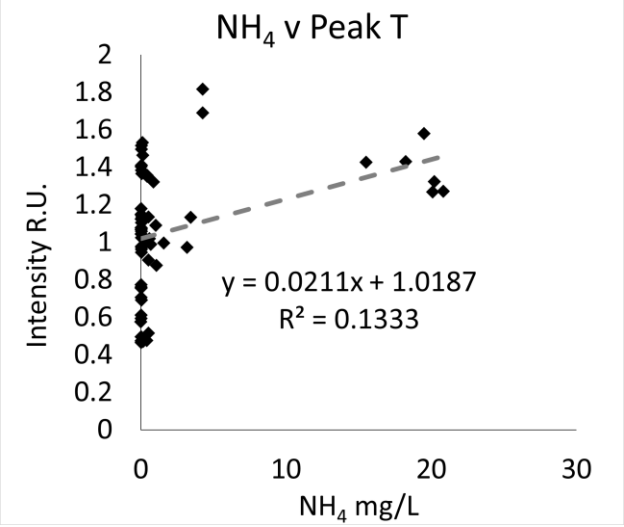

NH4 v FI
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
Loading
y = 0.0031x + 1.9272
R² = 0.0239
0
10
20
30
NH4 mg/L

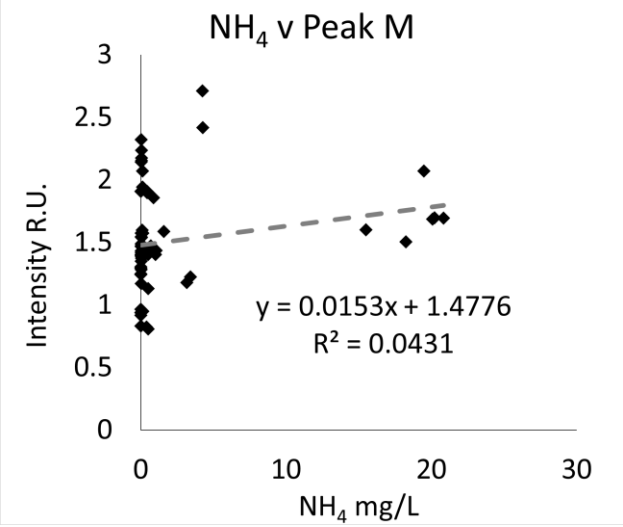

NH4 v FrI
Loading
NH4 mg/L
y = 0.0011x + 0.8098
R² = 0.0173

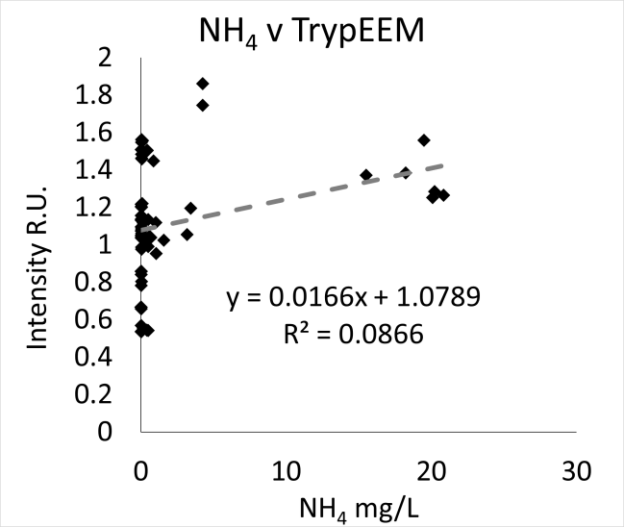

NH4 v HI
Loading
NH4 mg/L
y = -0.0547x + 3.967
R² = 0.1364

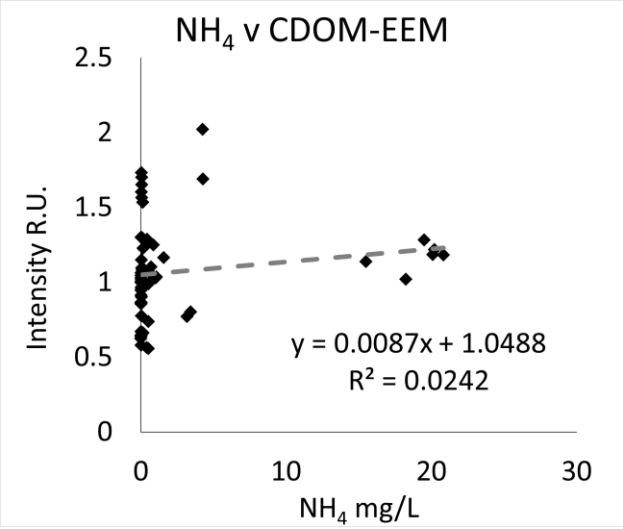

NH4 v Peak A
Intensity R.U.
NH4 mg/L
y = 0.0138x + 1.9696
R² = 0.0311

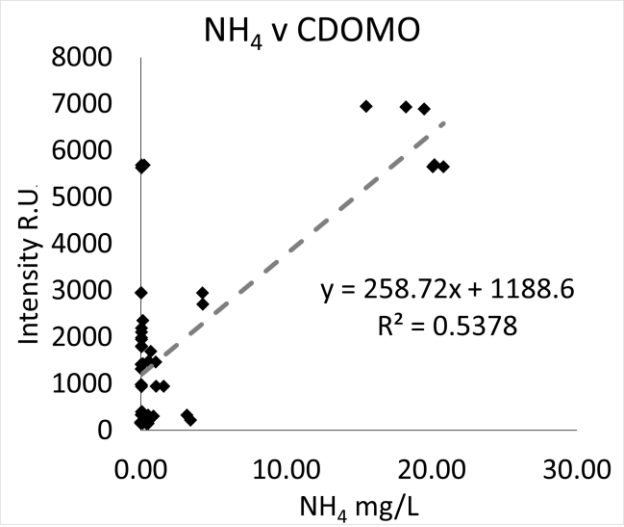

NH4 v Peak B
Intensity R.U.
NH4 mg/L
y = 0.0143x + 0.7301
R² = 0.1518

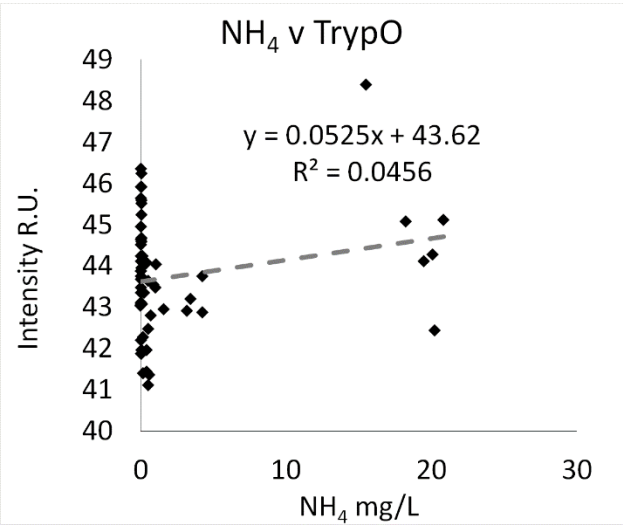

NH4 v Peak T
Intensity R.U.
NH4 mg/L
y = 0.0211x + 1.0187
R² = 0.1333

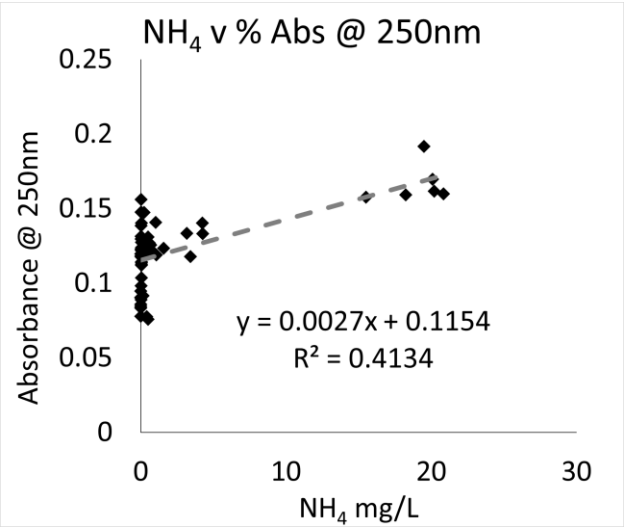

NH4 v Peak M
Intensity R.U.
NH4 mg/L
y = 0.0153x + 1.4776
R² = 0.0431

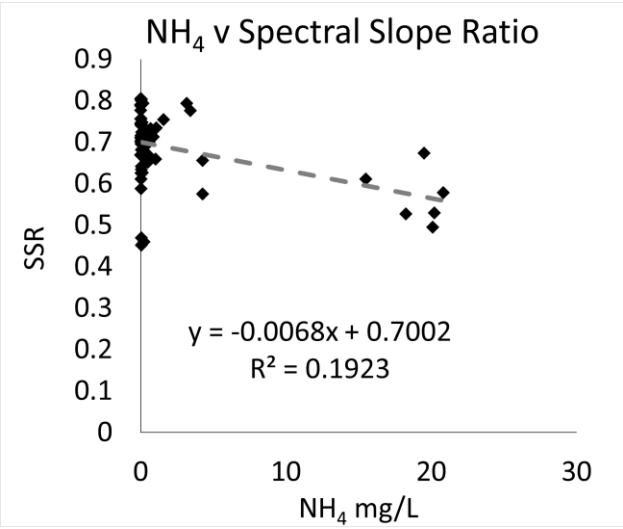

NH4 v TrypEEM
Intensity R.U.
NH4 mg/L
y = 0.0166x + 1.0789
R² = 0.0866


NH4 v CDOM-EEM
Intensity R.U.
NH4 mg/L
y = 0.0087x + 1.0488
R² = 0.0242


NH4 v CDOMO
Intensity R.U
NH4 mg/L
y = 258.72x + 1188.6
R² = 0.5378

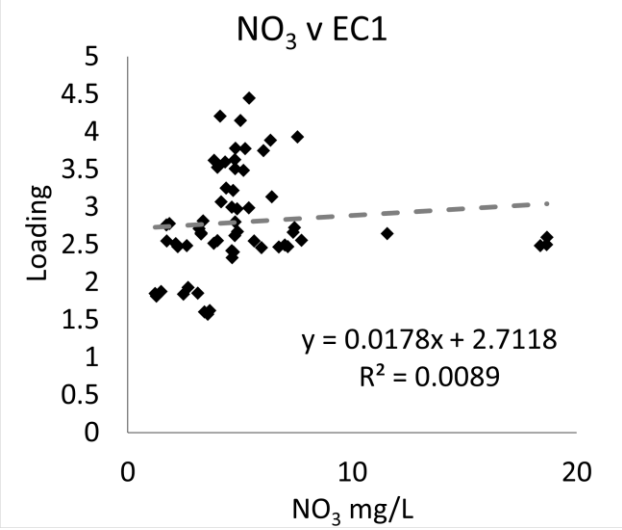

NH4 v TrypO
Intensity R.U.
NH4 mg/L
y = 0.0525x + 43.62
R² = 0.0456

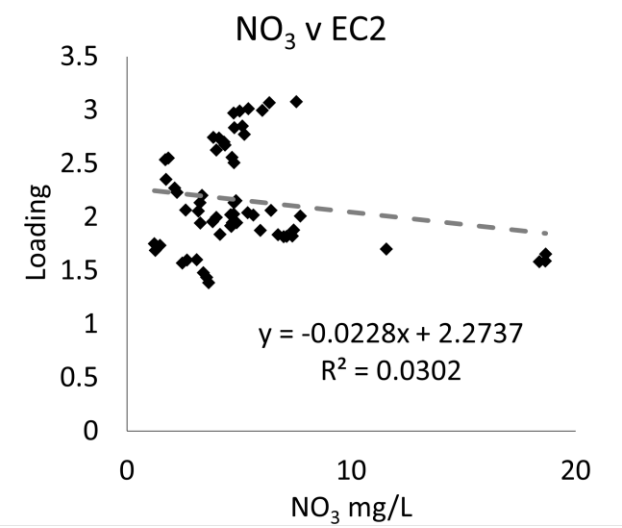

NH4 v % Abs @ 250nm
Absorbance @ 250nm
NH4 mg/L
y = 0.0027x + 0.1154
R² = 0.4134

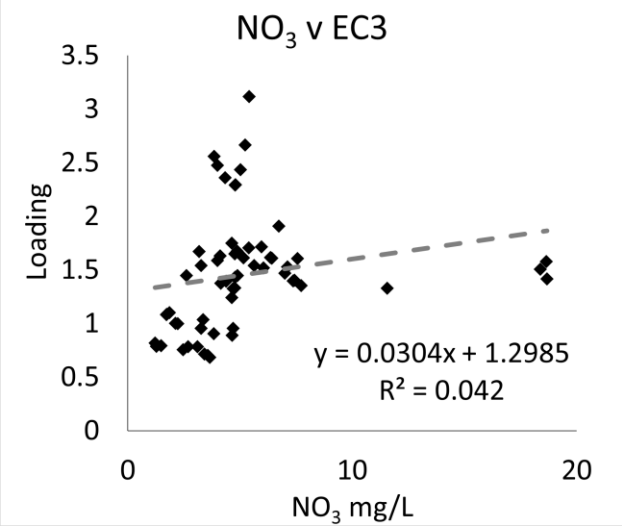

NH4 v Spectral Slope Ratio
SSR
NH4 mg/L
y = -0.0068x + 0.7002
R² = 0.1923

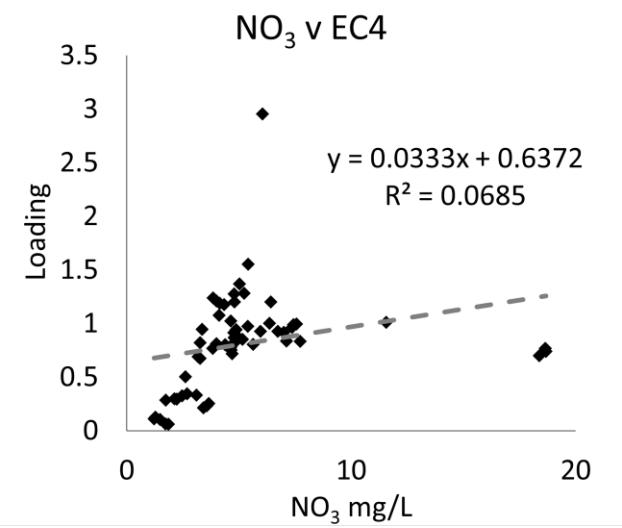
Nitrate

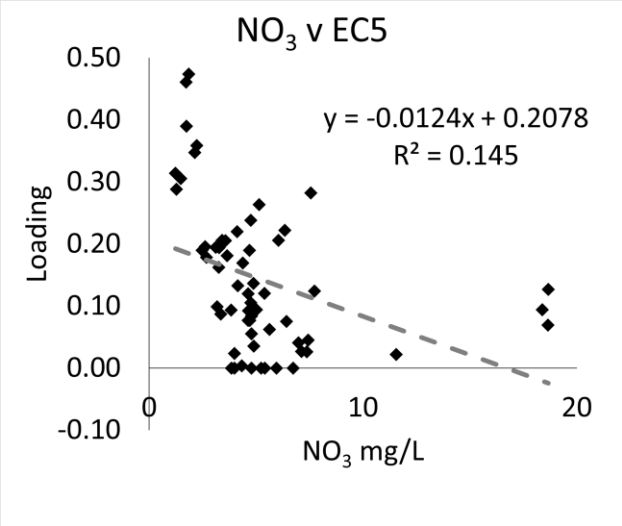
Effluent

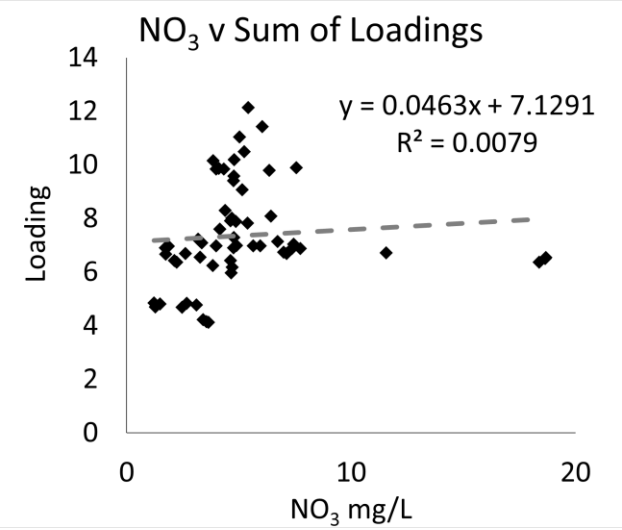


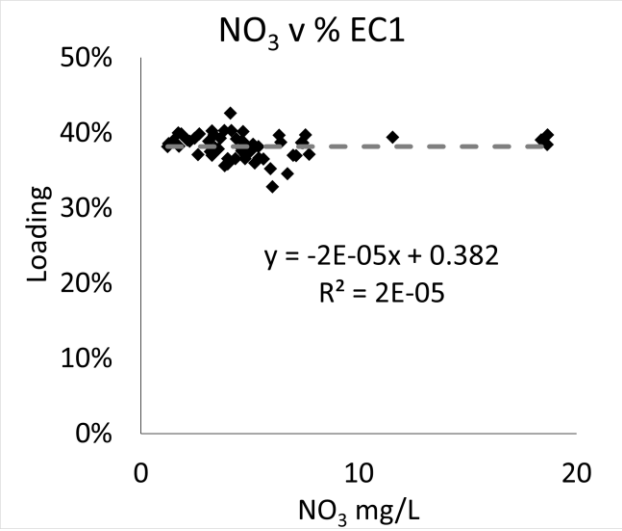


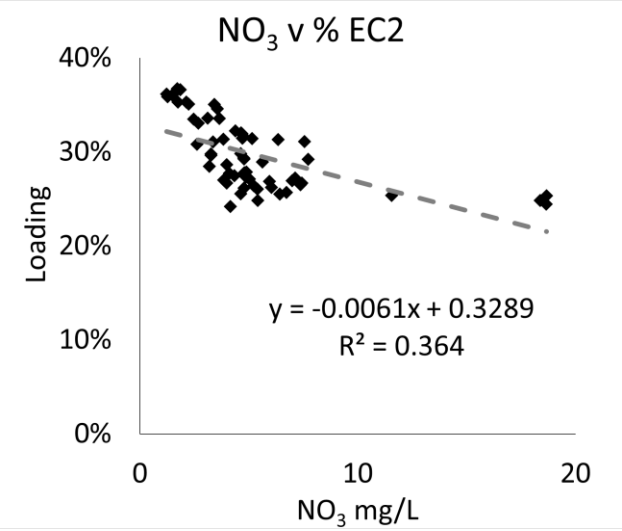


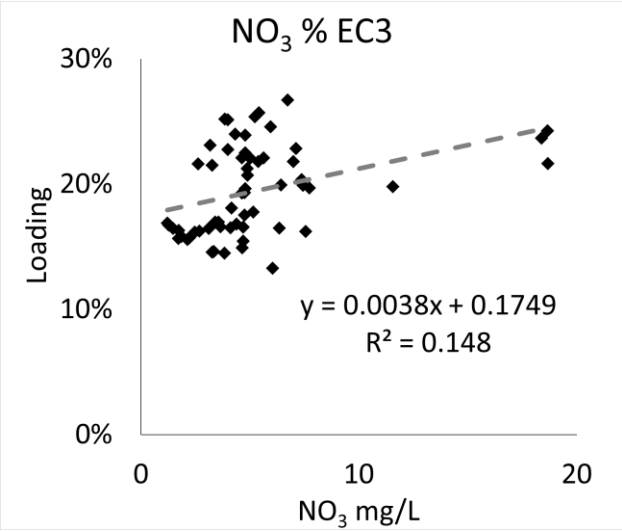


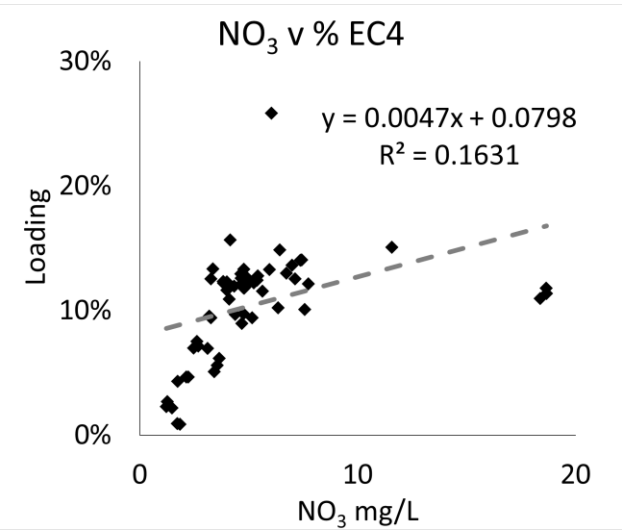

NO3 v EC5
y = -0.0124x + 0.2078
R² = 0.145
Loading
NO3 mg/L
0.50
0.40
0.30
0.20
0.10
0.00
-0.10
0
10
20

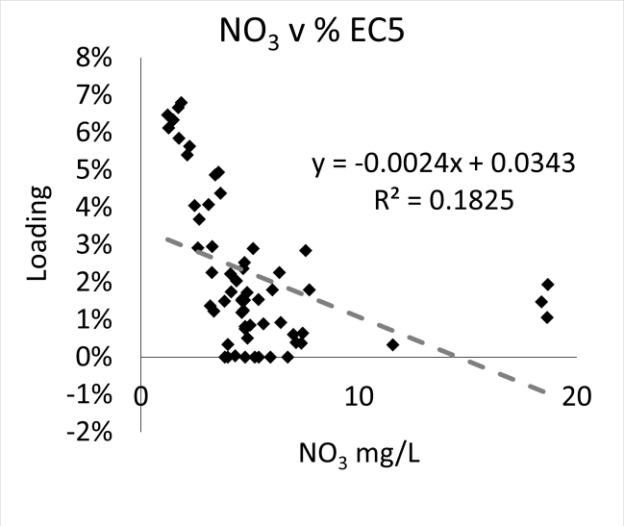

NO3 v Sum of Loadings
y = 0.0463x + 7.1291
R² = 0.0079
Loading
NO3 mg/L
14
12
10
8
6
4
2
0
0
10
20

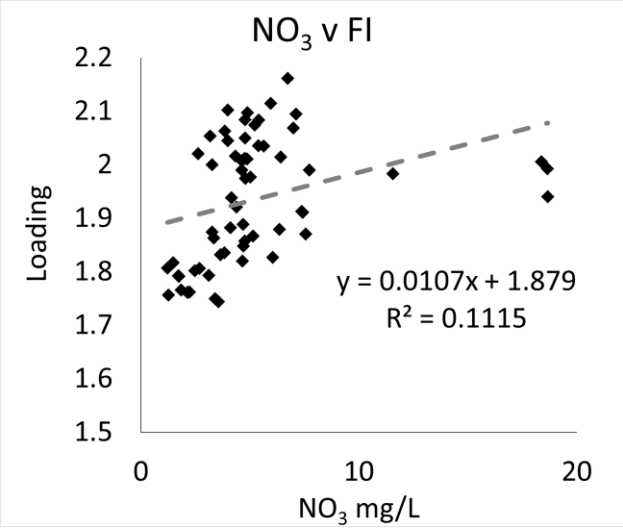

NO3 v % EC1
y = -2E-05x + 0.382
R² = 2E-05
Loading
NO3 mg/L
50%
40%
30%
20%
10%
0%
0
10
20

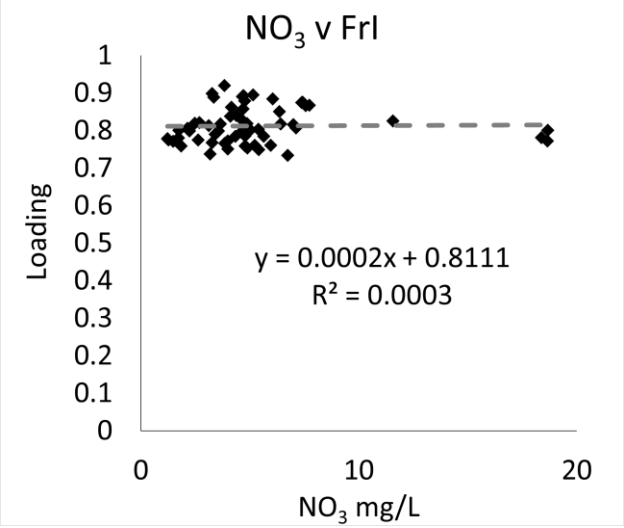

NO3 v % EC2
y = -0.0061x + 0.3289
R² = 0.364
Loading
NO3 mg/L
40%
30%
20%
10%
0%
0
10
20

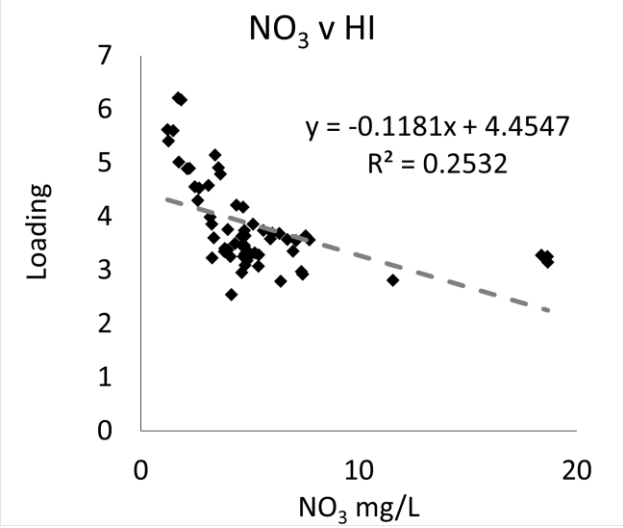

NO3 % EC3
y = 0.0038x + 0.1749
R² = 0.148
Loading
NO3 mg/L
30%
20%
10%
0%
0
10
20

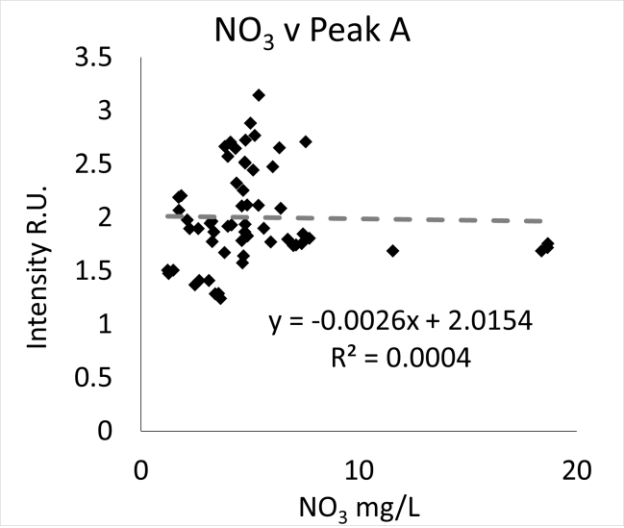

NO3 v % EC4
y = 0.0047x + 0.0798
R² = 0.1631
Loading
NO3 mg/L
30%
20%
10%
0%
0
10
20

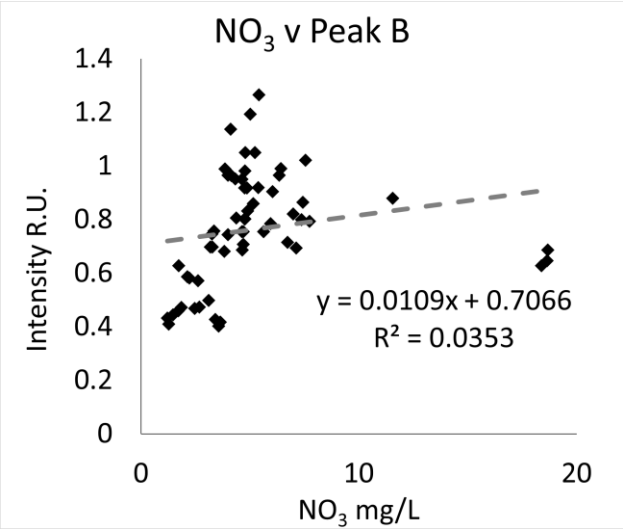

NO3 v % EC5
y = -0.0024x + 0.0343
R² = 0.1825
Loading
NO3 mg/L
8%
7%
6%
5%
4%
3%
2%
1%
0%
-1%
-2%
0
10
20

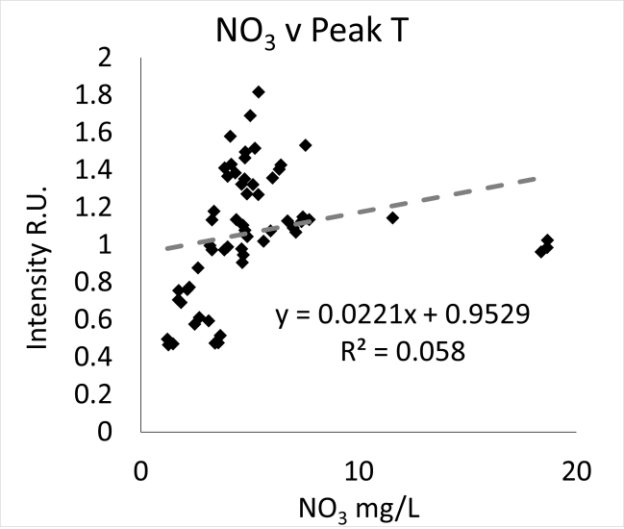

NO3 v FI
y = 0.0107x + 1.879
R² = 0.1115
Loading
NO3 mg/L
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
0
10
20

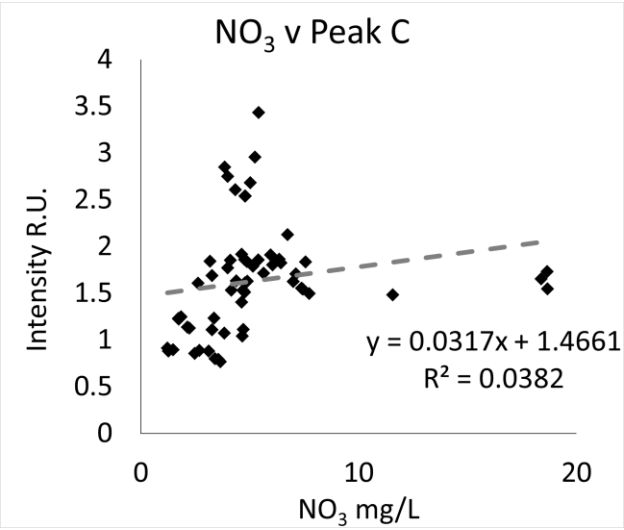

NO3 v FrI
y = 0.0002x + 0.8111
R² = 0.0003
Loading
NO3 mg/L
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
10
20

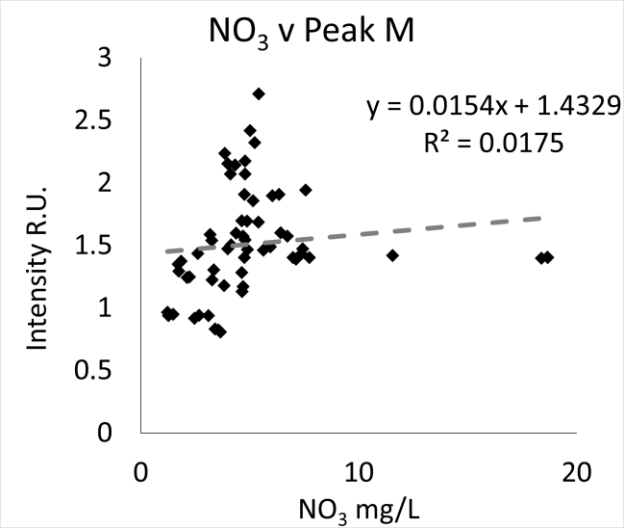

NO3 v HI
y = -0.1181x + 4.4547
R² = 0.2532
Loading
NO3 mg/L
7
6
5
4
3
2
1
0
0
10
20

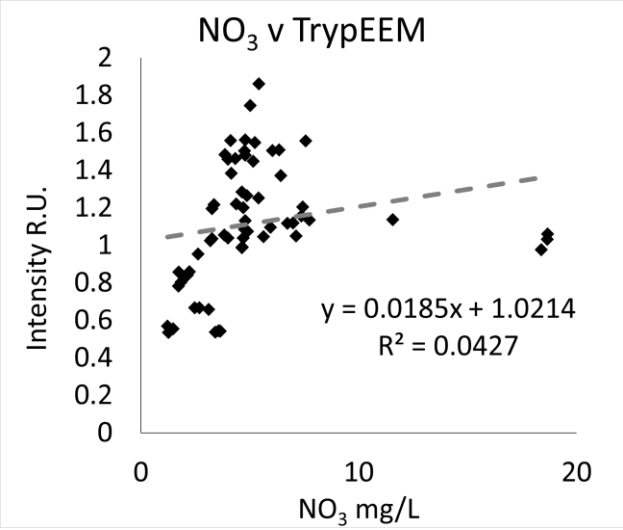

NO3 v Peak A
y = -0.0026x + 2.0154
R² = 0.0004
Intensity R.U.
NO3 mg/L
3.5
3
2.5
2
1.5
1
0.5
0
0
10
20

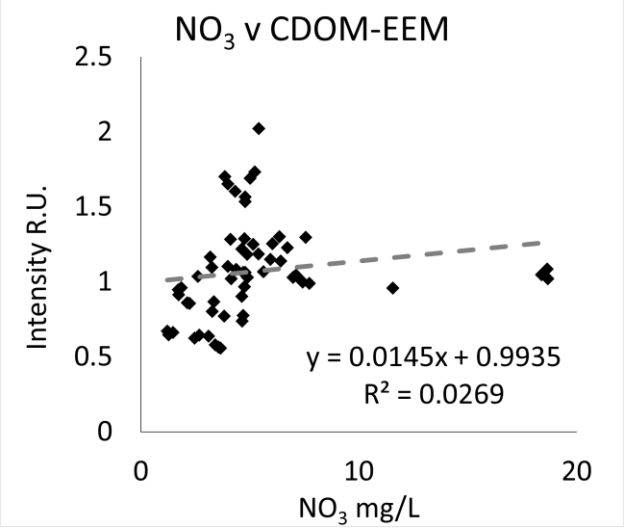

NO3 v Peak B
y = 0.0109x + 0.7066
R² = 0.0353
Intensity R.U.
NO3 mg/L
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0
10
20

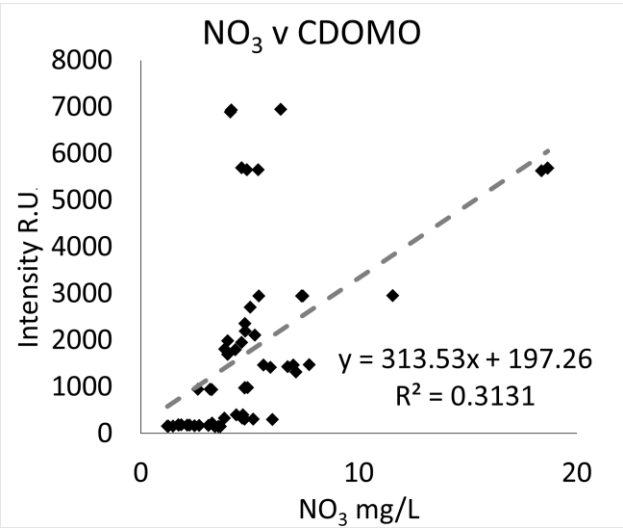

NO3 v Peak T
Intensity R.U.
NO3 mg/L
y = 0.0221x + 0.9529
R² = 0.058

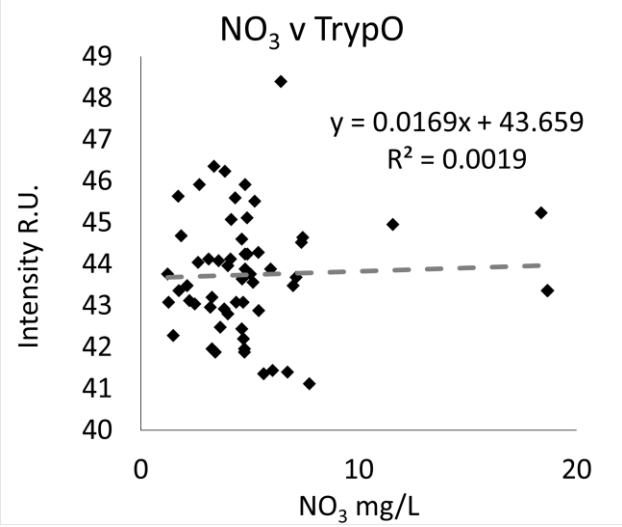

NO3 v Peak C
Intensity R.U.
NO3 mg/L
y = 0.0317x + 1.4661
R² = 0.0382

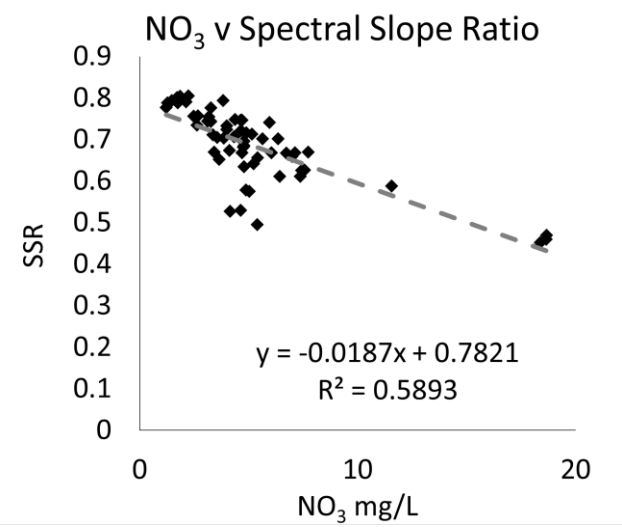

NO3 v Peak M
Intensity R.U.
NO3 mg/L
y = 0.0154x + 1.4329
R² = 0.0175

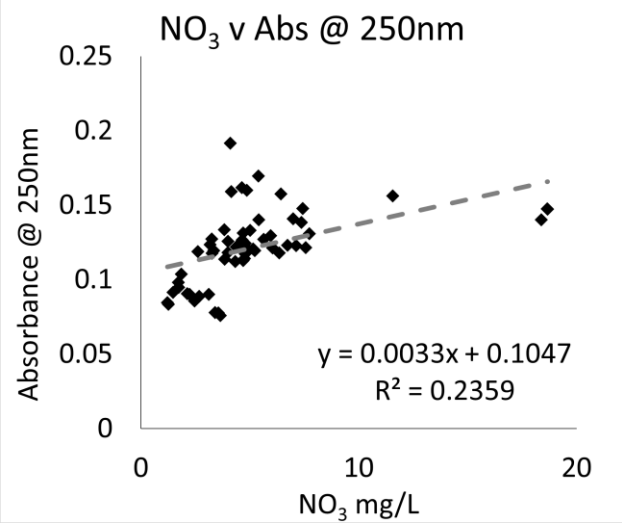

NO3 v TrypEEM
Intensity R.U.
NO3 mg/L
y = 0.0185x + 1.0214
R² = 0.0427


NO3 v CDOM-EEM
Intensity R.U.
NO3 mg/L
y = 0.0145x + 0.9935
R² = 0.0269


NO3 v CDOMO
Intensity R.U.
NO3 mg/L
y = 313.53x + 197.26
R² = 0.3131

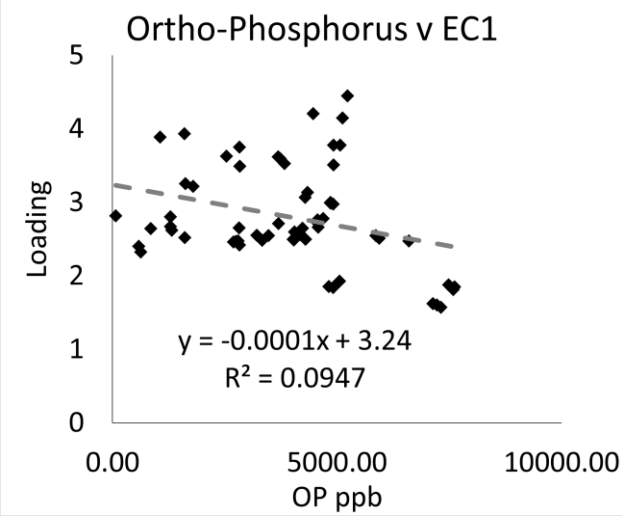


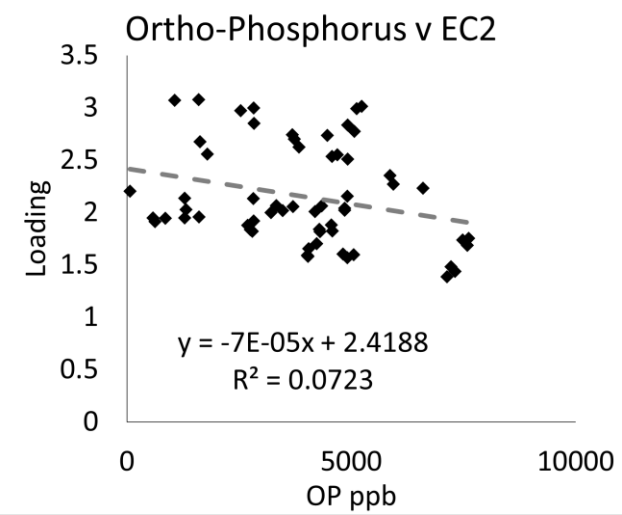


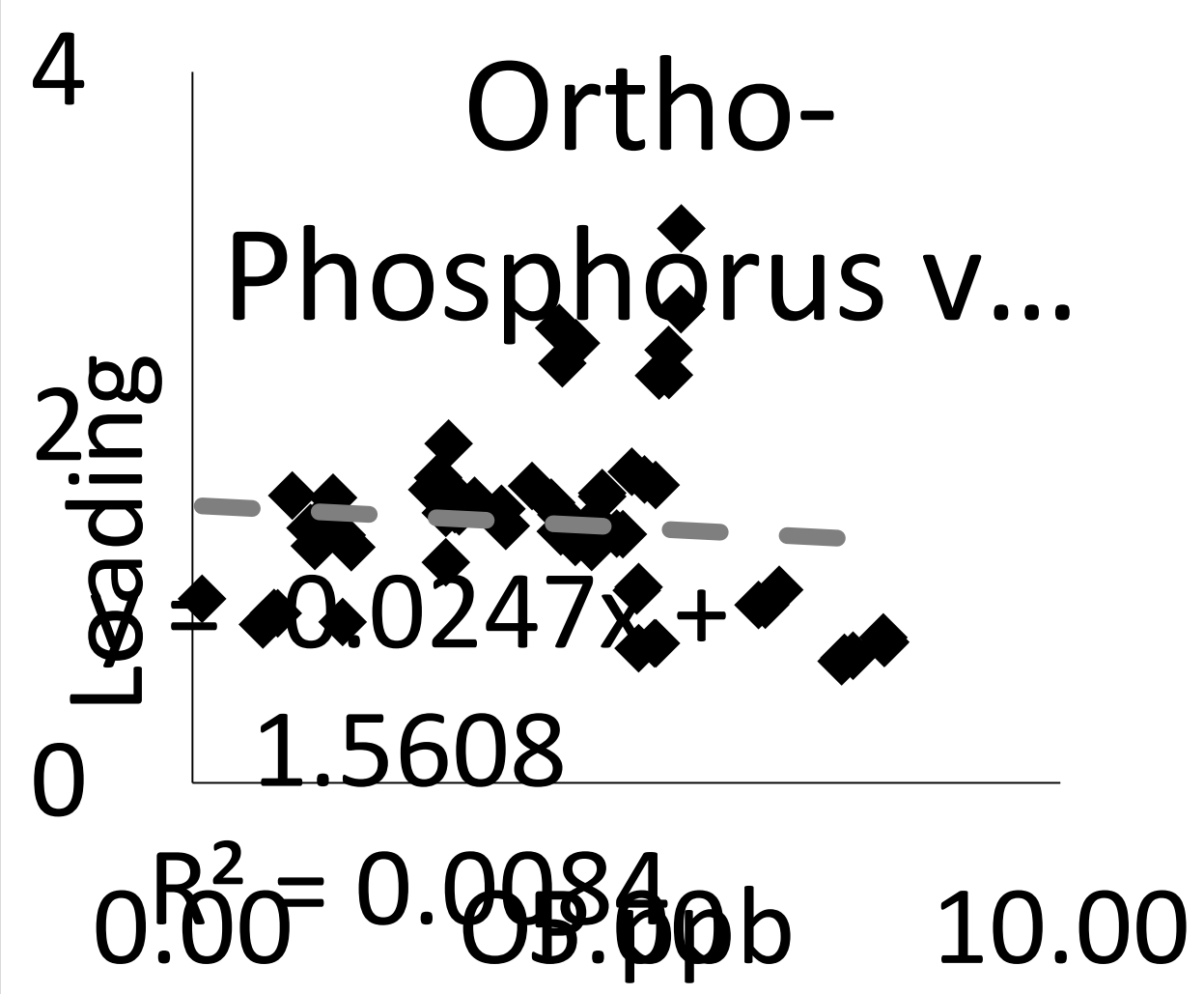


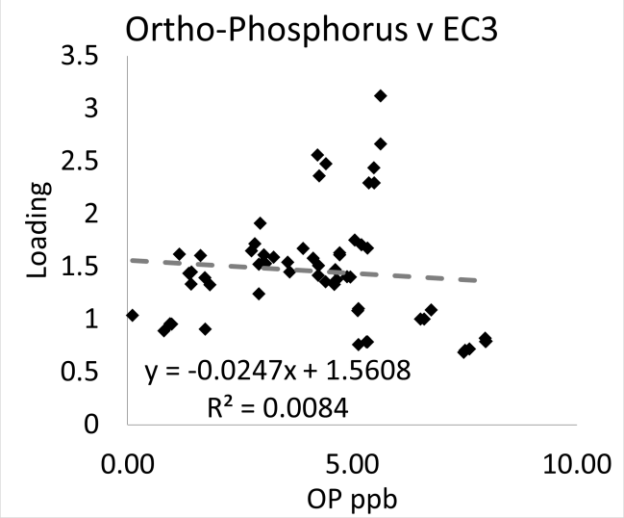
Ortho-phosphorus

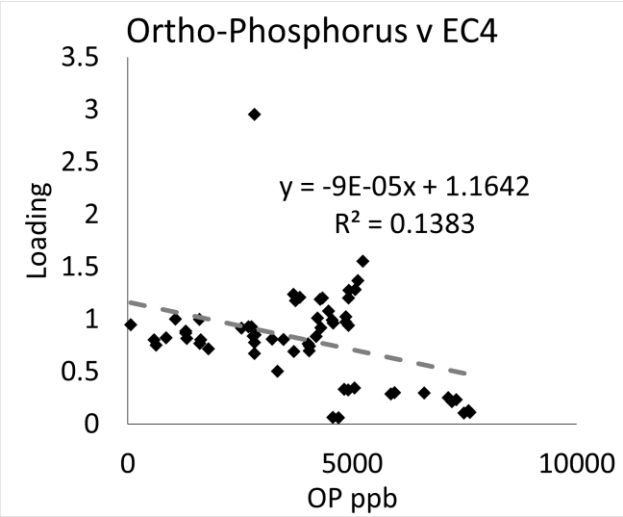
Effluent

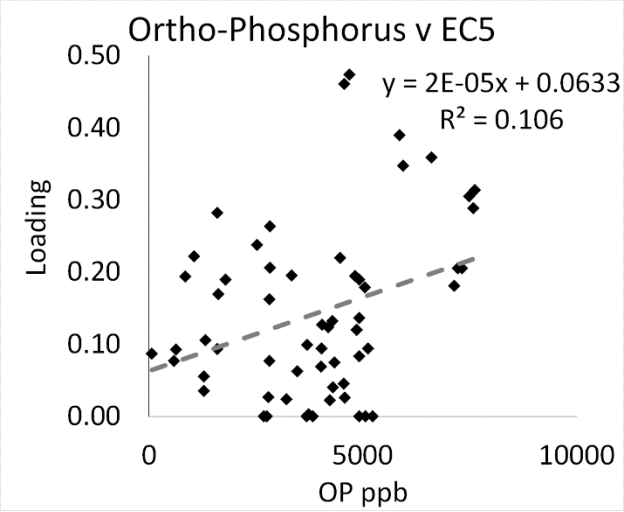

Ortho-Phosphorus v EC1
Loading
OP ppb
y = -0.0001x + 3.24
R² = 0.0947
0
1
2
3
4
5
0.00
5000.00
10000.00

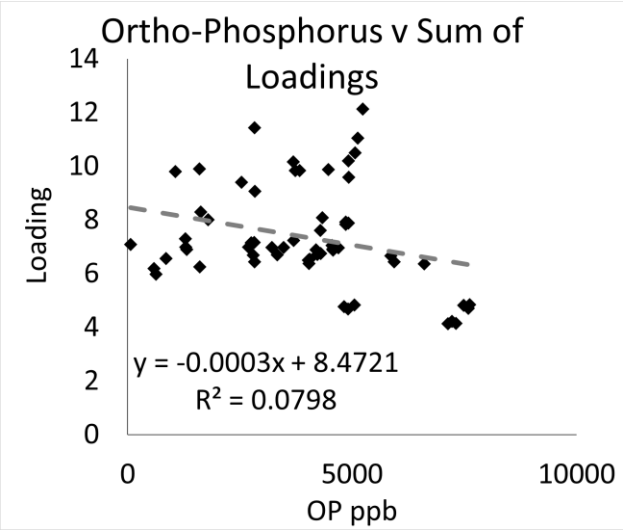

Ortho-Phosphorus v EC2
Loading
OP ppb
y = -7E-05x + 2.4188
R² = 0.0723
0
0.5
1
1.5
2
2.5
3
3.5
0
5000
10000

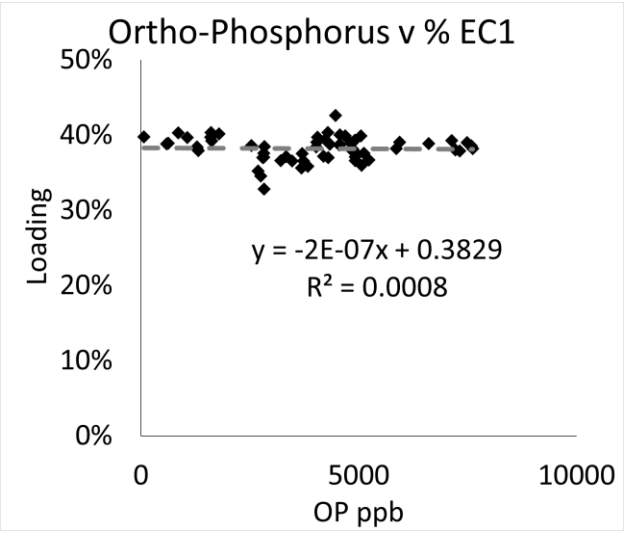

Ortho-Phosphorus v...
Loading
y = 0.0247x + 1.5608
R² = 0.0084
0
2
4
0.00
OP ppb
10.00

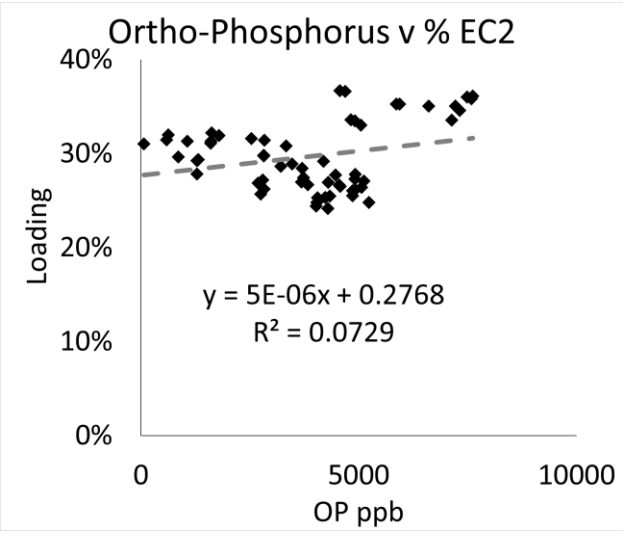

Ortho-Phosphorus v EC3
Loading
OP ppb
y = -0.0247x + 1.5608
R² = 0.0084
0.00
5.00
10.00
0
0.5
1
1.5
2
2.5
3
3.5

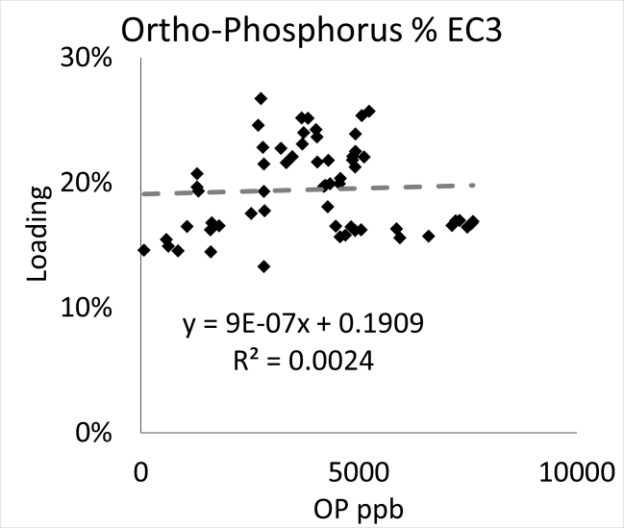

Ortho-Phosphorus v EC4
Loading
OP ppb
y = -9E-05x + 1.1642
R² = 0.1383
0
5000
10000
0
0.5
1
1.5
2
2.5
3
3.5

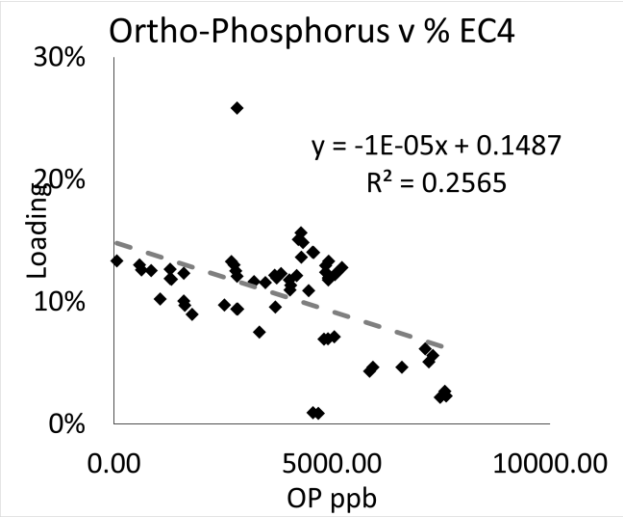

Ortho-Phosphorus v EC5
Loading
OP ppb
y = 2E-05x + 0.0633
R² = 0.106
0
5000
10000
0.00
0.10
0.20
0.30
0.40
0.50

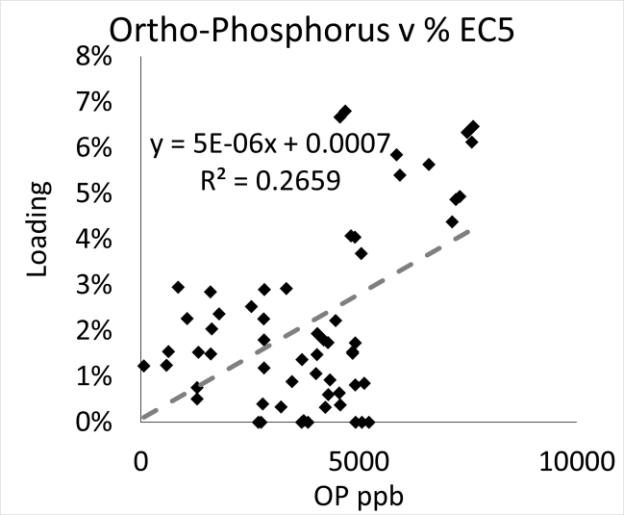

Ortho-Phosphorus v Sum of Loadings
Loading
OP ppb
y = -0.0003x + 8.4721
R² = 0.0798
0
5000
10000
0
2
4
6
8
10
12
14

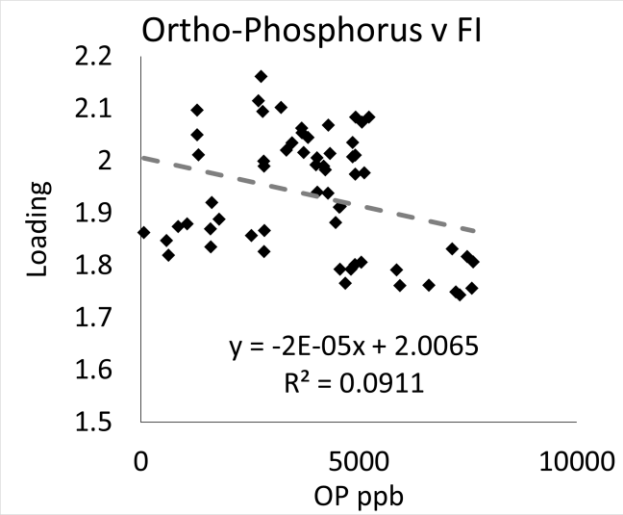

Ortho-Phosphorus v % EC1
Loading
OP ppb
y = -2E-07x + 0.3829
R² = 0.0008
0
5000
10000
0%
10%
20%
30%
40%
50%

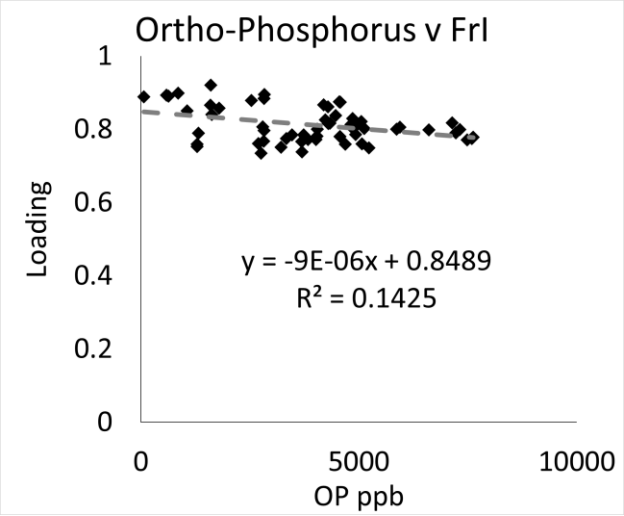

Ortho-Phosphorus v % EC2
Loading
OP ppb
y = 5E-06x + 0.2768
R² = 0.0729
0
5000
10000
0%
10%
20%
30%
40%

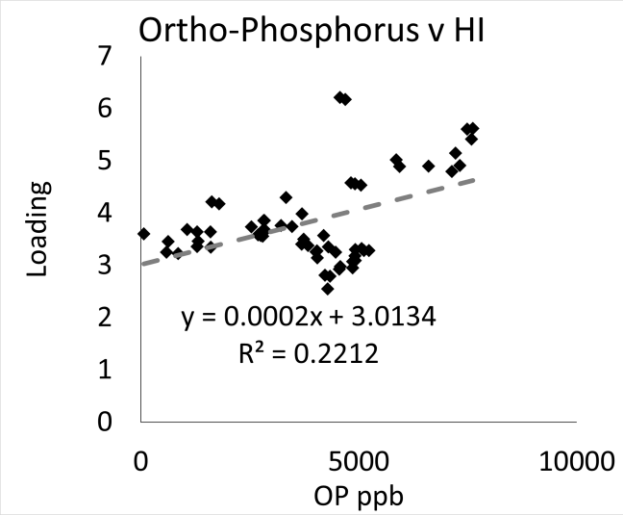

Ortho-Phosphorus % EC3
30%
20%
10%
0%
Loading
y = 9E-07x + 0.1909
R² = 0.0024
0
5000
10000
OP ppb

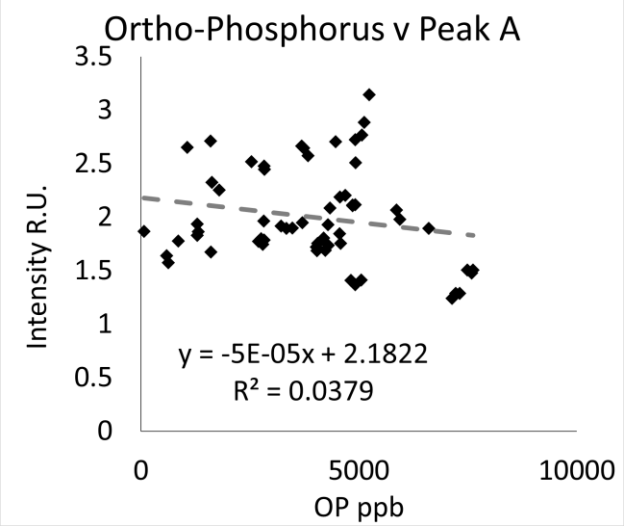

Ortho-Phosphorus v % EC4
30%
20%
10%
0%
Loading
y = -1E-05x + 0.1487
R² = 0.2565
0.00
5000.00
10000.00
OP ppb

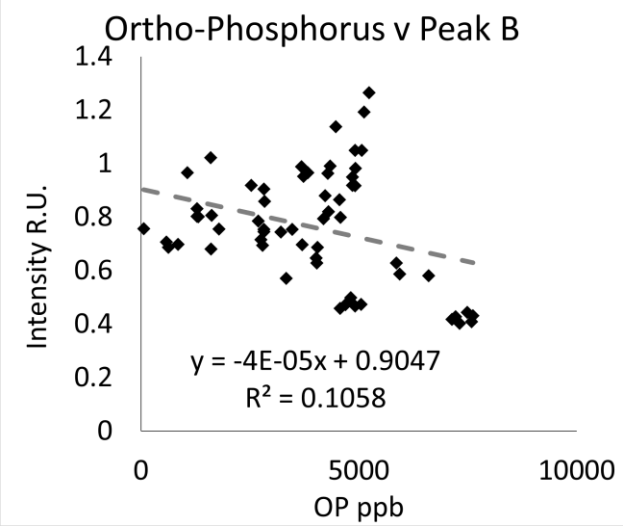

Ortho-Phosphorus v % EC5
8%
7%
6%
5%
4%
3%
2%
1%
0%
Loading
y = 5E-06x + 0.0007
R² = 0.2659
0
5000
10000
OP ppb

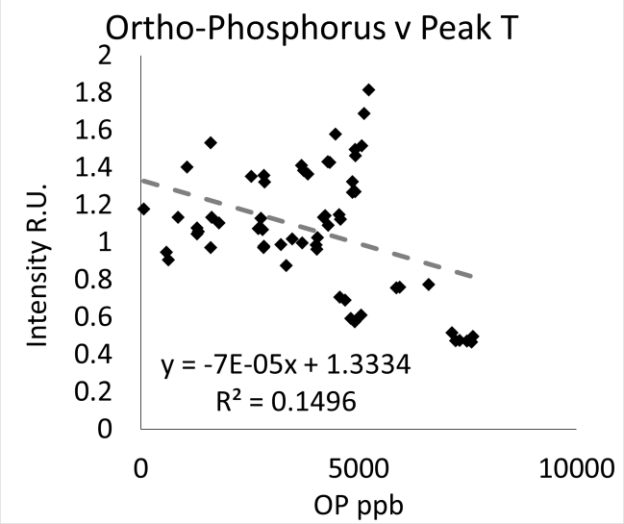

Ortho-Phosphorus v FI
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
Loading
y = -2E-05x + 2.0065
R² = 0.0911
0
5000
10000
OP ppb

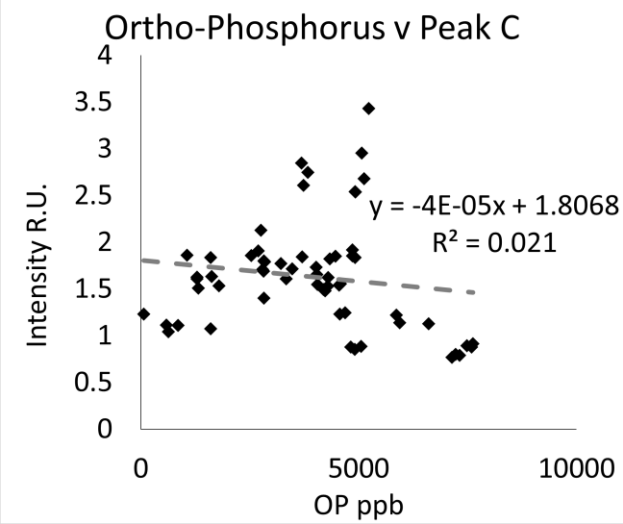

Ortho-Phosphorus v FrI
1
0.8
0.6
0.4
0.2
0
Loading
y = -9E-06x + 0.8489
R² = 0.1425
0
5000
10000
OP ppb

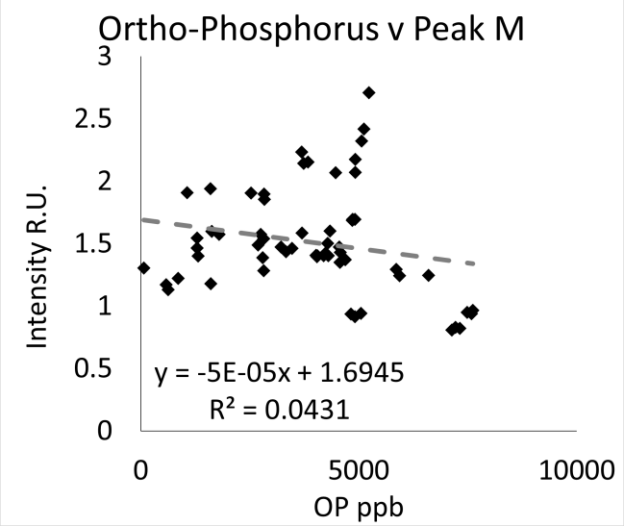

Ortho-Phosphorus v HI
7
6
5
4
3
2
1
0
Loading
y = 0.0002x + 3.0134
R² = 0.2212
0
5000
10000
OP ppb

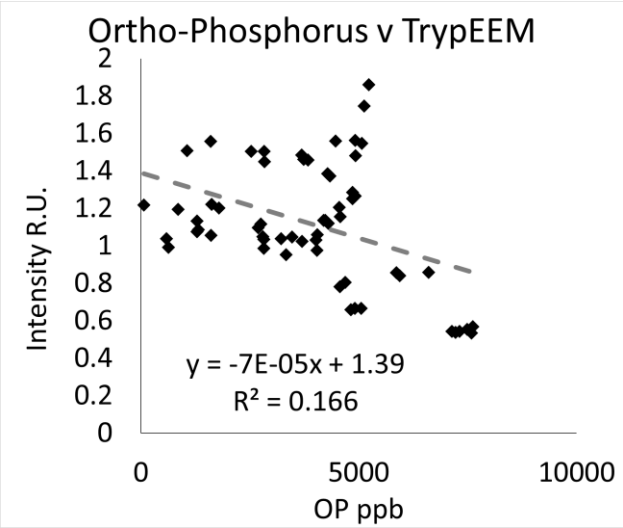

Ortho-Phosphorus v Peak A
Intensity R.U.
OP ppb
y = -5E-05x + 2.1822
R² = 0.0379
0
0.5
1
1.5
2
2.5
3
3.5
0
5000
10000

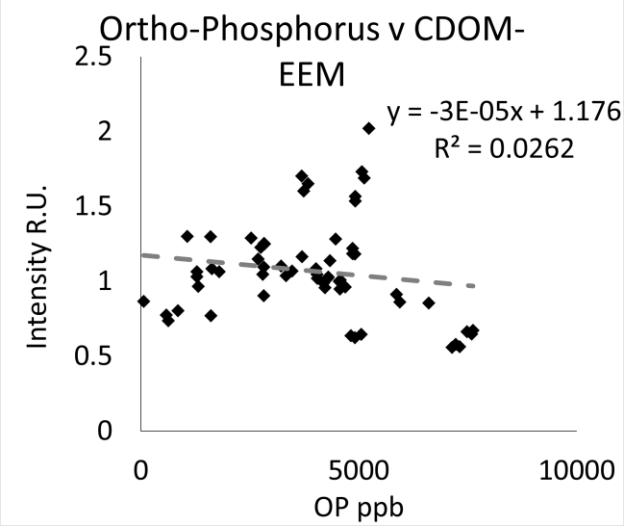

Ortho-Phosphorus v Peak B
Intensity R.U.
OP ppb
y = -4E-05x + 0.9047
R² = 0.1058
0
0.2
0.4
0.6
0.8
1
1.2
1.4
0
5000
10000

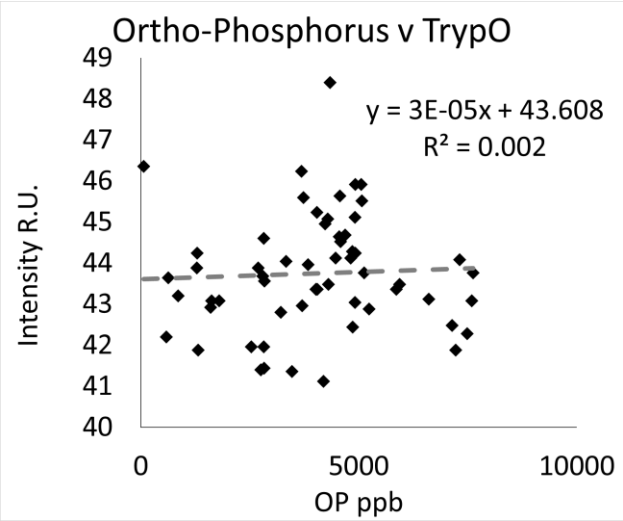

Ortho-Phosphorus v Peak T
Intensity R.U.
OP ppb
y = -7E-05x + 1.3334
R² = 0.1496
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0
5000
10000

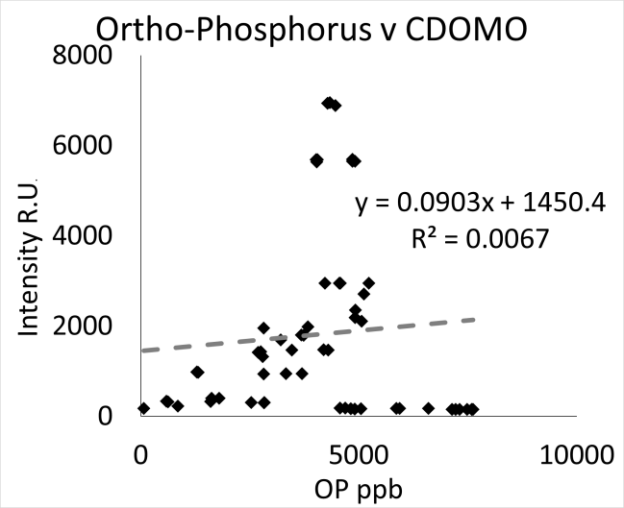

Ortho-Phosphorus v Peak C
Intensity R.U.
OP ppb
y = -4E-05x + 1.8068
R² = 0.021
0
0.5
1
1.5
2
2.5
3
3.5
4
0
5000
10000

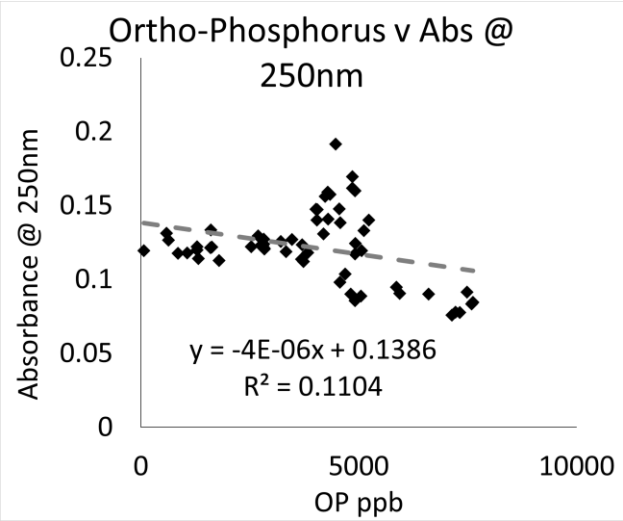

Ortho-Phosphorus v Peak M
Intensity R.U.
OP ppb
y = -5E-05x + 1.6945
R² = 0.0431
0
0.5
1
1.5
2
2.5
3
0
5000
10000

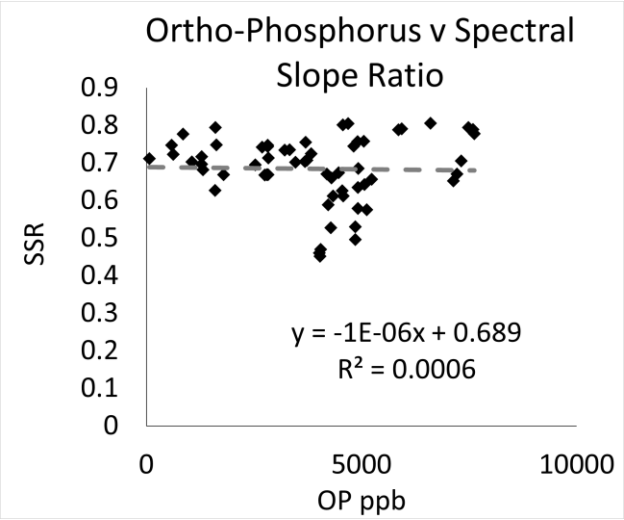

Ortho-Phosphorus v TrypEEM
Intensity R.U.
OP ppb
y = -7E-05x + 1.39
R² = 0.166
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0
5000
10000


Ortho-Phosphorus v CDOM-EEM
y = -3E-05x + 1.176
R² = 0.0262
Intensity R.U.
OP ppb
2.5
2
1.5
1
0.5
0
0
5000
10000


Ortho-Phosphorus v TrypO
y = 3E-05x + 43.608
R² = 0.002
Intensity R.U.
OP ppb
49
48
47
46
45
44
43
42
41
40
0
5000
10000

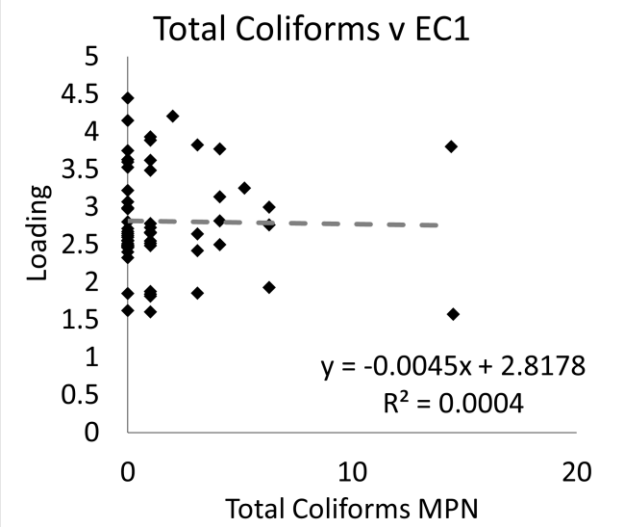

Ortho-Phosphorus v CDOMO
y = 0.0903x + 1450.4
R² = 0.0067
Intensity R.U.
OP ppb
8000
6000
4000
2000
0
0
5000
10000

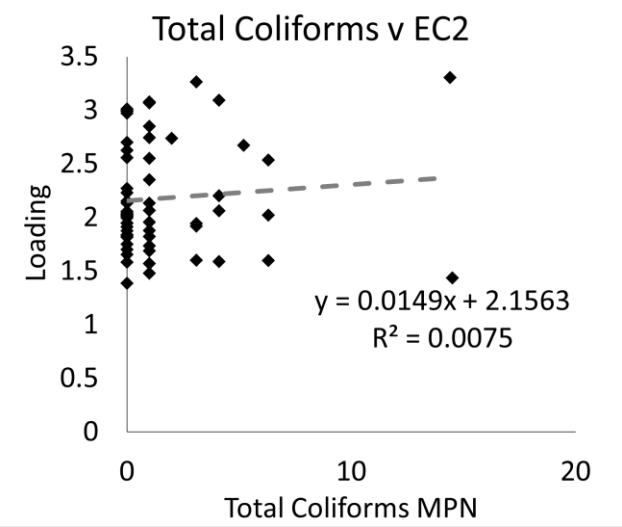

Ortho-Phosphorus v Abs @ 250nm
y = -4E-06x + 0.1386
R² = 0.1104
Absorbance @ 250nm
OP ppb
0.25
0.2
0.15
0.1
0.05
0
0
5000
10000

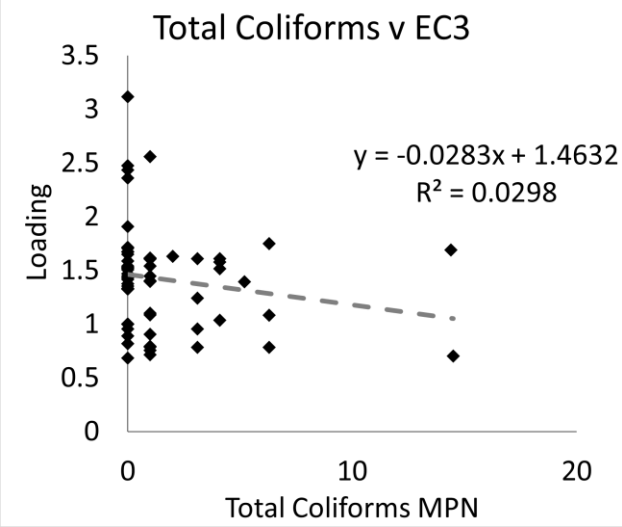

Ortho-Phosphorus v Spectral Slope Ratio
y = -1E-06x + 0.689
R² = 0.0006
SSR
OP ppb
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
5000
10000

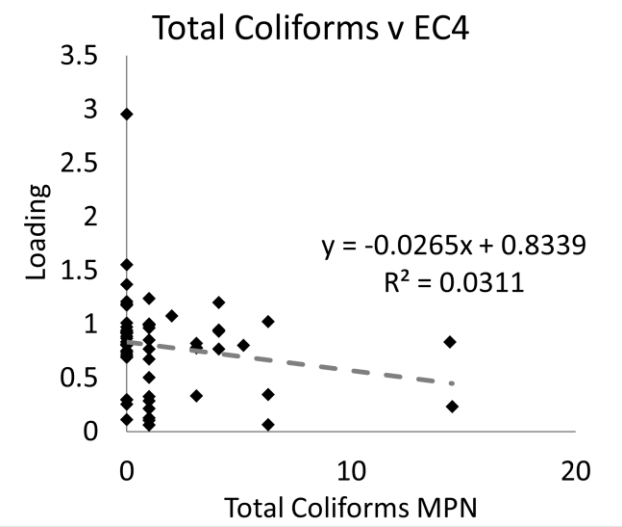
Total coliforms

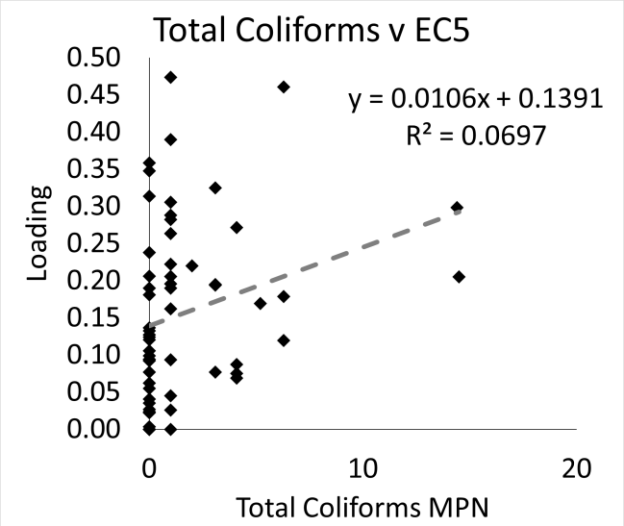
Effluent

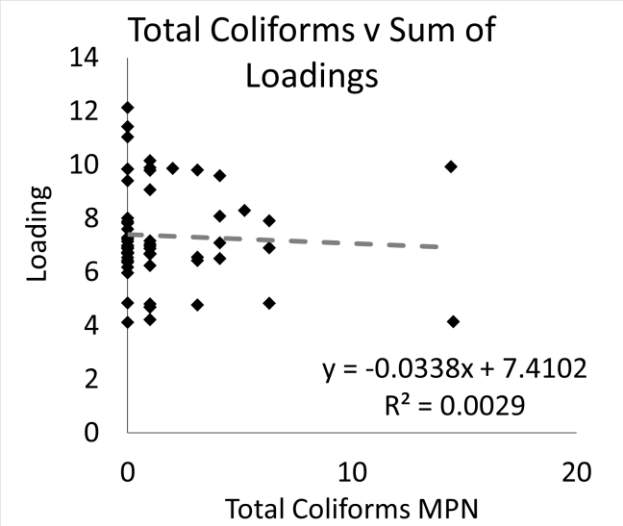


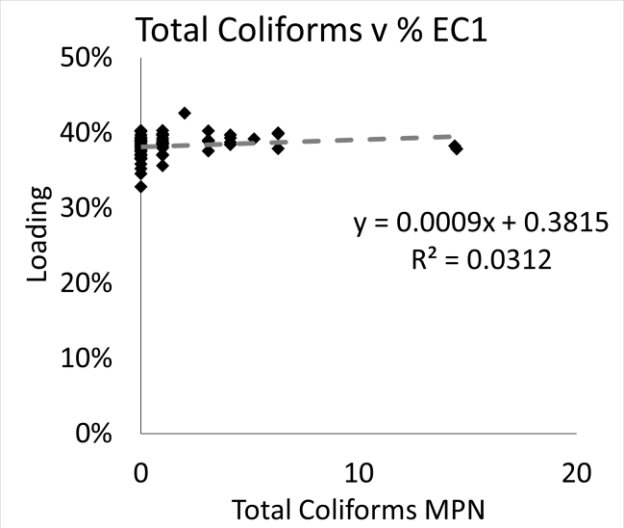


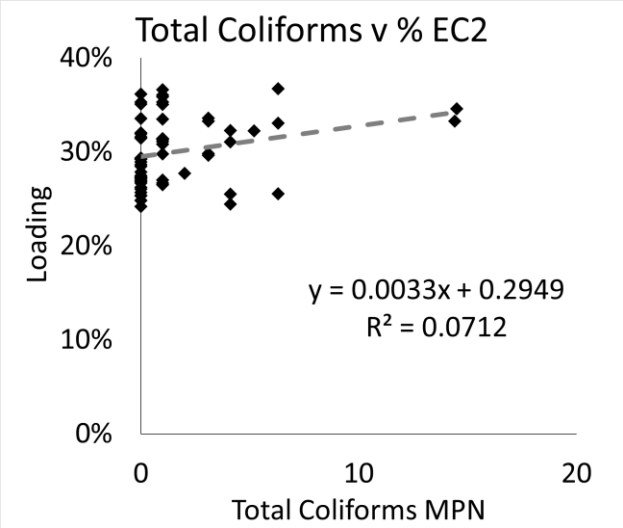


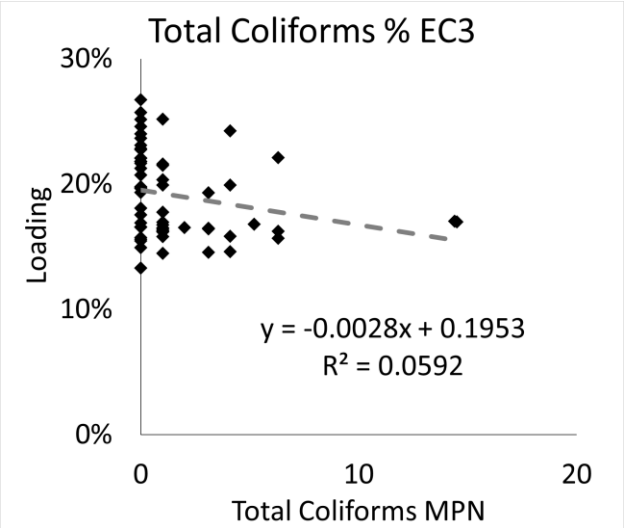


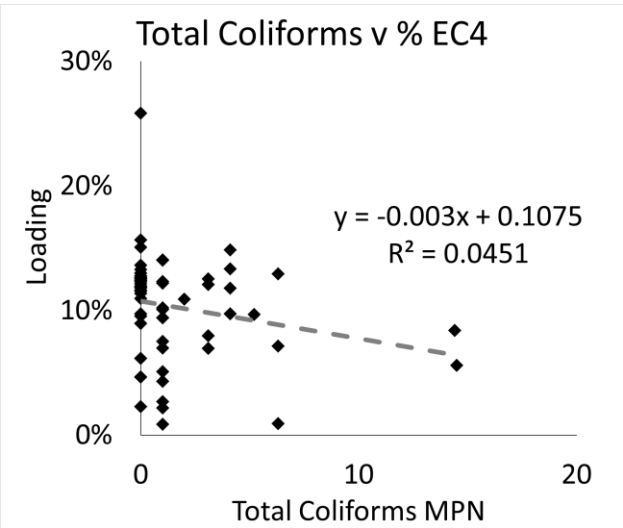

Total Coliforms v EC5
y = 0.0106x + 0.1391
R² = 0.0697
Loading
Total Coliforms MPN
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20

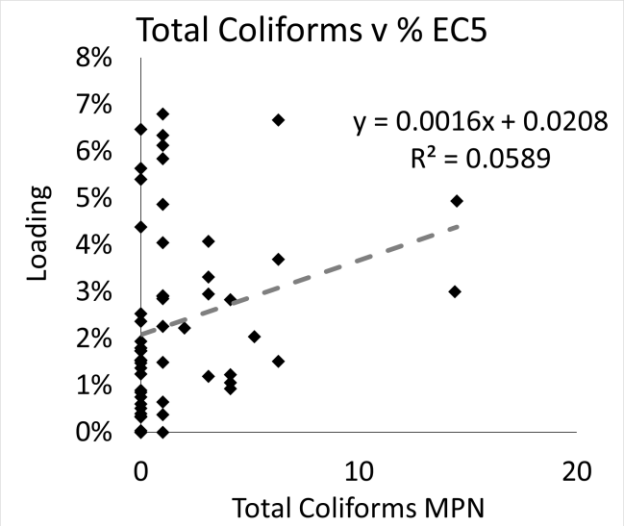

Total Coliforms v Sum of Loadings
y = -0.0338x + 7.4102
R² = 0.0029
Loading
Total Coliforms MPN
14
12
10
8
6
4
2
0
0
10
20

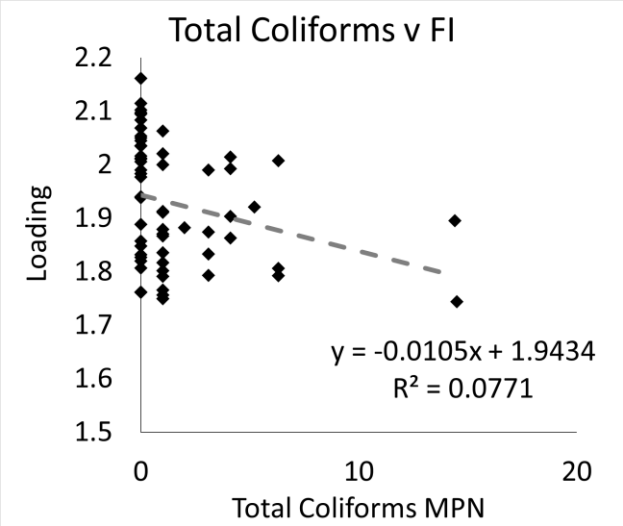

Total Coliforms v % EC1
y = 0.0009x + 0.3815
R² = 0.0312
Loading
Total Coliforms MPN
50%
40%
30%
20%
10%
0%
0
10
20

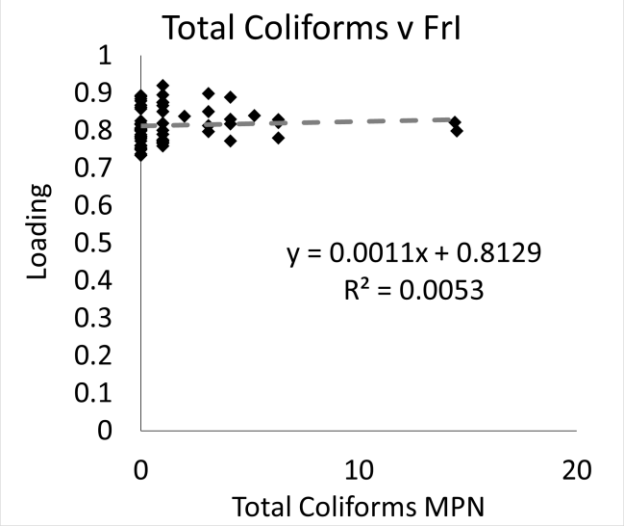

Total Coliforms v % EC2
y = 0.0033x + 0.2949
R² = 0.0712
Loading
Total Coliforms MPN
40%
30%
20%
10%
0%
0
10
20

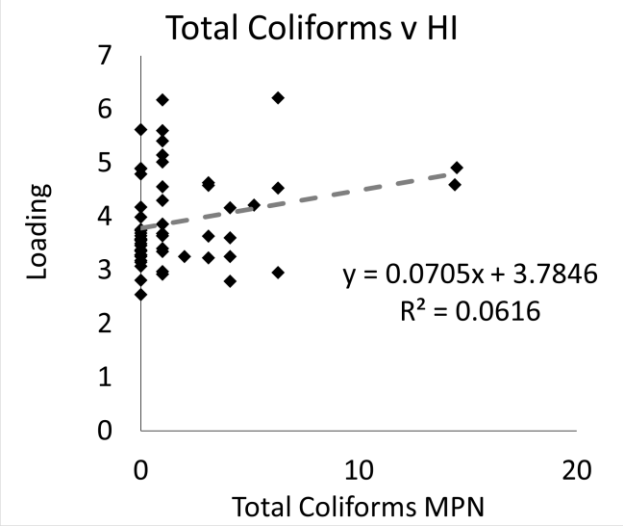

Total Coliforms % EC3
y = -0.0028x + 0.1953
R² = 0.0592
Loading
Total Coliforms MPN
30%
20%
10%
0%
0
10
20

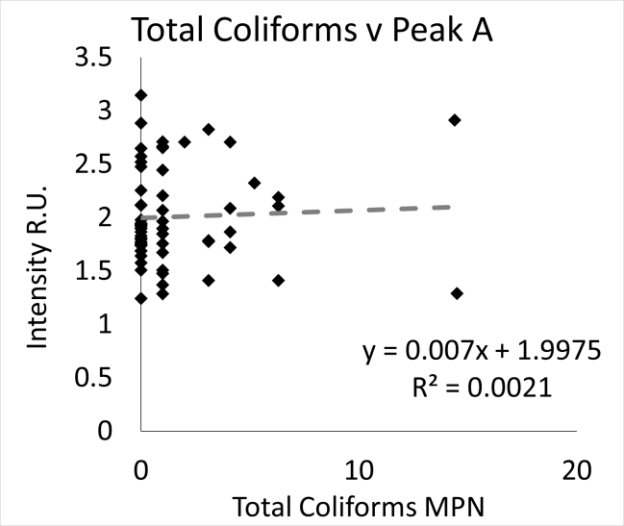

Total Coliforms v % EC4
y = -0.003x + 0.1075
R² = 0.0451
Loading
Total Coliforms MPN
30%
20%
10%
0%
0
10
20

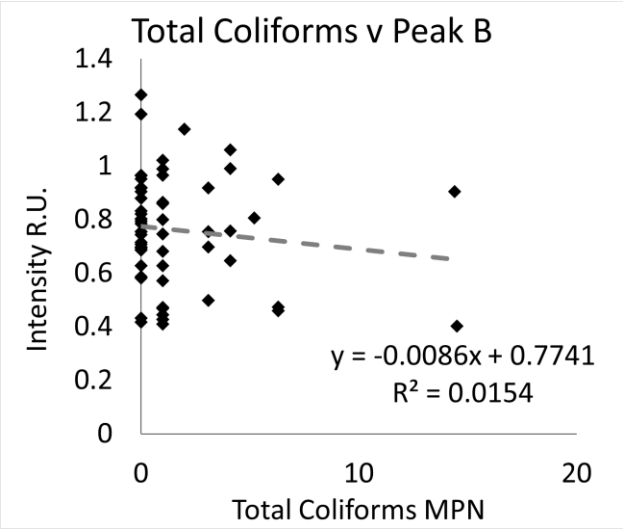

Total Coliforms v % EC5
y = 0.0016x + 0.0208
R² = 0.0589
Loading
Total Coliforms MPN
8%
7%
6%
5%
4%
3%
2%
1%
0%
0
10
20

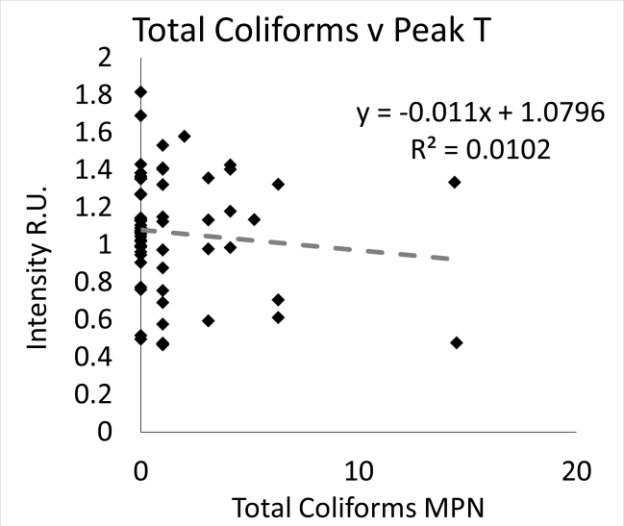

Total Coliforms v FI
y = -0.0105x + 1.9434
R² = 0.0771
Loading
Total Coliforms MPN
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
0
10
20

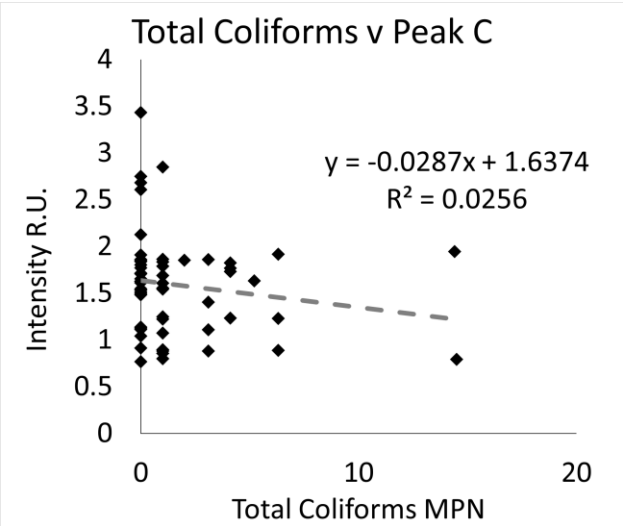

Total Coliforms v FrI
y = 0.0011x + 0.8129
R² = 0.0053
Loading
Total Coliforms MPN
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
10
20

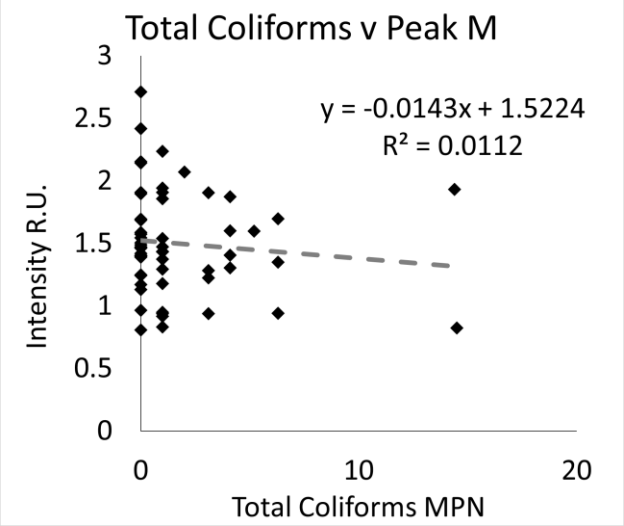

Total Coliforms v HI
y = 0.0705x + 3.7846
R² = 0.0616
Loading
Total Coliforms MPN
7
6
5
4
3
2
1
0
0
10
20

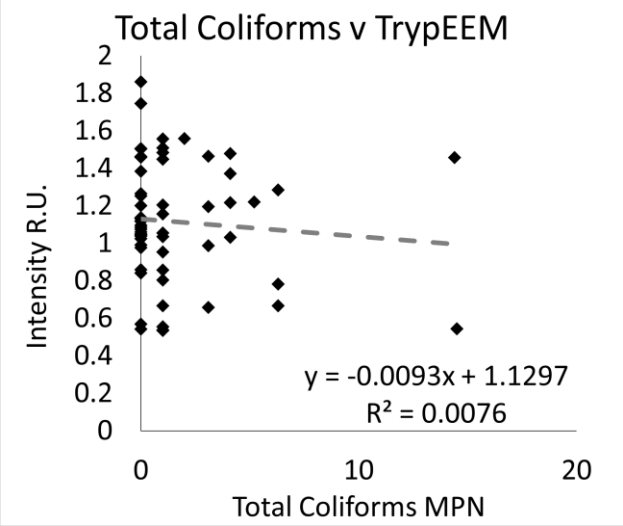

Total Coliforms v Peak A
y = 0.007x + 1.9975
R² = 0.0021
Intensity R.U.
Total Coliforms MPN
3.5
3
2.5
2
1.5
1
0.5
0
0
10
20

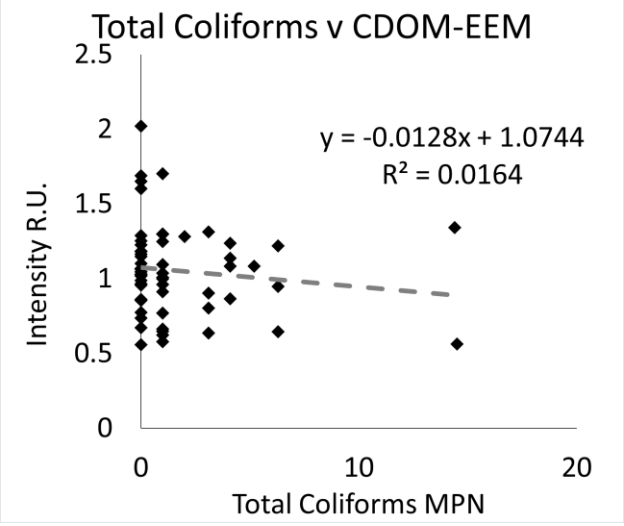

Total Coliforms v Peak B
y = -0.0086x + 0.7741
R² = 0.0154
Intensity R.U.
Total Coliforms MPN
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0
10
20

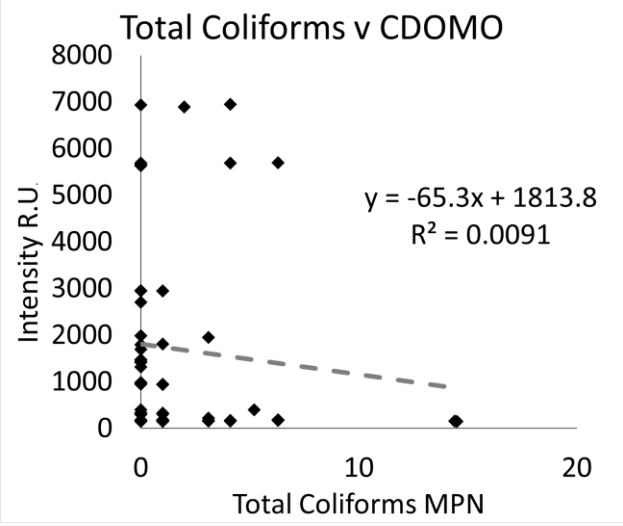

Total Coliforms v Peak T
y = -0.011x + 1.0796
R² = 0.0102
Intensity R.U.
Total Coliforms MPN

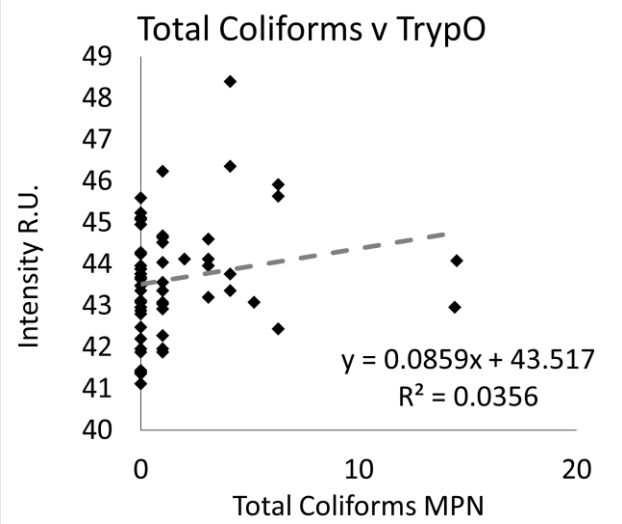

Total Coliforms v Peak C
y = -0.0287x + 1.6374
R² = 0.0256
Intensity R.U.
Total Coliforms MPN

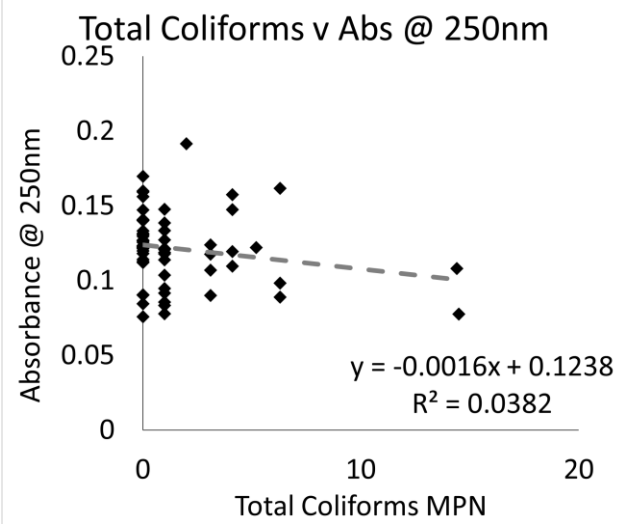

Total Coliforms v Peak M
y = -0.0143x + 1.5224
R² = 0.0112
Intensity R.U.
Total Coliforms MPN

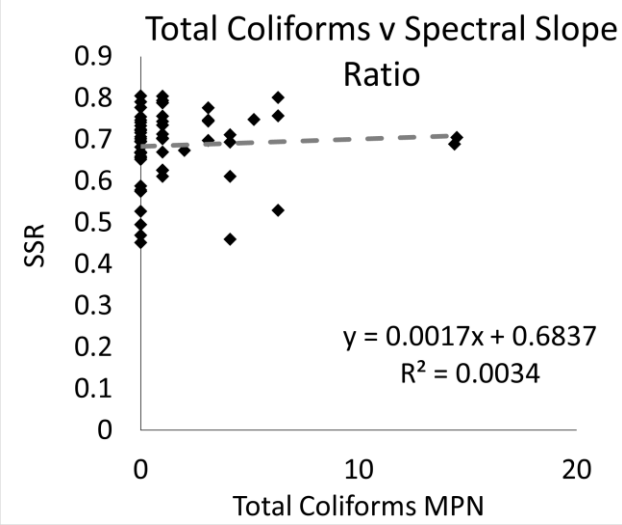

Total Coliforms v TrypEEM
y = -0.0093x + 1.1297
R² = 0.0076
Intensity R.U.
Total Coliforms MPN


Total Coliforms v CDOM-EEM
y = -0.0128x + 1.0744
R² = 0.0164
Intensity R.U.
Total Coliforms MPN


Total Coliforms v CDOMO
y = -65.3x + 1813.8
R² = 0.0091
Intensity R.U.
Total Coliforms MPN

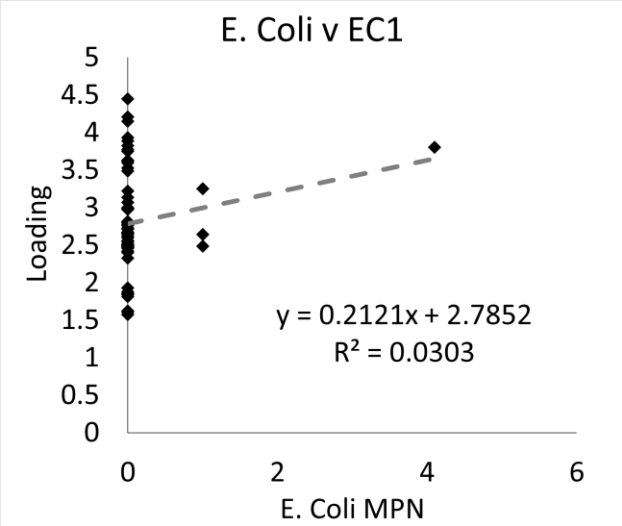


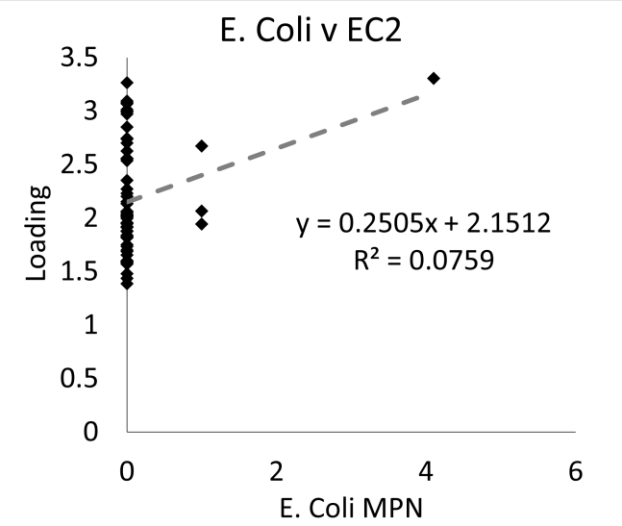


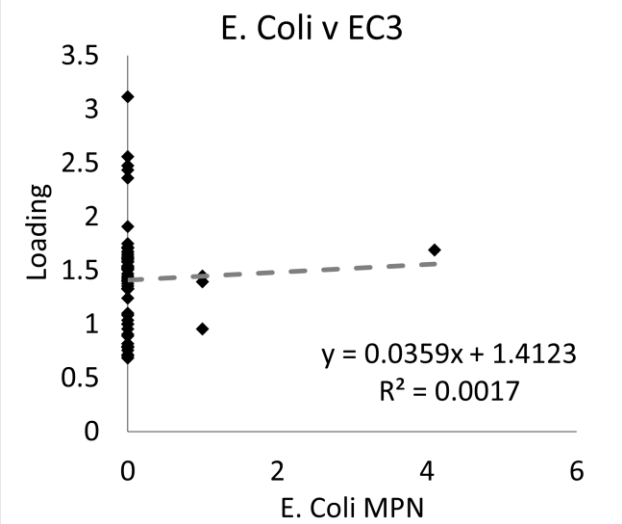


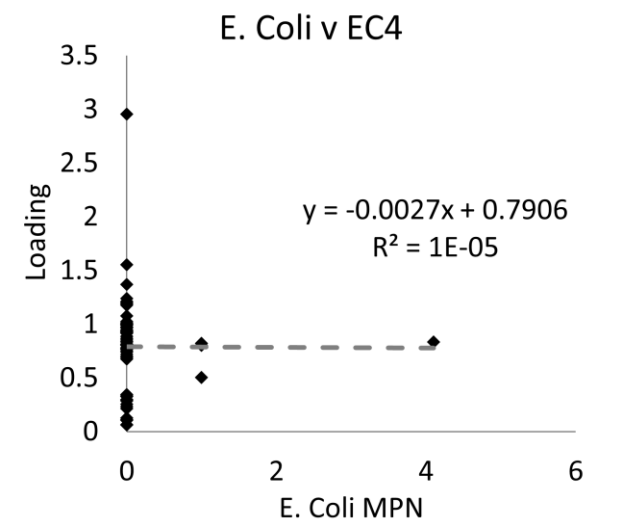
E. Coli

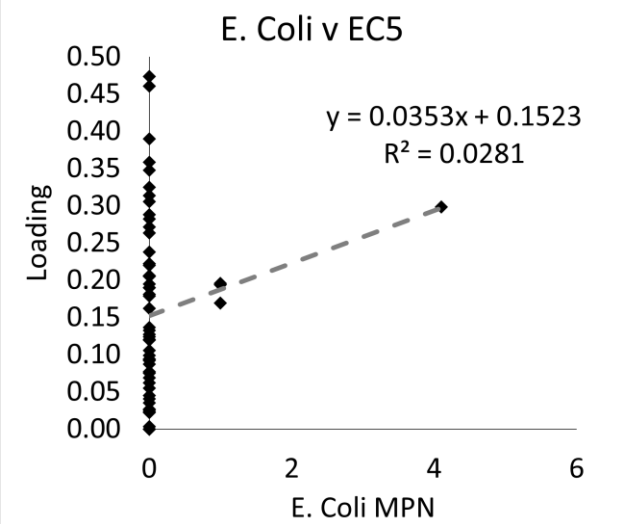
Effluent

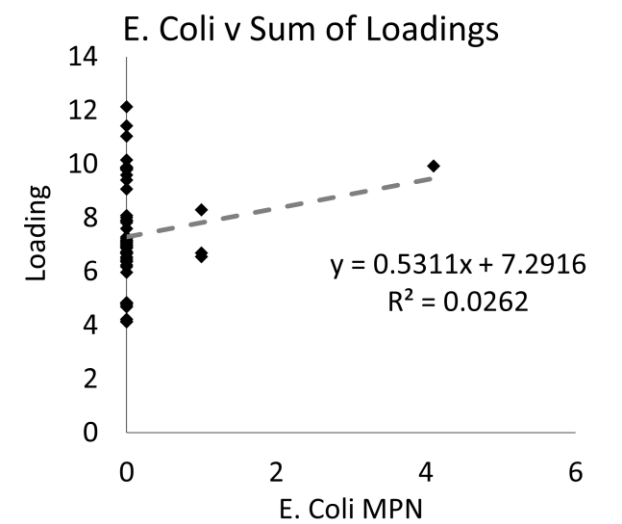

E. Coli v EC1
Loading
E. Coli MPN
y = 0.2121x + 2.7852
R² = 0.0303

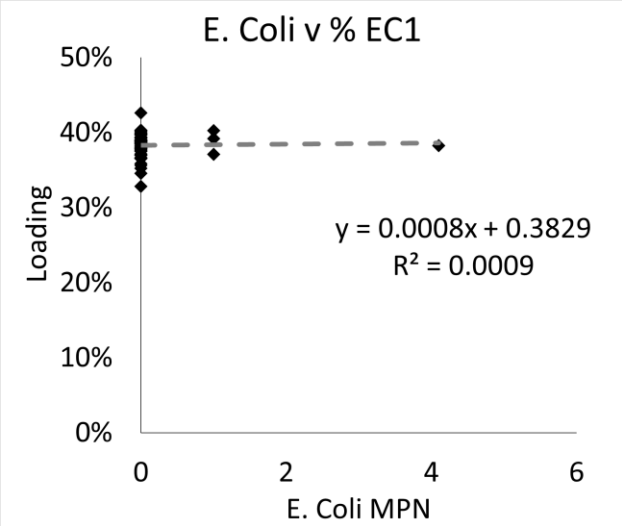

E. Coli v EC2
Loading
E. Coli MPN
y = 0.2505x + 2.1512
R² = 0.0759

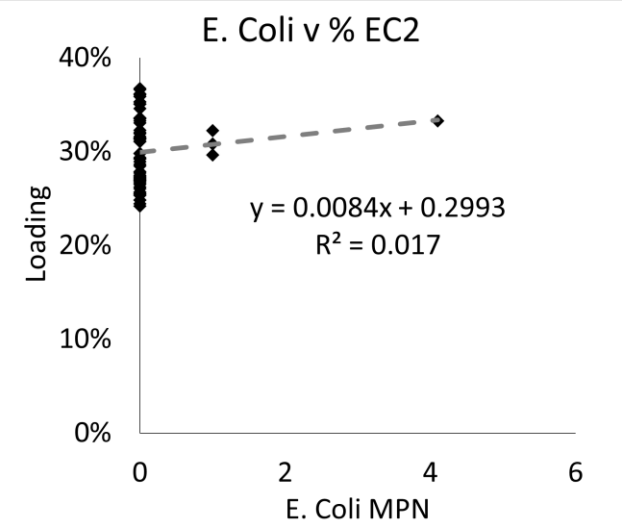

E. Coli v EC3
Loading
E. Coli MPN
y = 0.0359x + 1.4123
R² = 0.0017

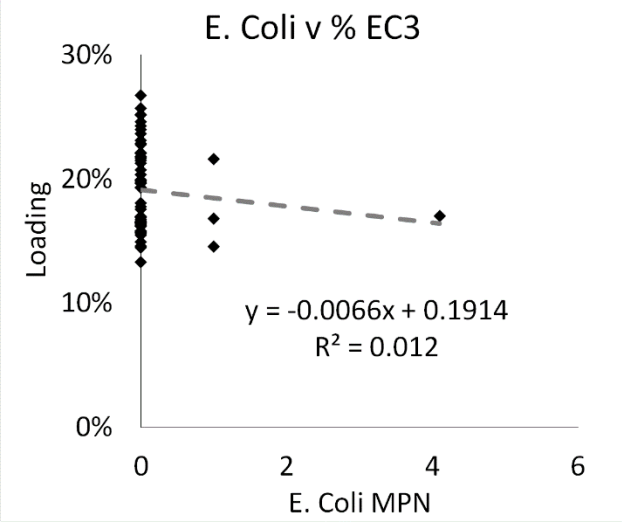

E. Coli v EC4
Loading
E. Coli MPN
y = -0.0027x + 0.7906
R² = 1E-05

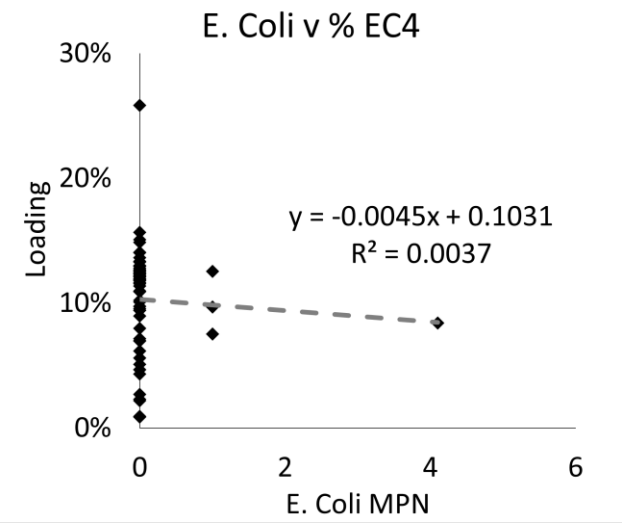

E. Coli v EC5
Loading
E. Coli MPN
y = 0.0353x + 0.1523
R² = 0.0281

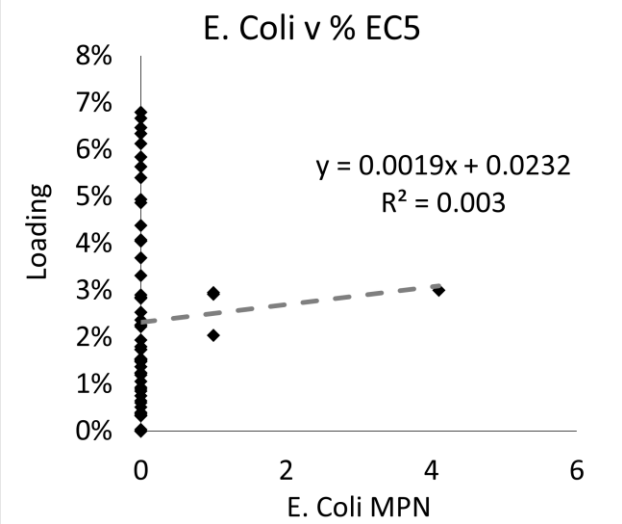

E. Coli v Sum of Loadings
Loading
E. Coli MPN
y = 0.5311x + 7.2916
R² = 0.0262

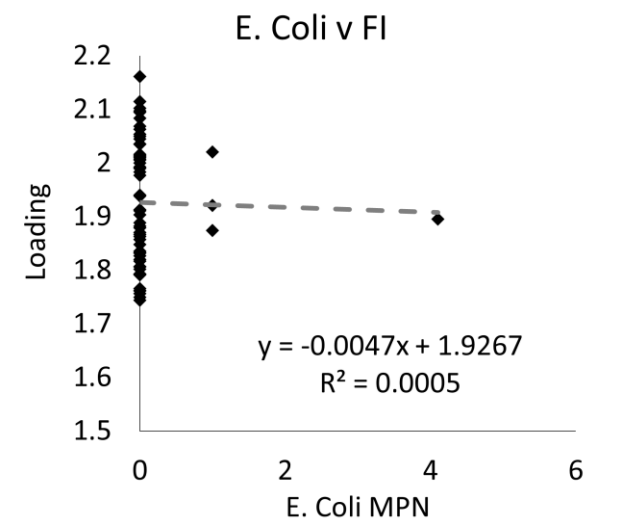

E. Coli v % EC1
50%
40%
30%
20%
10%
0%
Loading
y = 0.0008x + 0.3829
R² = 0.0009
0
2
4
6
E. Coli MPN

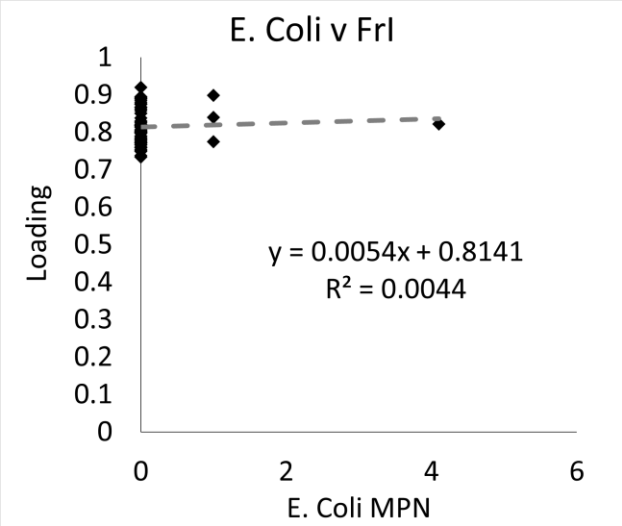

E. Coli v % EC2
40%
30%
20%
10%
0%
Loading
y = 0.0084x + 0.2993
R² = 0.017
0
2
4
6
E. Coli MPN

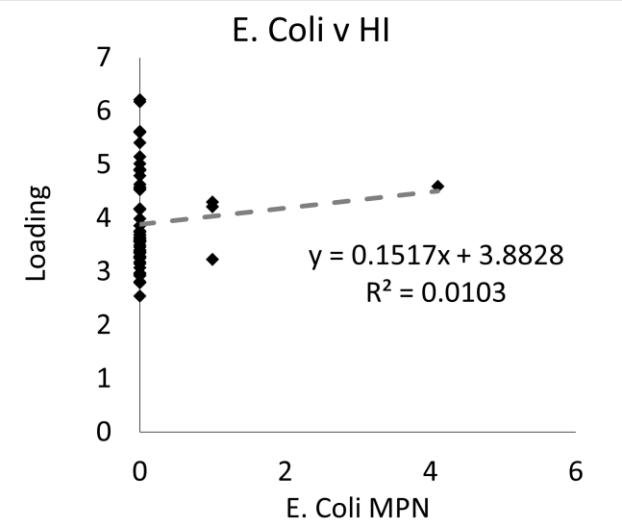

E. Coli v % EC3
30%
20%
10%
0%
Loading
y = -0.0066x + 0.1914
R² = 0.012
0
2
4
6
E. Coli MPN

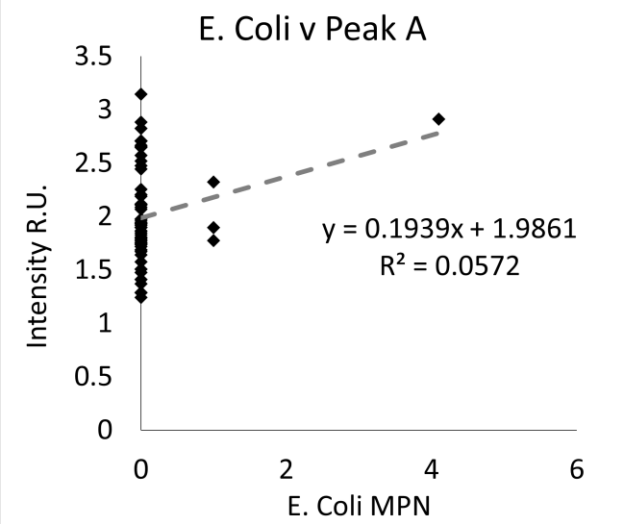

E. Coli v % EC4
30%
20%
10%
0%
Loading
y = -0.0045x + 0.1031
R² = 0.0037
0
2
4
6
E. Coli MPN

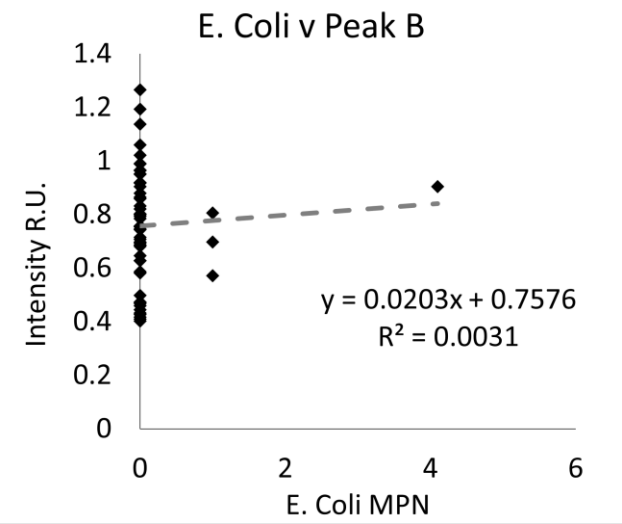

E. Coli v % EC5
8%
7%
6%
5%
4%
3%
2%
1%
0%
Loading
y = 0.0019x + 0.0232
R² = 0.003
0
2
4
6
E. Coli MPN

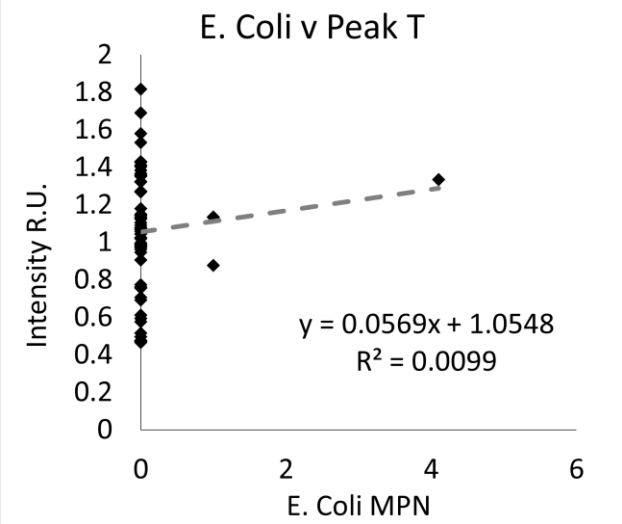

E. Coli v FI
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
Loading
y = -0.0047x + 1.9267
R² = 0.0005
0
2
4
6
E. Coli MPN

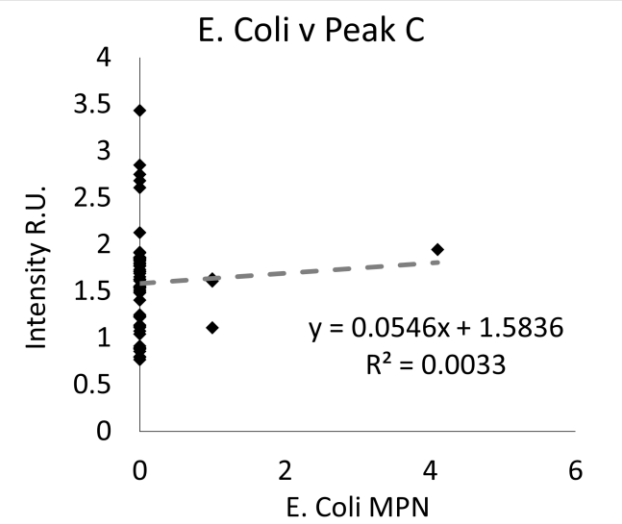

E. Coli v FrI
Loading
E. Coli MPN
y = 0.0054x + 0.8141
R² = 0.0044

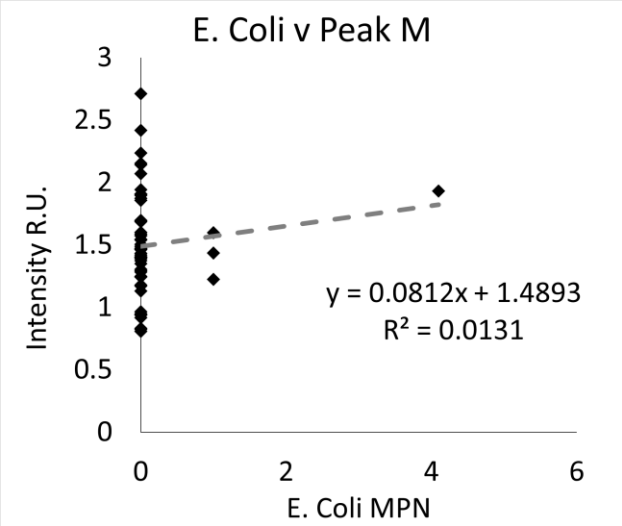

E. Coli v HI
Loading
E. Coli MPN
y = 0.1517x + 3.8828
R² = 0.0103

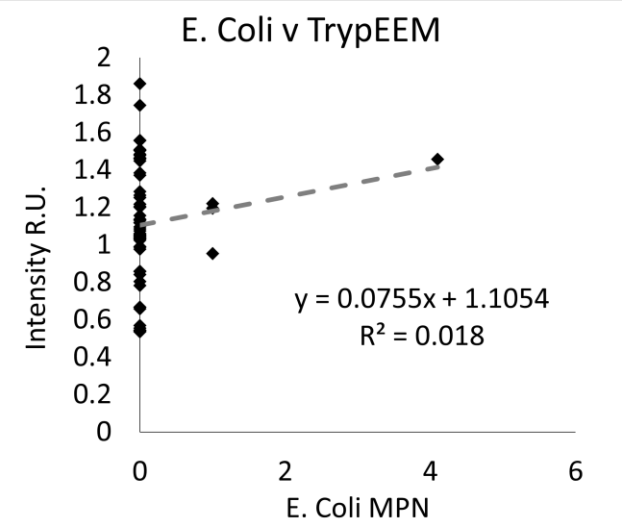

E. Coli v Peak A
Intensity R.U.
E. Coli MPN
y = 0.1939x + 1.9861
R² = 0.0572

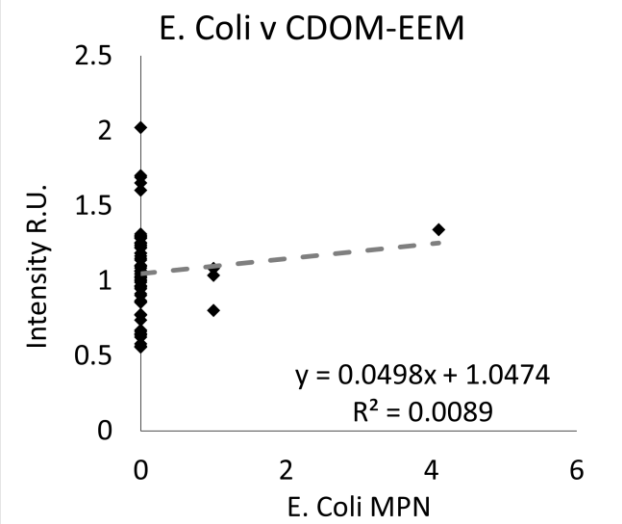

E. Coli v Peak B
Intensity R.U.
E. Coli MPN
y = 0.0203x + 0.7576
R² = 0.0031

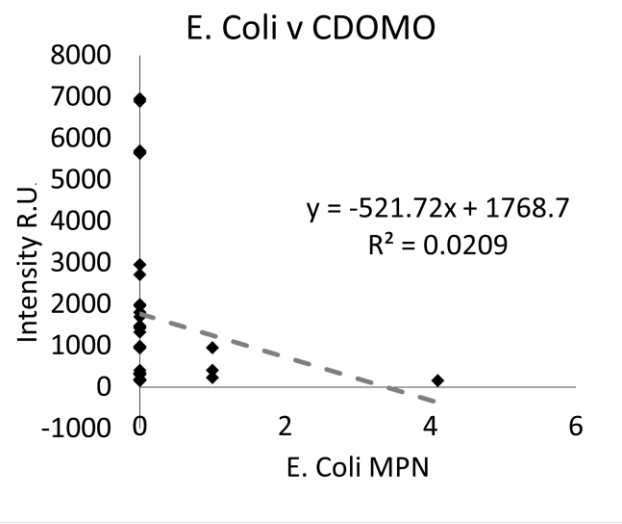

E. Coli v Peak T
Intensity R.U.
E. Coli MPN
y = 0.0569x + 1.0548
R² = 0.0099

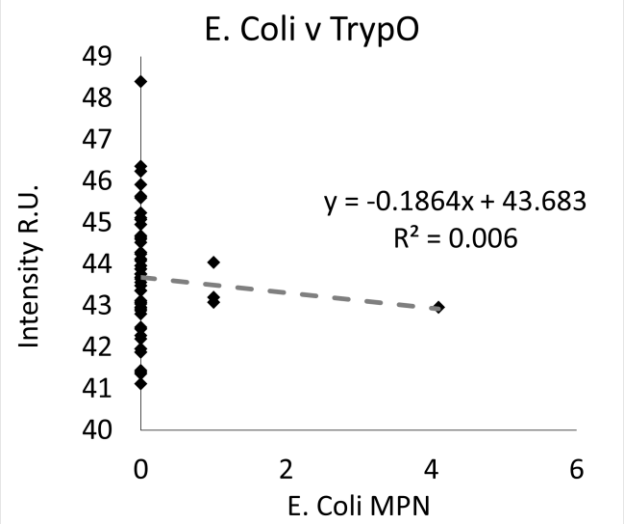

E. Coli v Peak C
Intensity R.U.
E. Coli MPN
y = 0.0546x + 1.5836
R² = 0.0033

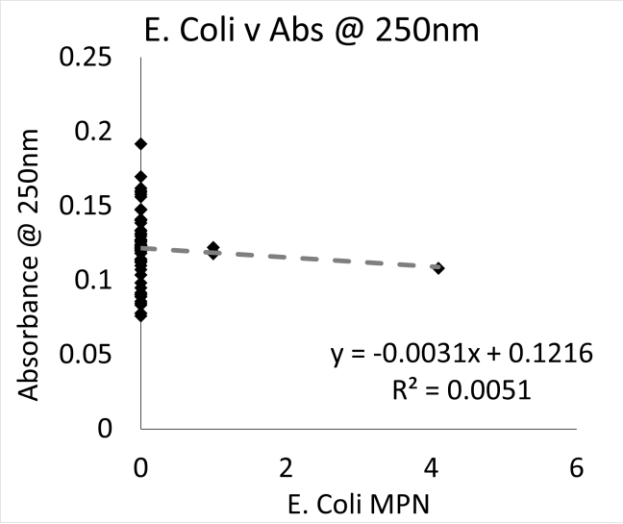

E. Coli v Peak M
Intensity R.U.
E. Coli MPN
y = 0.0812x + 1.4893
R² = 0.0131

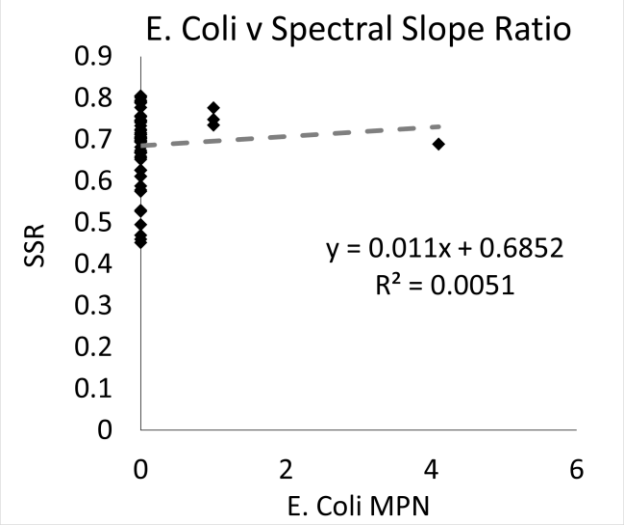

E. Coli v TrypEEM
Intensity R.U.
E. Coli MPN
y = 0.0755x + 1.1054
R² = 0.018


E. Coli v CDOM-EEM
Intensity R.U.
E. Coli MPN
y = 0.0498x + 1.0474
R² = 0.0089


E. Coli v CDOMO
Intensity R.U
E. Coli MPN
y = -521.72x + 1768.7
R² = 0.0209

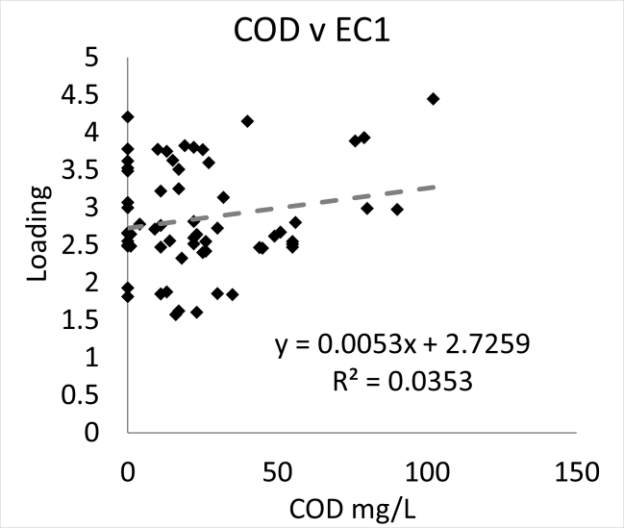


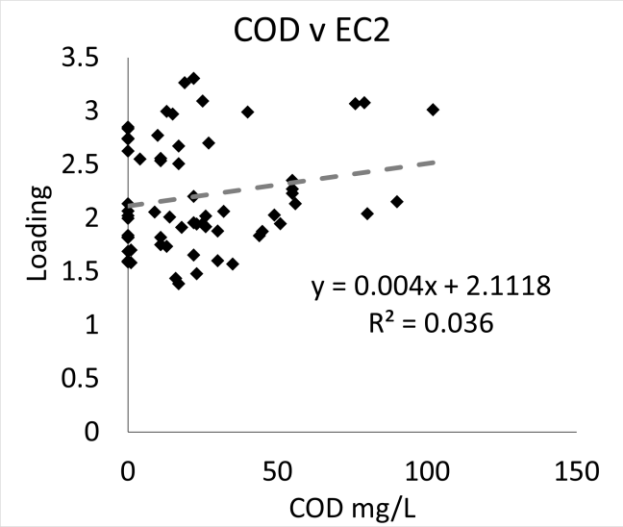


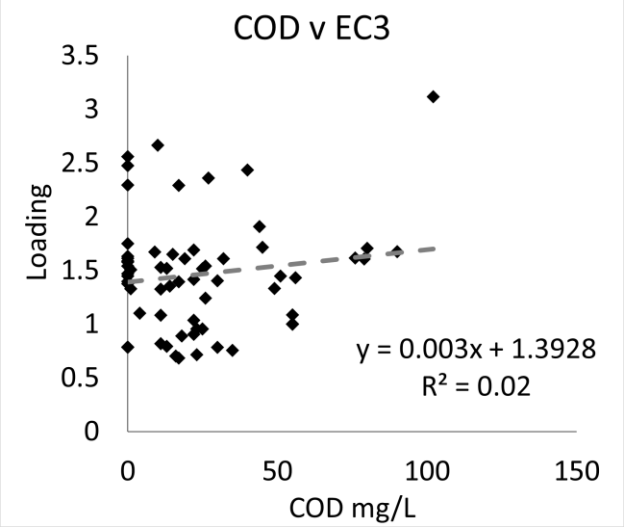


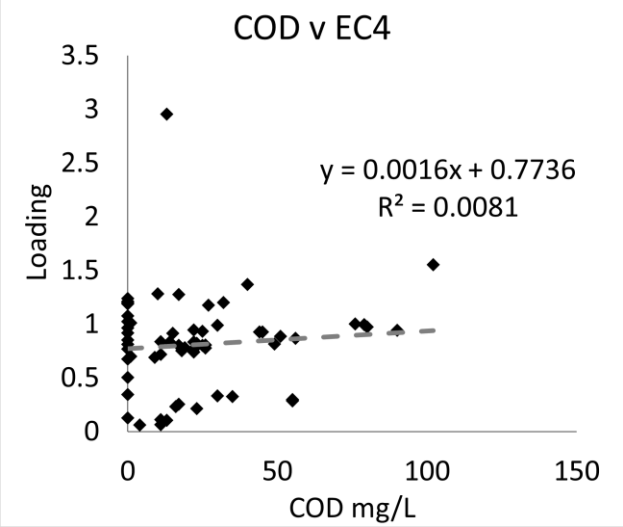
Chemical oxygen demand

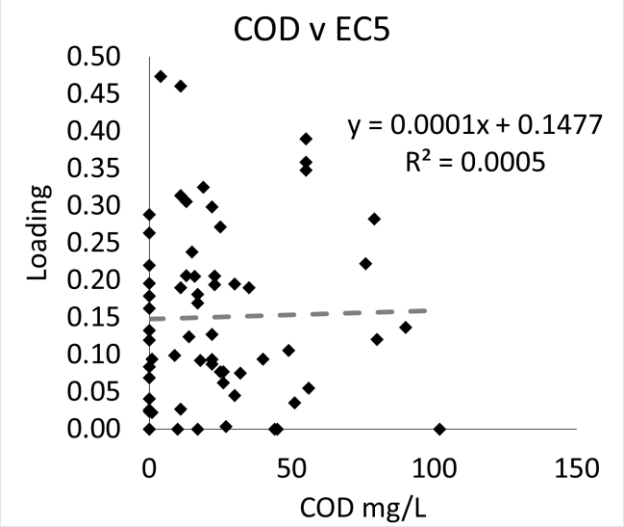
Effluent

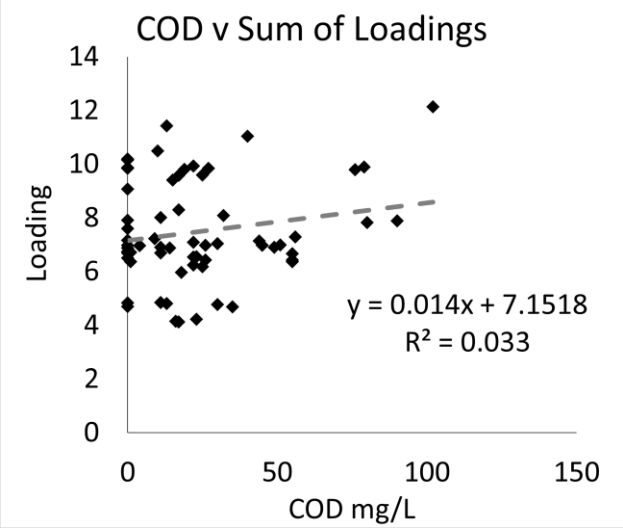

COD v EC1
Loading
COD mg/L
y = 0.0053x + 2.7259
R² = 0.0353

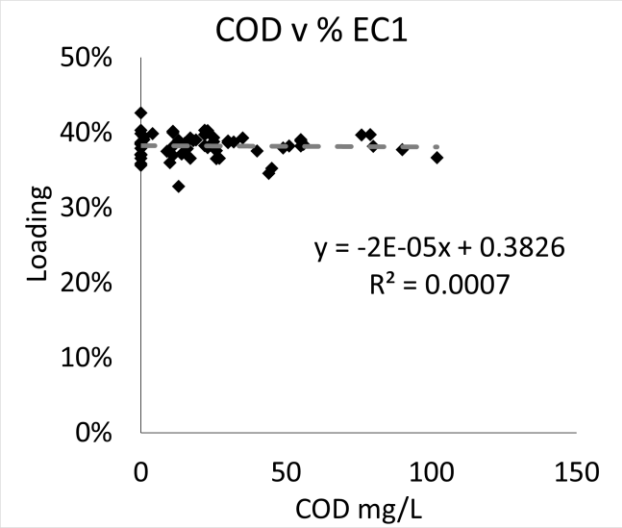

COD v EC2
Loading
COD mg/L
y = 0.004x + 2.1118
R² = 0.036

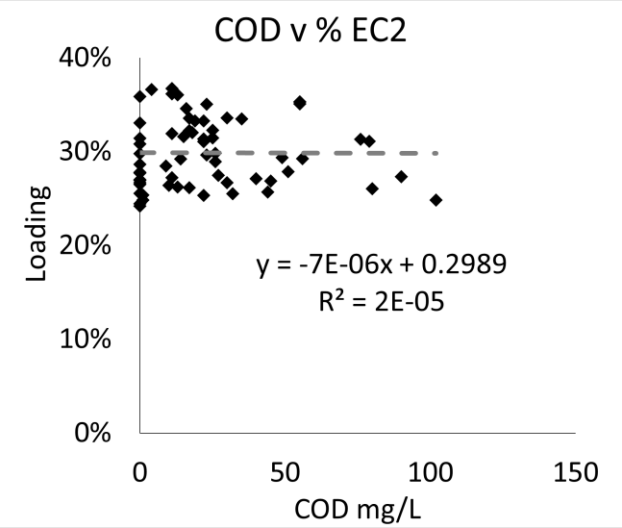

COD v EC3
Loading
COD mg/L
y = 0.003x + 1.3928
R² = 0.02

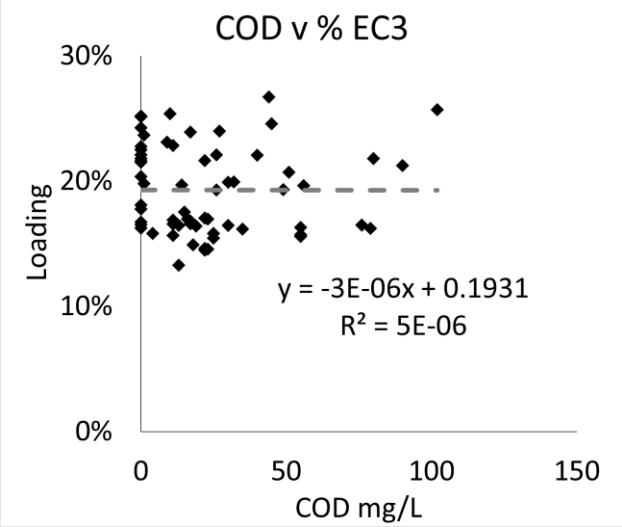

COD v EC4
Loading
COD mg/L
y = 0.0016x + 0.7736
R² = 0.0081

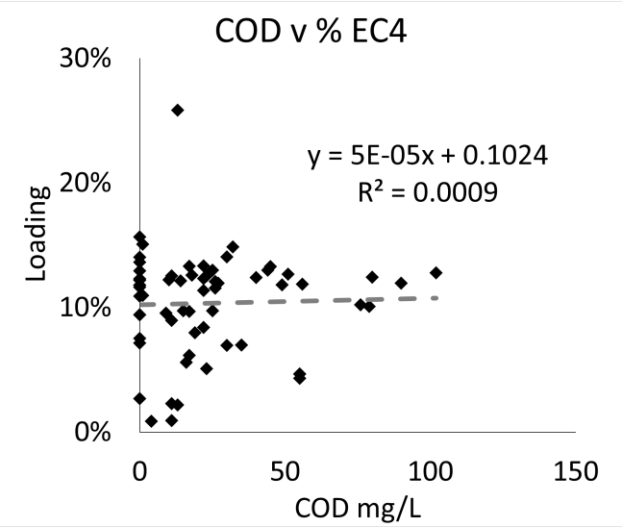

COD v EC5
Loading
COD mg/L
y = 0.0001x + 0.1477
R² = 0.0005

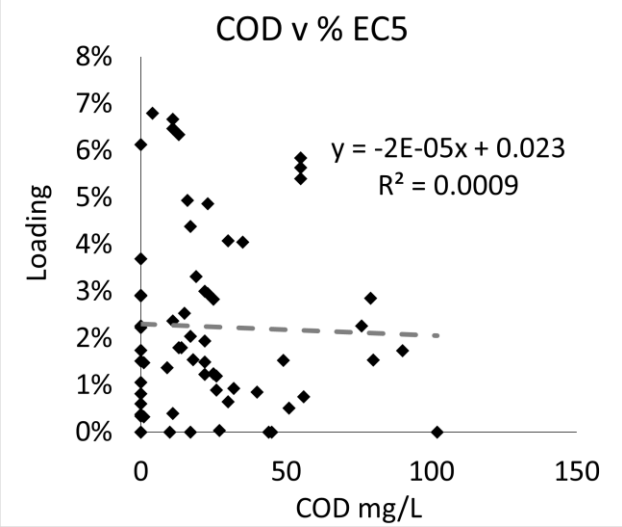

COD v Sum of Loadings
Loading
COD mg/L
y = 0.014x + 7.1518
R² = 0.033

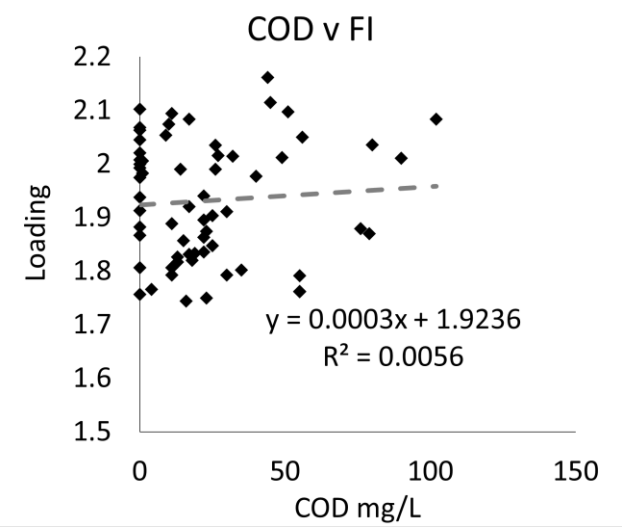

COD v % EC1
50%
40%
30%
20%
10%
0%
Loading
y = -2E-05x + 0.3826
R² = 0.0007
0
50
100
150
COD mg/L

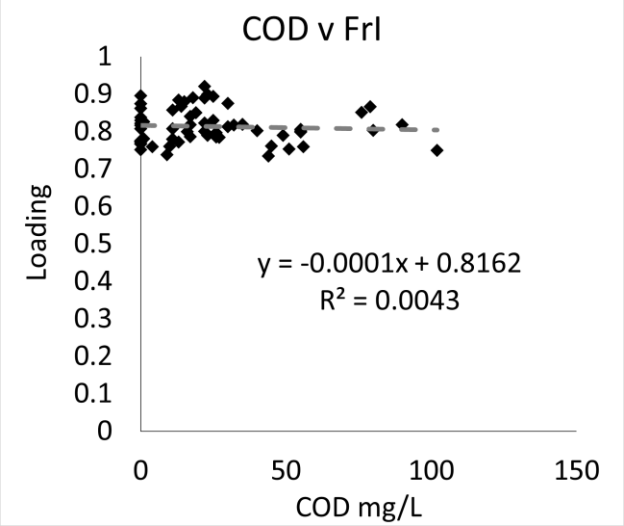

COD v % EC2
40%
30%
20%
10%
0%
Loading
y = -7E-06x + 0.2989
R² = 2E-05
0
50
100
150
COD mg/L

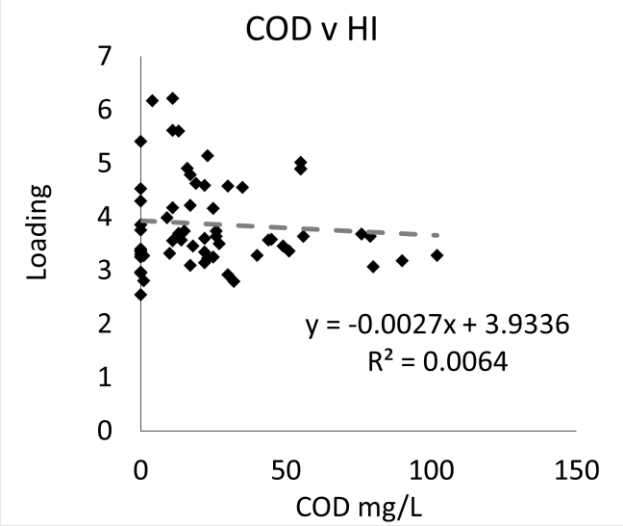

COD v % EC3
30%
20%
10%
0%
Loading
y = -3E-06x + 0.1931
R² = 5E-06
0
50
100
150
COD mg/L

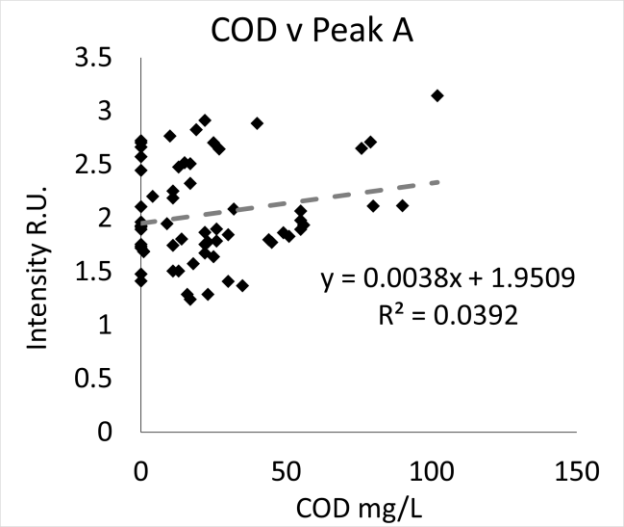

COD v % EC4
30%
20%
10%
0%
Loading
y = 5E-05x + 0.1024
R² = 0.0009
0
50
100
150
COD mg/L

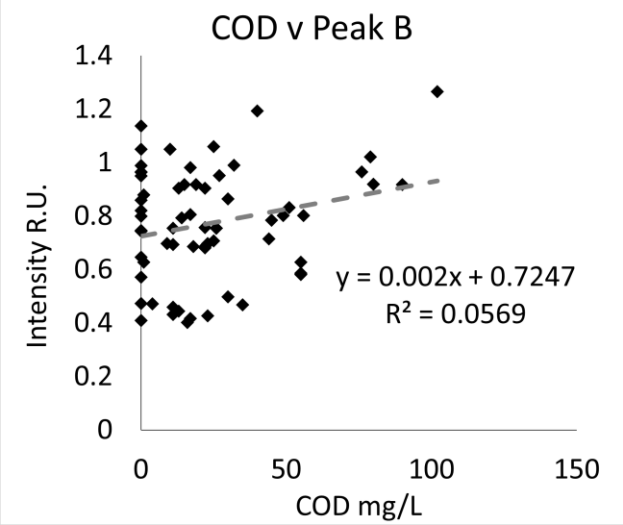

COD v % EC5
8%
7%
6%
5%
4%
3%
2%
1%
0%
Loading
y = -2E-05x + 0.023
R² = 0.0009
0
50
100
150
COD mg/L

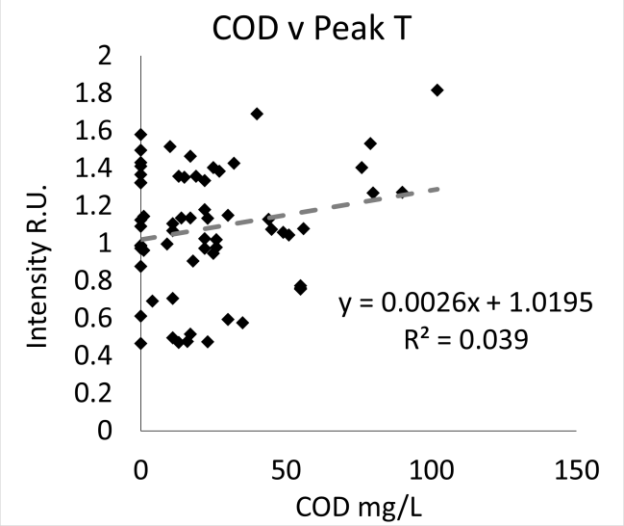

COD v FI
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
Loading
y = 0.0003x + 1.9236
R² = 0.0056
0
50
100
150
COD mg/L

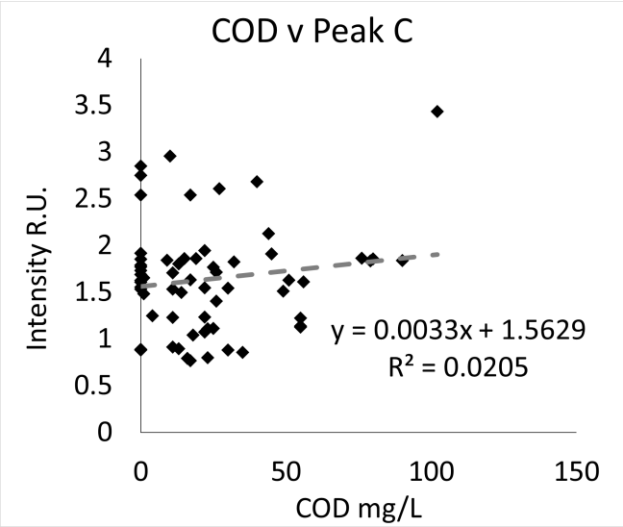

COD v FrI
Loading
COD mg/L
y = -0.0001x + 0.8162
R² = 0.0043

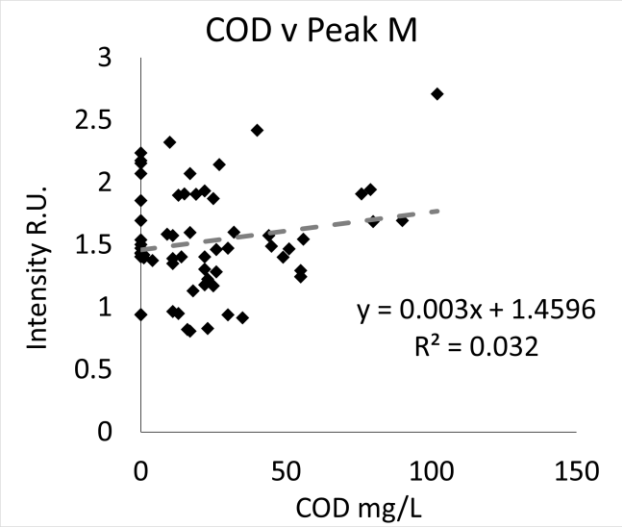

COD v HI
Loading
COD mg/L
y = -0.0027x + 3.9336
R² = 0.0064

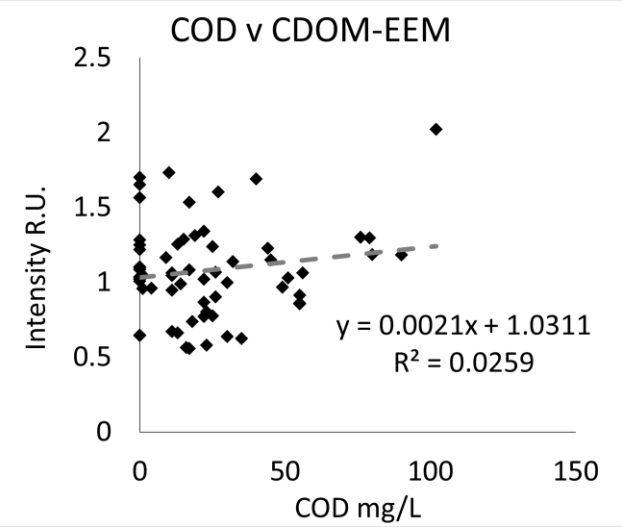

COD v Peak A
Intensity R.U.
COD mg/L
y = 0.0038x + 1.9509
R² = 0.0392

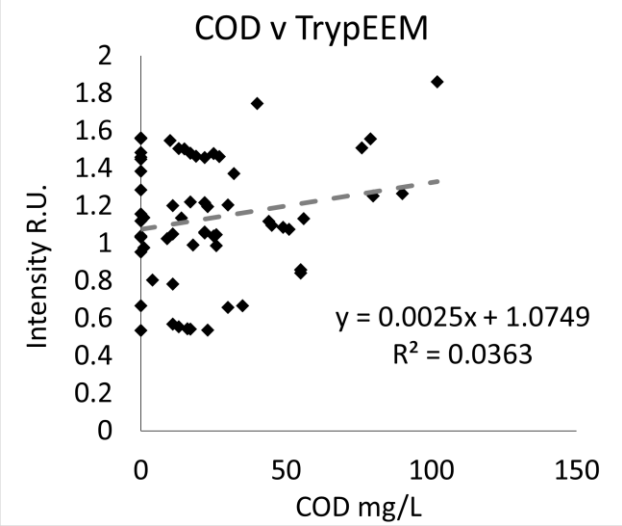

COD v Peak B
Intensity R.U.
COD mg/L
y = 0.002x + 0.7247
R² = 0.0569

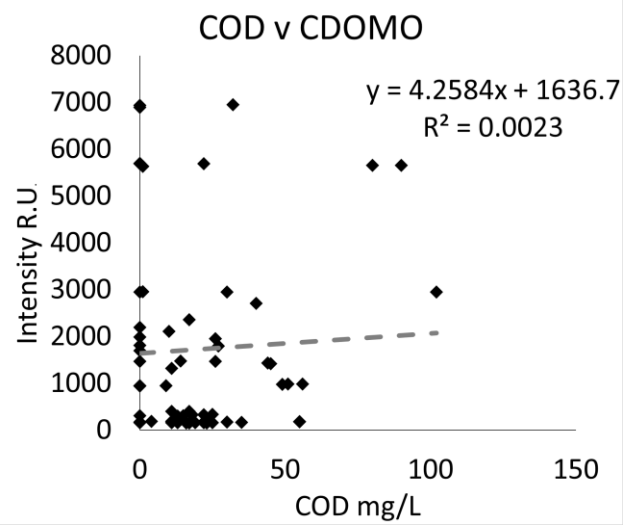

COD v Peak T
Intensity R.U.
COD mg/L
y = 0.0026x + 1.0195
R² = 0.039

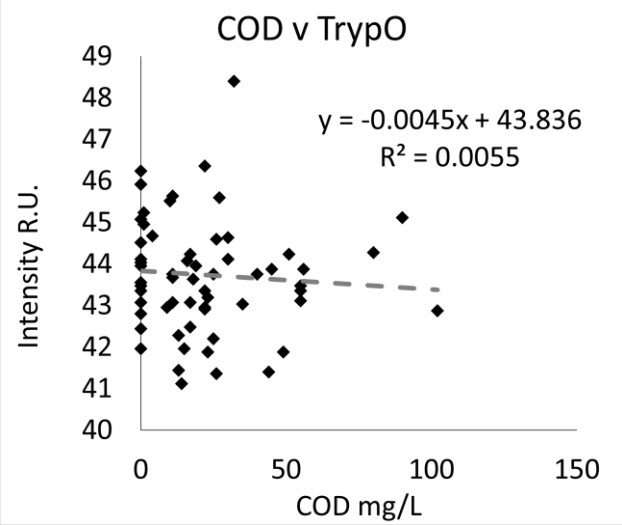

COD v Peak C
Intensity R.U.
COD mg/L
y = 0.0033x + 1.5629
R² = 0.0205

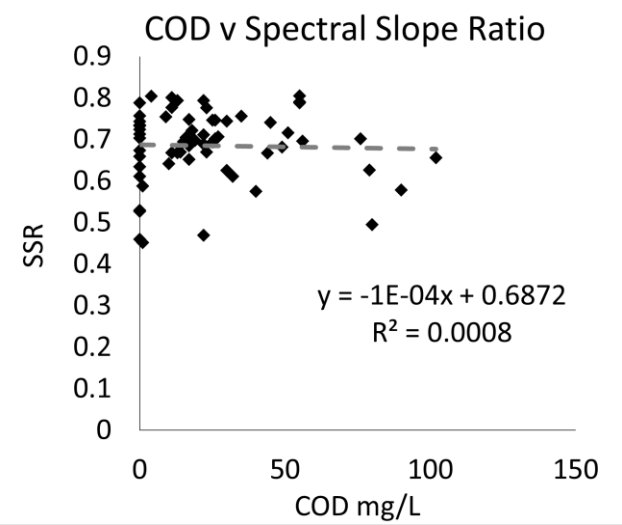

COD v Peak M
Intensity R.U.
COD mg/L
y = 0.003x + 1.4596
R² = 0.032
0
0.5
1
1.5
2
2.5
3
0
50
100
150

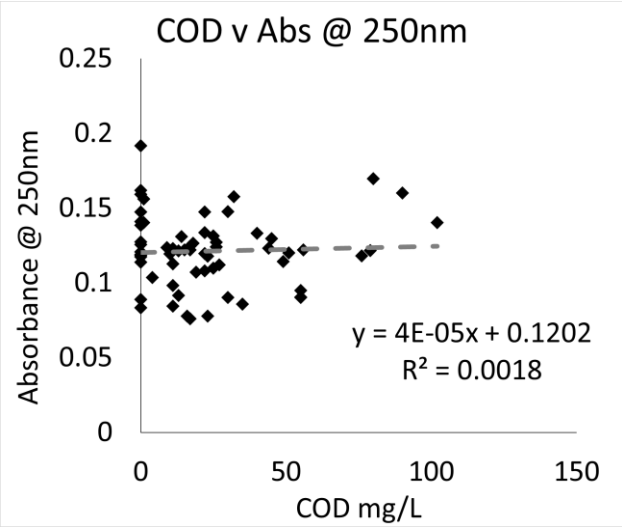

COD v CDOM-EEM
Intensity R.U.
COD mg/L
y = 0.0021x + 1.0311
R² = 0.0259
0
0.5
1
1.5
2
2.5
0
50
100
150


COD v TrypEEM
Intensity R.U.
COD mg/L
y = 0.0025x + 1.0749
R² = 0.0363
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0
50
100
150

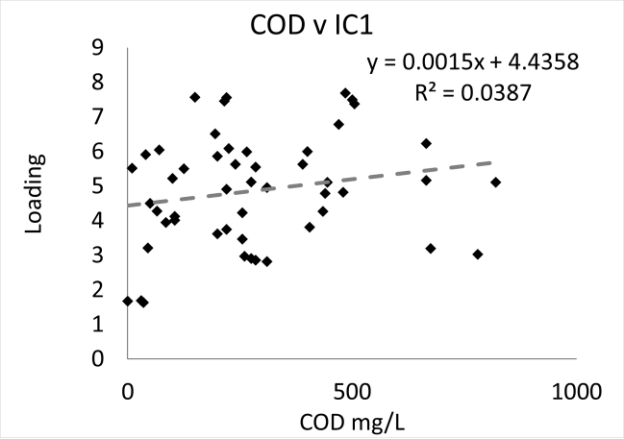

COD v CDOMO
Intensity R.U
COD mg/L
y = 4.2584x + 1636.7
R² = 0.0023
0
1000
2000
3000
4000
5000
6000
7000
8000
0
50
100
150

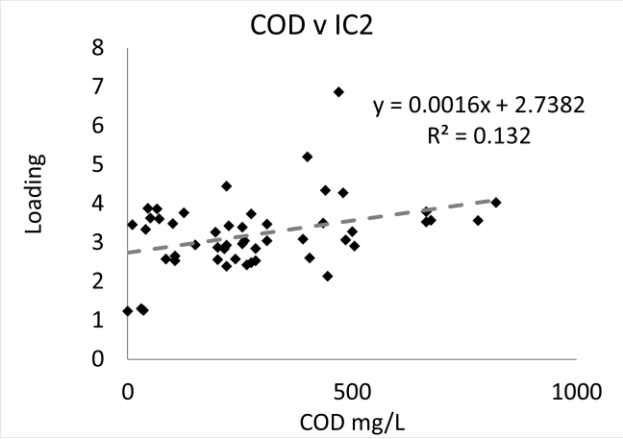

COD v TrypO
y = -0.0045x + 43.836
R² = 0.0055
Intensity R.U.
COD mg/L
49
48
47
46
45
44
43
42
41
40
0
50
100
150

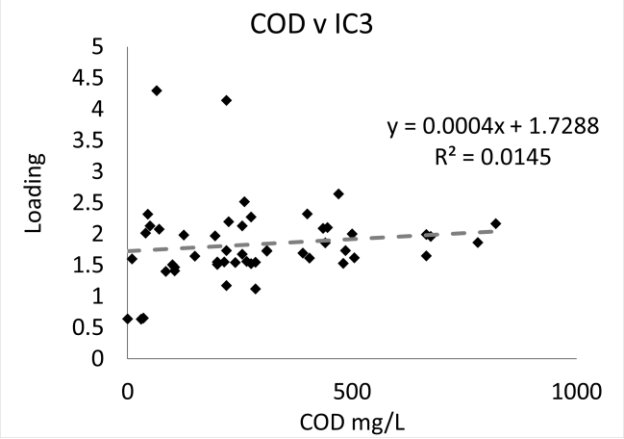

COD v Spectral Slope Ratio
y = -1E-04x + 0.6872
R² = 0.0008
SSR
COD mg/L
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
50
100
150

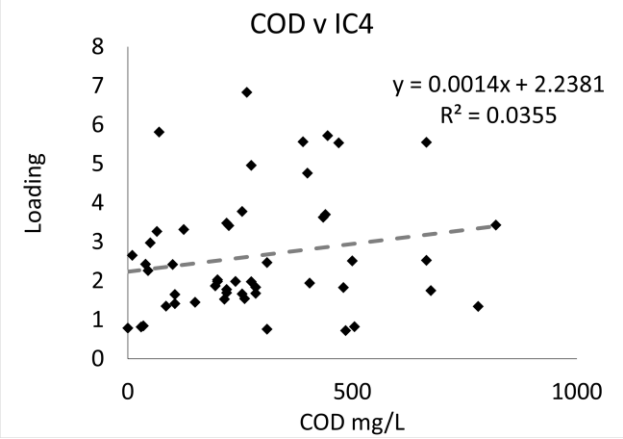

COD v Abs @ 250nm
y = 4E-05x + 0.1202
R² = 0.0018
Absorbance @ 250nm
COD mg/L
0.25
0.2
0.15
0.1
0.05
0
0
50
100
150

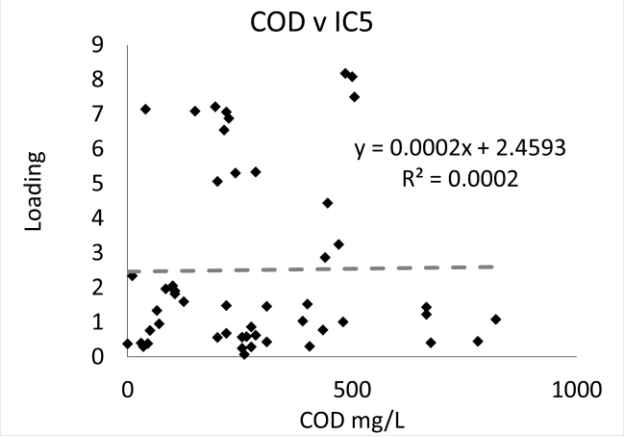
Influent

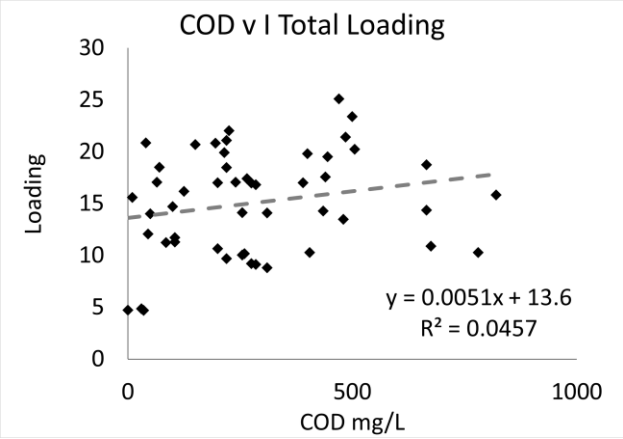

COD v IC1
y = 0.0015x + 4.4358
R² = 0.0387
Loading
COD mg/L
0
500
1000

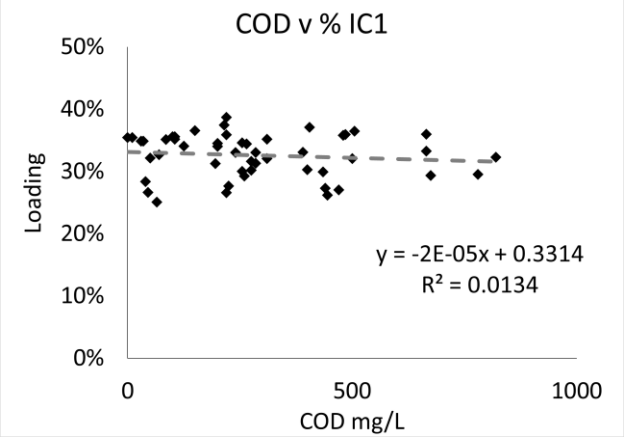

COD v IC2
y = 0.0016x + 2.7382
R² = 0.132
Loading
COD mg/L
0
500
1000

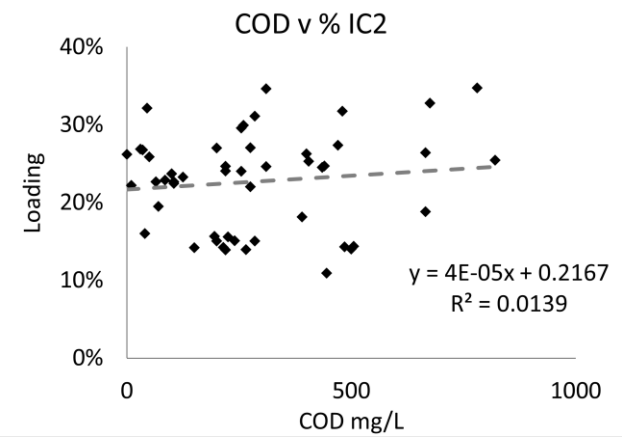

COD v IC3
y = 0.0004x + 1.7288
R² = 0.0145
Loading
COD mg/L
0
500
1000

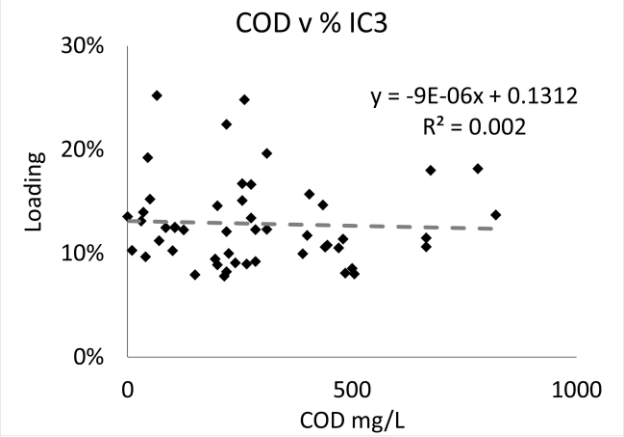

COD v IC4
y = 0.0014x + 2.2381
R² = 0.0355
Loading
COD mg/L
0
500
1000

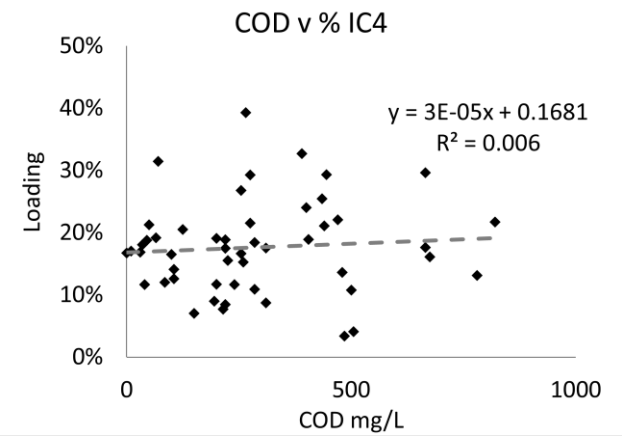

COD v IC5
y = 0.0002x + 2.4593
R² = 0.0002
Loading
COD mg/L
0
500
1000

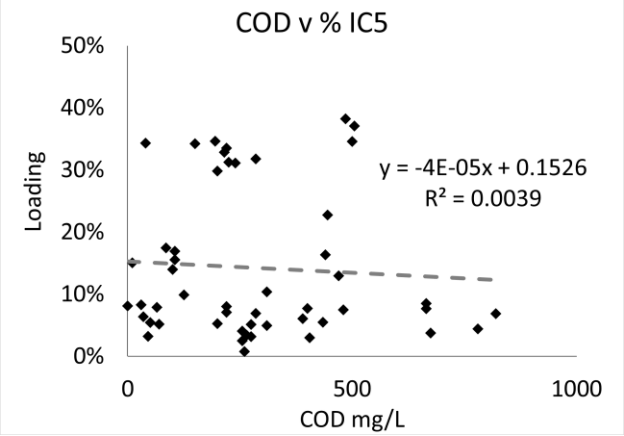

COD v I Total Loading
y = 0.0051x + 13.6
R² = 0.0457
Loading
COD mg/L
0
500
1000

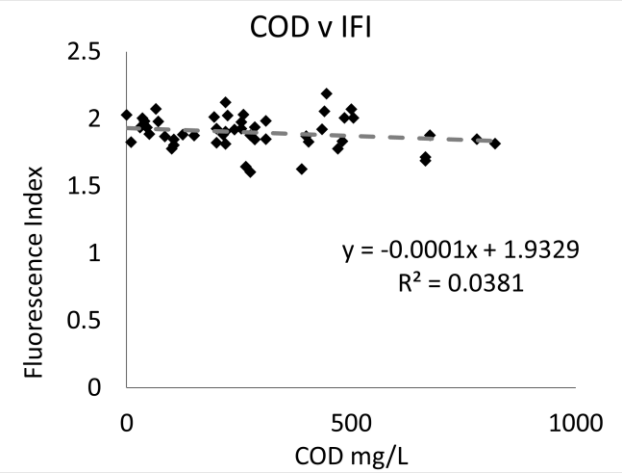

COD v % IC1
Loading
50%
40%
30%
20%
10%
0%
0
500
1000
COD mg/L
y = -2E-05x + 0.3314
R² = 0.0134

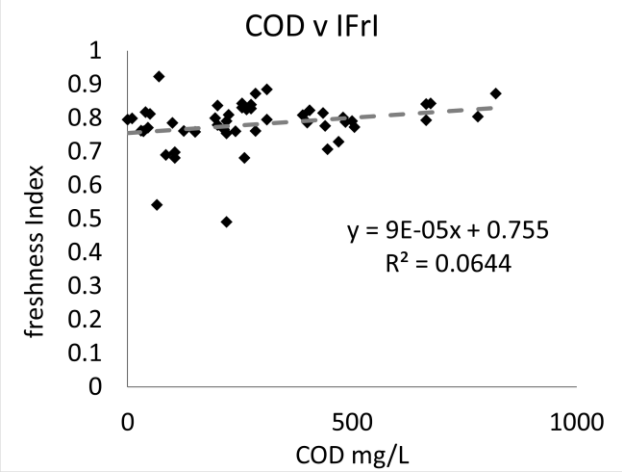

COD v % IC2
Loading
40%
30%
20%
10%
0%
0
500
1000
COD mg/L
y = 4E-05x + 0.2167
R² = 0.0139

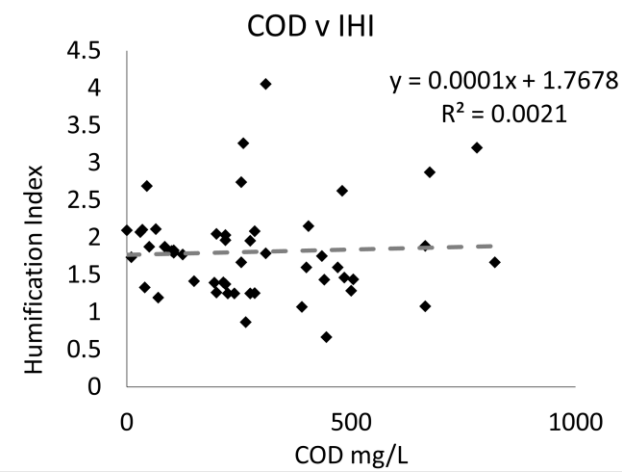

COD v % IC3
Loading
30%
20%
10%
0%
0
500
1000
COD mg/L
y = -9E-06x + 0.1312
R² = 0.002

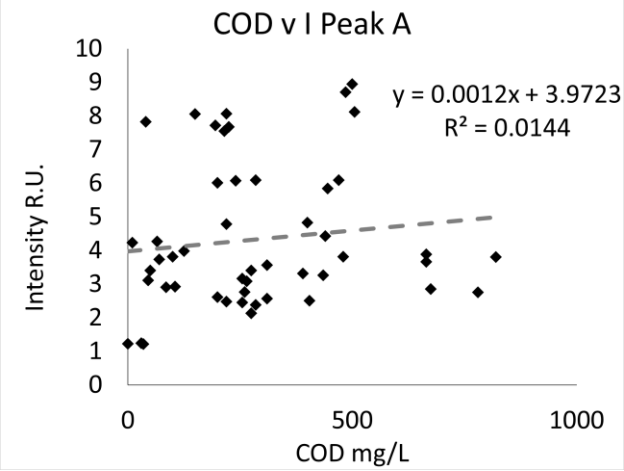

COD v % IC4
Loading
50%
40%
30%
20%
10%
0%
0
500
1000
COD mg/L
y = 3E-05x + 0.1681
R² = 0.006

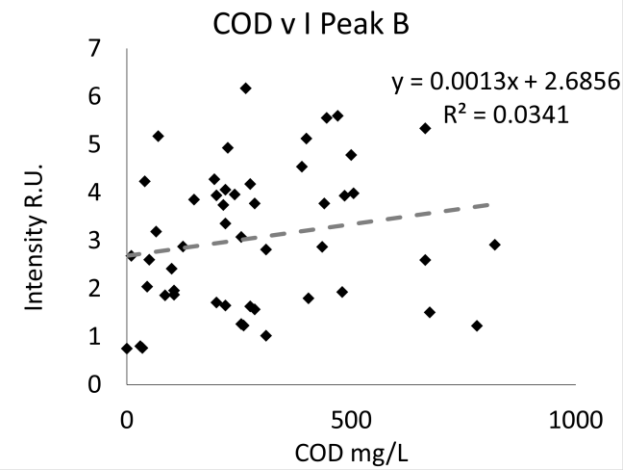

COD v % IC5
Loading
50%
40%
30%
20%
10%
0%
0
500
1000
COD mg/L
y = -4E-05x + 0.1526
R² = 0.0039

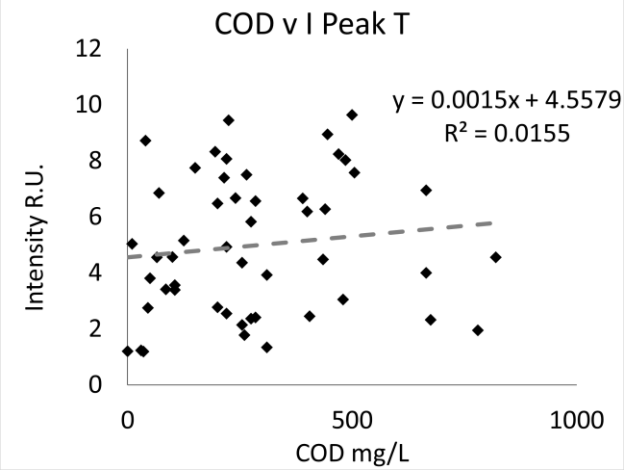

COD v IFI
Fluorescence Index
2.5
2
1.5
1
0.5
0
0
500
1000
COD mg/L
y = -0.0001x + 1.9329
R² = 0.0381

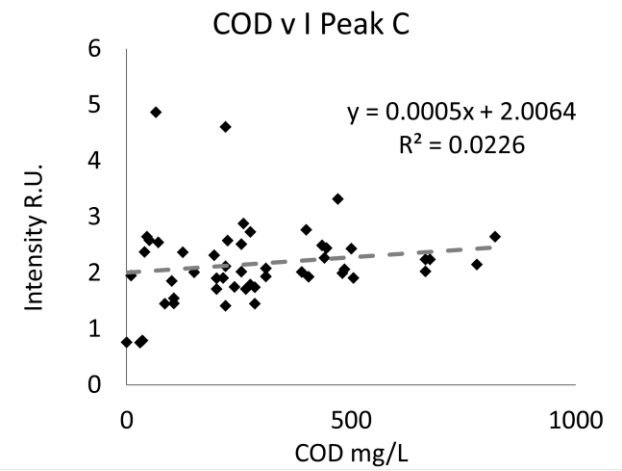

COD v IFrI
freshness Index
y = 9E-05x + 0.755
R² = 0.0644
COD mg/L

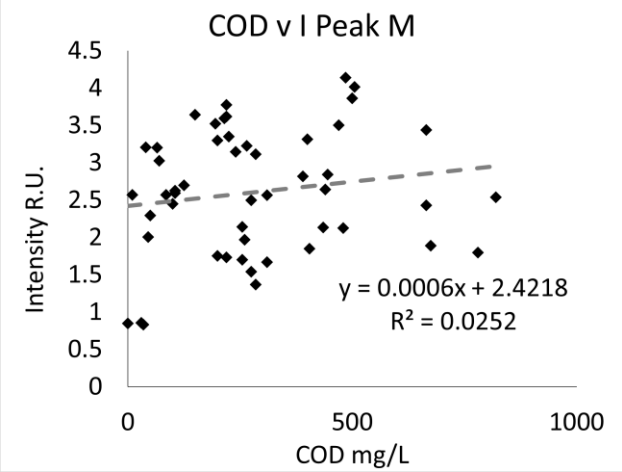

COD v IHI
Humification Index
y = 0.0001x + 1.7678
R² = 0.0021
COD mg/L

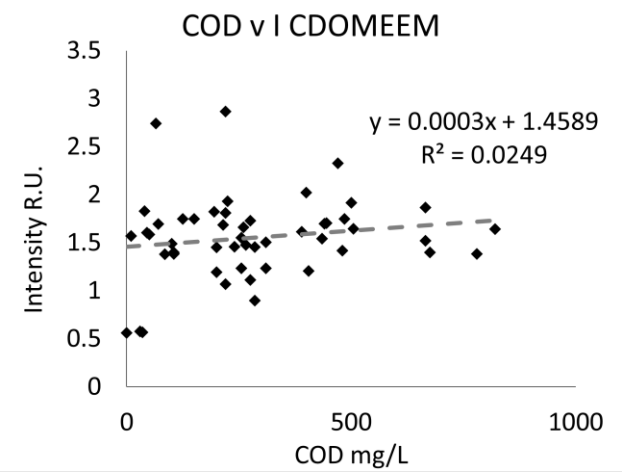

COD v I Peak A
Intensity R.U.
y = 0.0012x + 3.9723
R² = 0.0144
COD mg/L

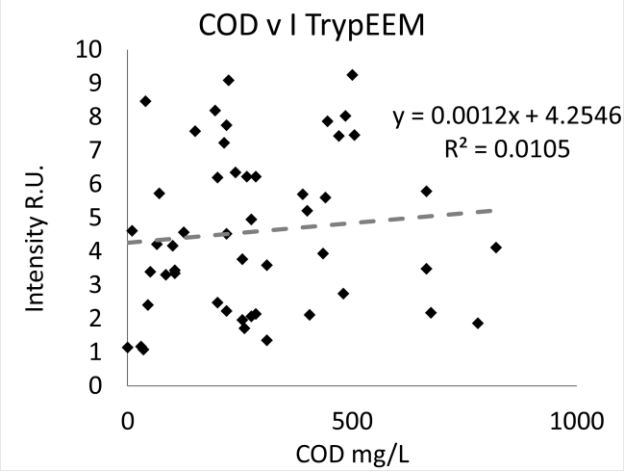

COD v I Peak B
Intensity R.U.
y = 0.0013x + 2.6856
R² = 0.0341
COD mg/L

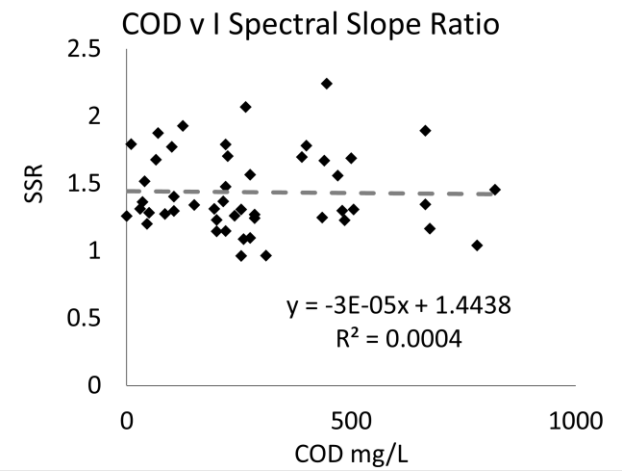

COD v I Peak T
Intensity R.U.
y = 0.0015x + 4.5579
R² = 0.0155
COD mg/L

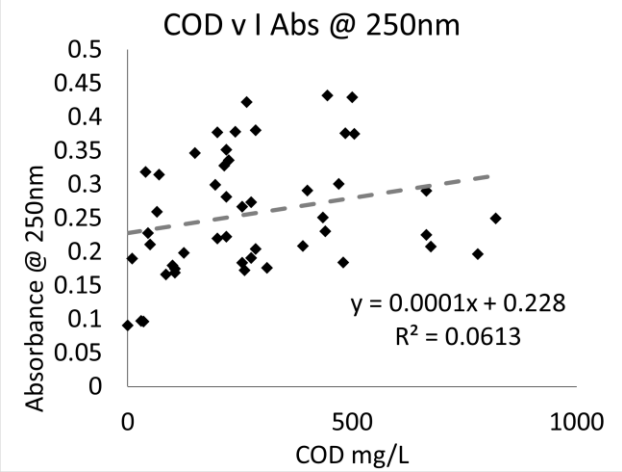

COD v I Peak C
Intensity R.U.
y = 0.0005x + 2.0064
R² = 0.0226
COD mg/L





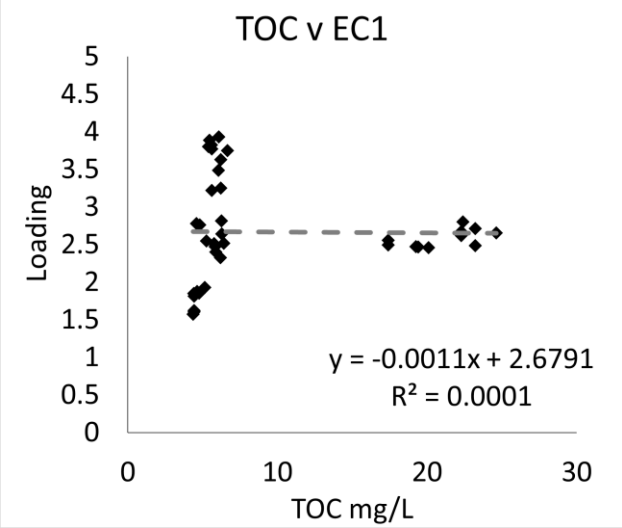


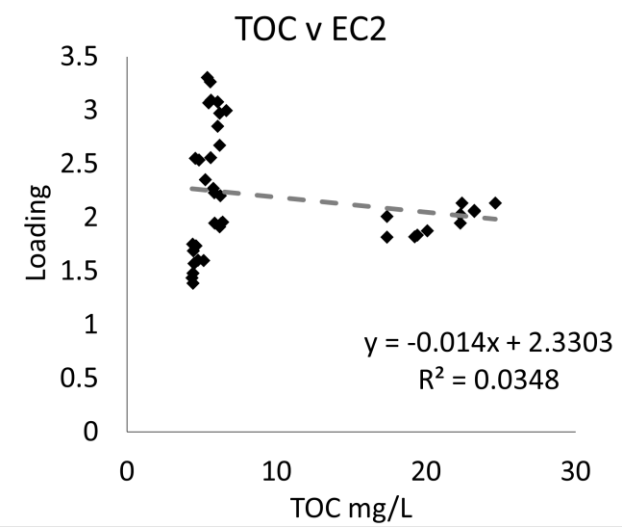


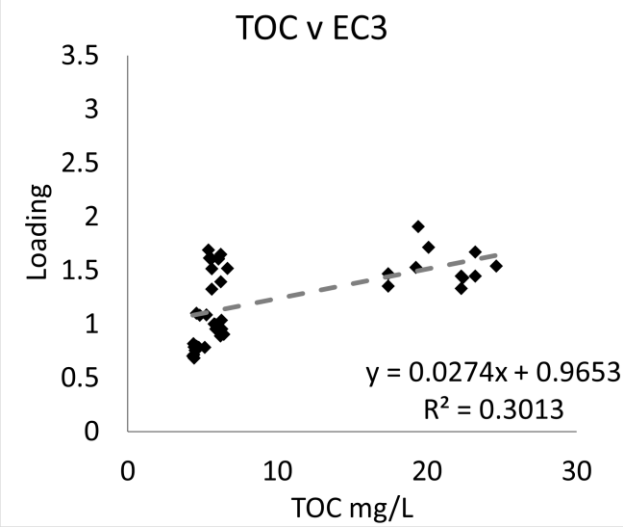


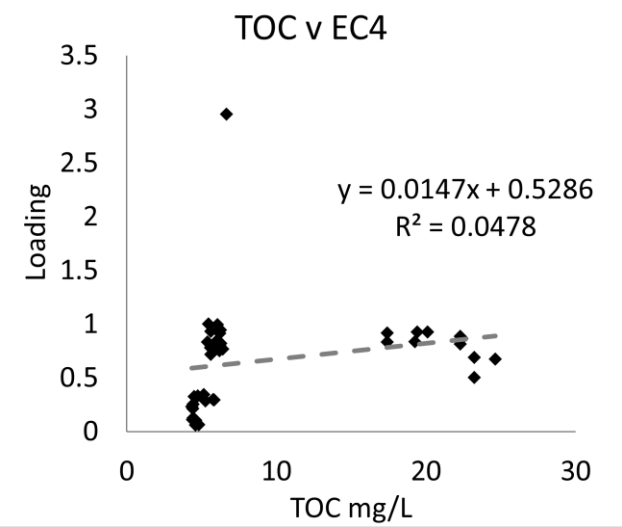
Total organic carbon

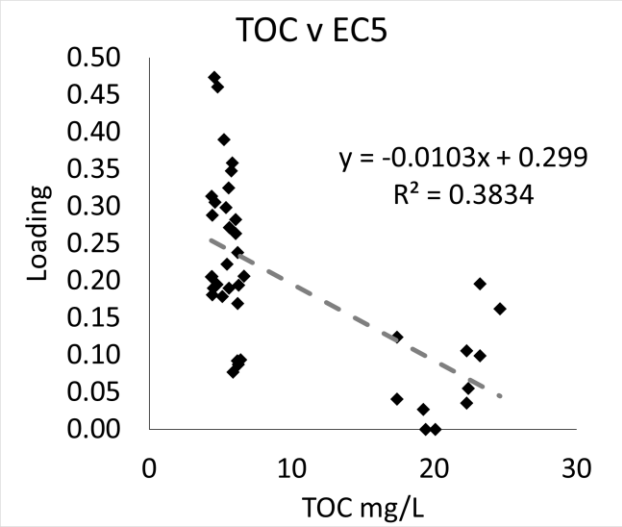
Effluent

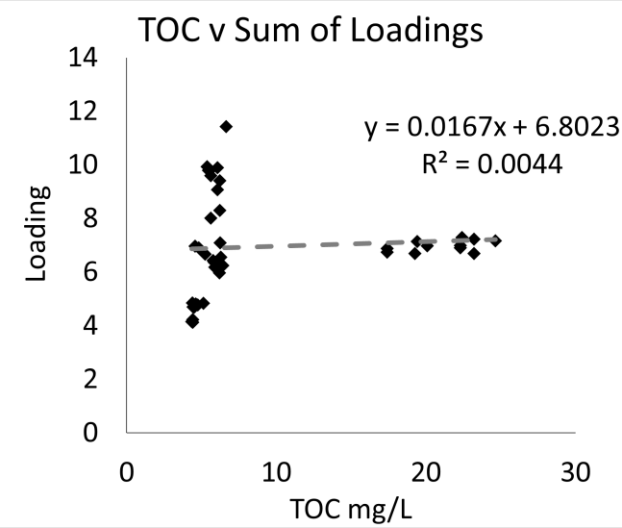

TOC v EC1
Loading
TOC mg/L
y = -0.0011x + 2.6791
R² = 0.0001

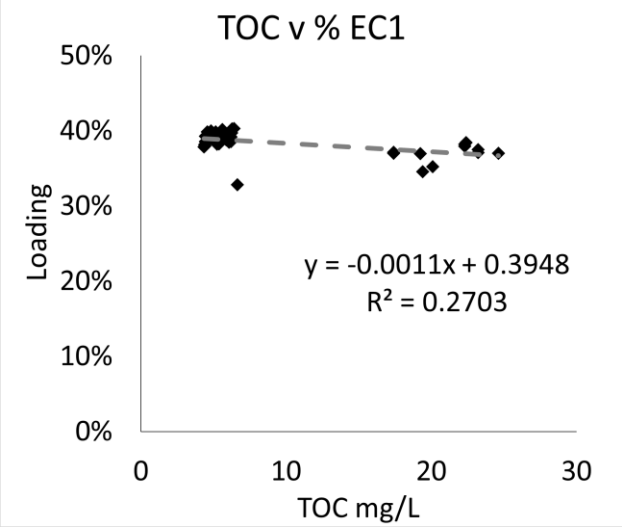

TOC v EC2
Loading
TOC mg/L
y = -0.014x + 2.3303
R² = 0.0348

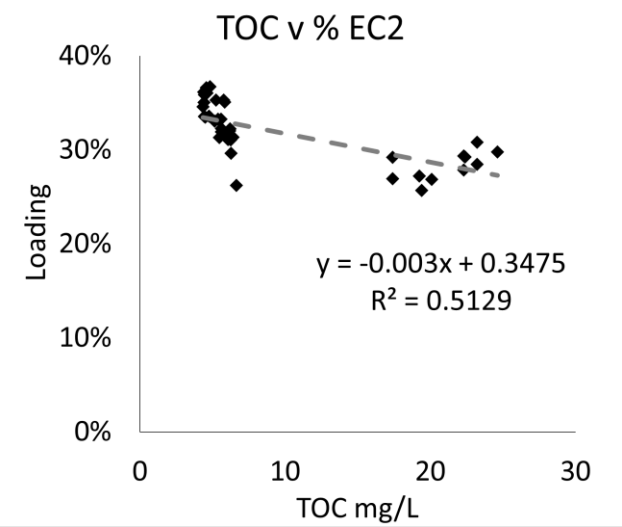

TOC v EC3
Loading
TOC mg/L
y = 0.0274x + 0.9653
R² = 0.3013

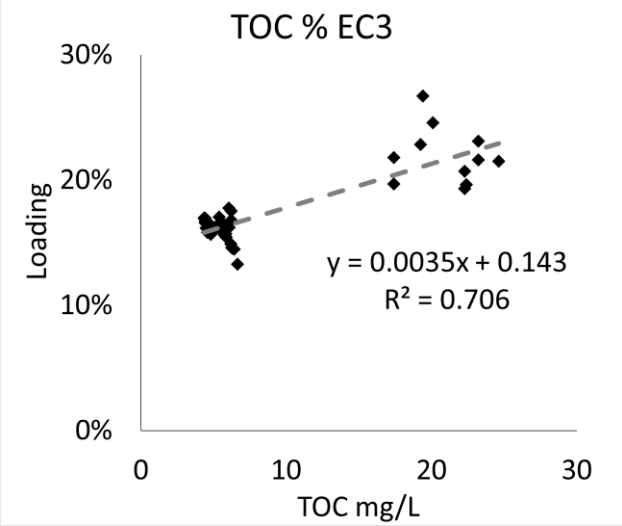

TOC v EC4
Loading
TOC mg/L
y = 0.0147x + 0.5286
R² = 0.0478

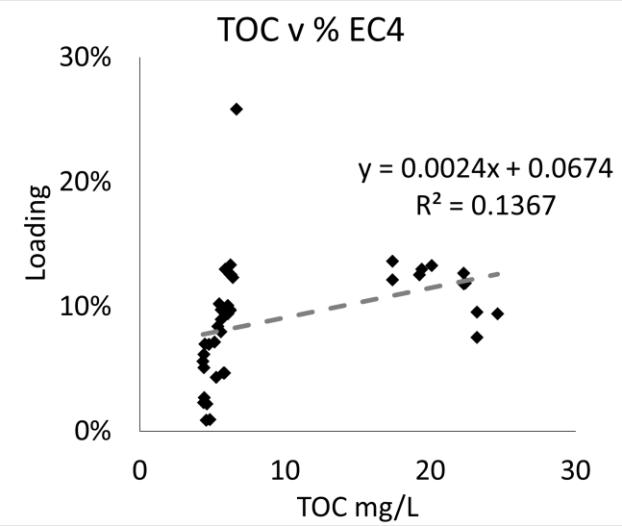

TOC v EC5
Loading
TOC mg/L
y = -0.0103x + 0.299
R² = 0.3834
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20
30

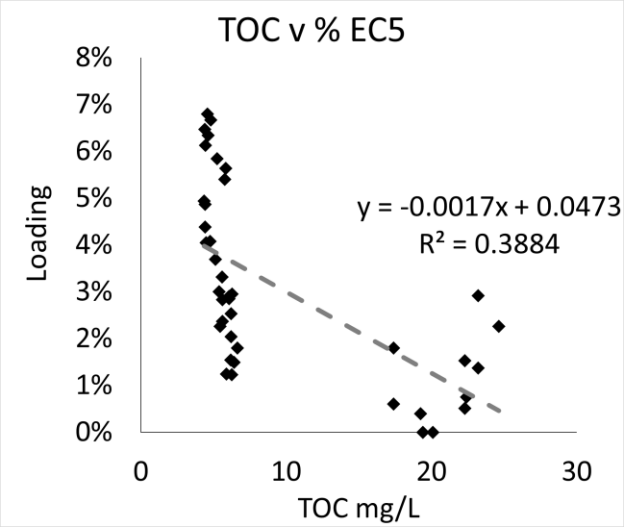

TOC v Sum of Loadings
Loading
TOC mg/L
y = 0.0167x + 6.8023
R² = 0.0044
14
12
10
8
6
4
2
0
0
10
20
30

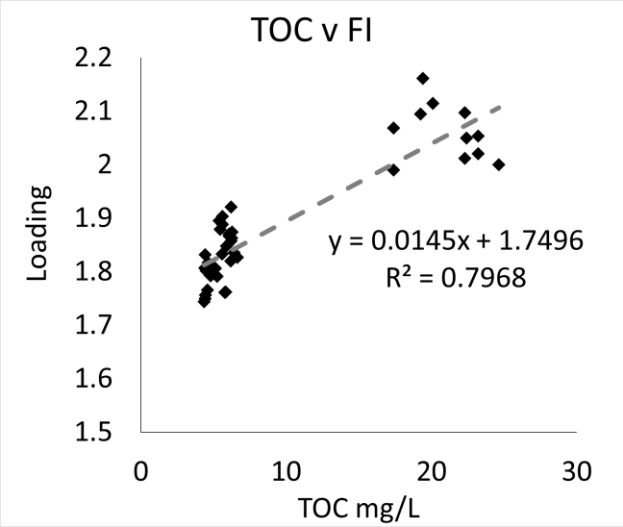

TOC v % EC1
Loading
TOC mg/L
y = -0.0011x + 0.3948
R² = 0.2703
50%
40%
30%
20%
10%
0%
0
10
20
30

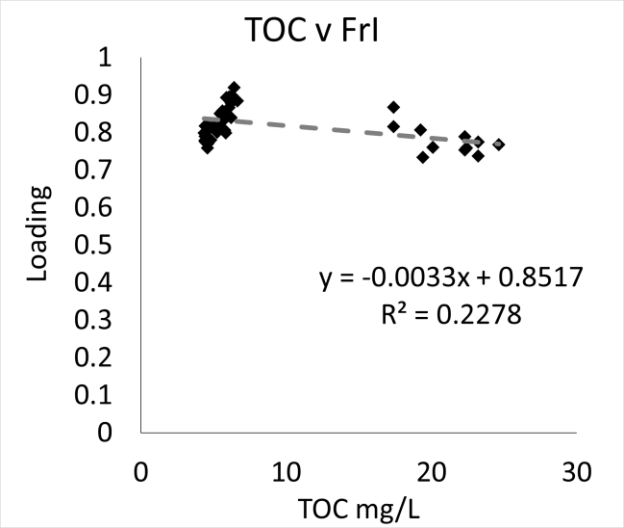

TOC v % EC2
Loading
TOC mg/L
y = -0.003x + 0.3475
R² = 0.5129
40%
30%
20%
10%
0%
0
10
20
30

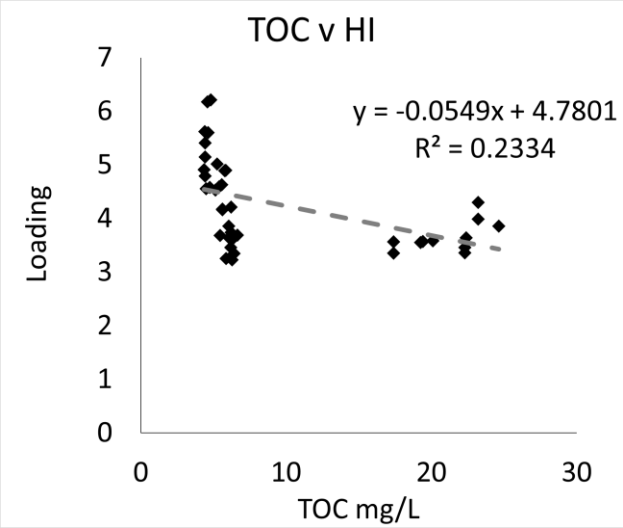

TOC % EC3
Loading
TOC mg/L
y = 0.0035x + 0.143
R² = 0.706
30%
20%
10%
0%
0
10
20
30

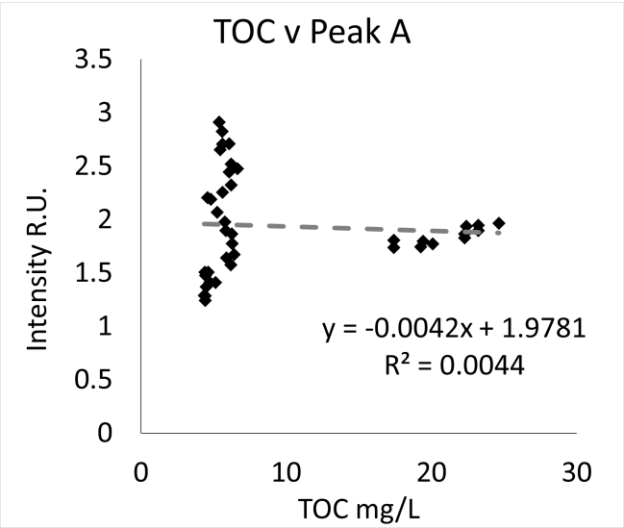

TOC v % EC4
Loading
TOC mg/L
y = 0.0024x + 0.0674
R² = 0.1367
30%
20%
10%
0%
0
10
20
30

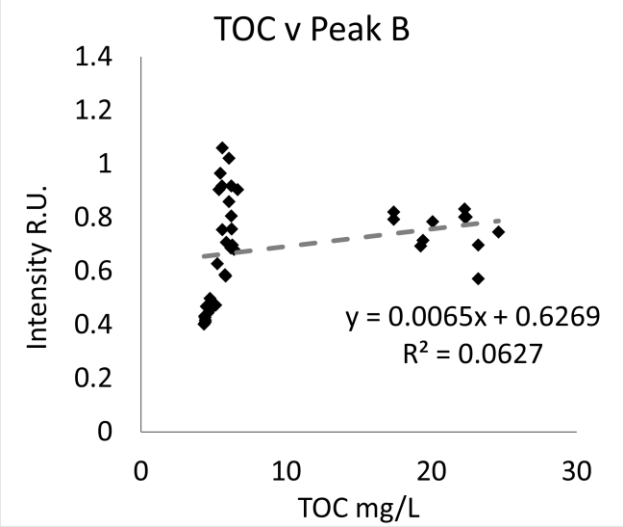

TOC v % EC5
Loading
TOC mg/L
y = -0.0017x + 0.0473
R² = 0.3884
8%
7%
6%
5%
4%
3%
2%
1%
0%
0
10
20
30

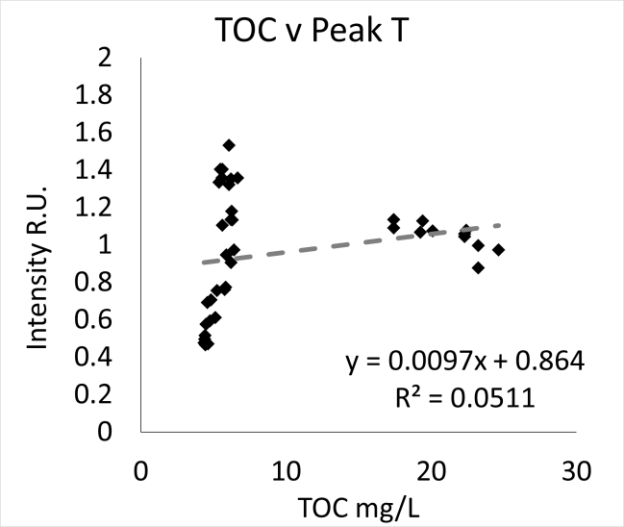

TOC v FI
Loading
TOC mg/L
y = 0.0145x + 1.7496
R² = 0.7968
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
0
10
20
30

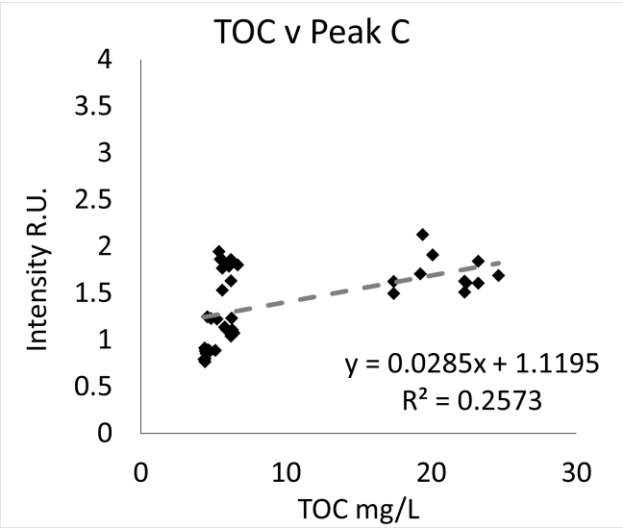

TOC v FrI
Loading
TOC mg/L
y = -0.0033x + 0.8517
R² = 0.2278
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
10
20
30

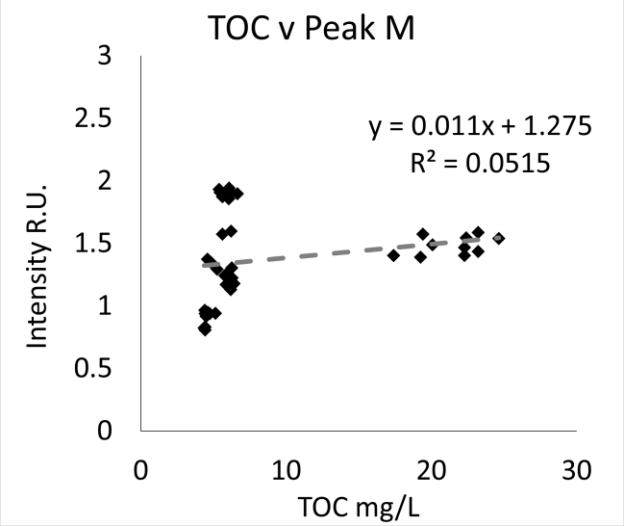

TOC v HI
Loading
TOC mg/L
y = -0.0549x + 4.7801
R² = 0.2334
7
6
5
4
3
2
1
0
0
10
20
30

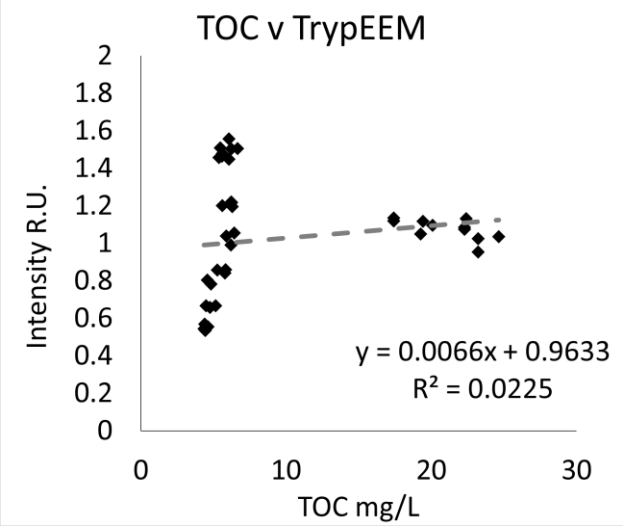

TOC v Peak A
Intensity R.U.
TOC mg/L
y = -0.0042x + 1.9781
R² = 0.0044
3.5
3
2.5
2
1.5
1
0.5
0
0
10
20
30

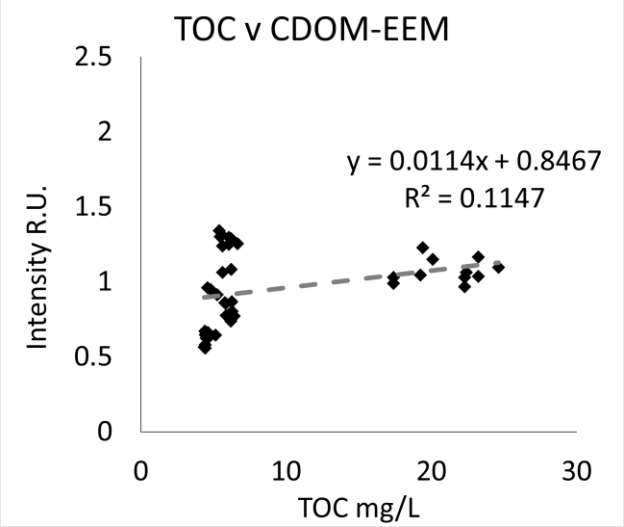

TOC v Peak B
Intensity R.U.
TOC mg/L
y = 0.0065x + 0.6269
R² = 0.0627
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0
10
20
30

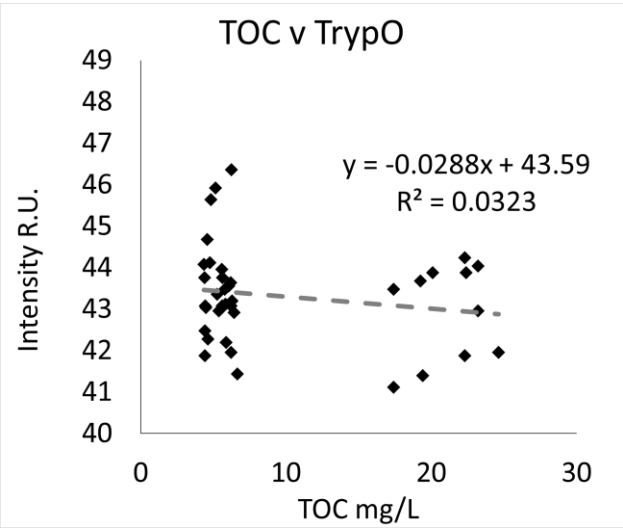

TOC v Peak T
Intensity R.U.
TOC mg/L
y = 0.0097x + 0.864
R² = 0.0511

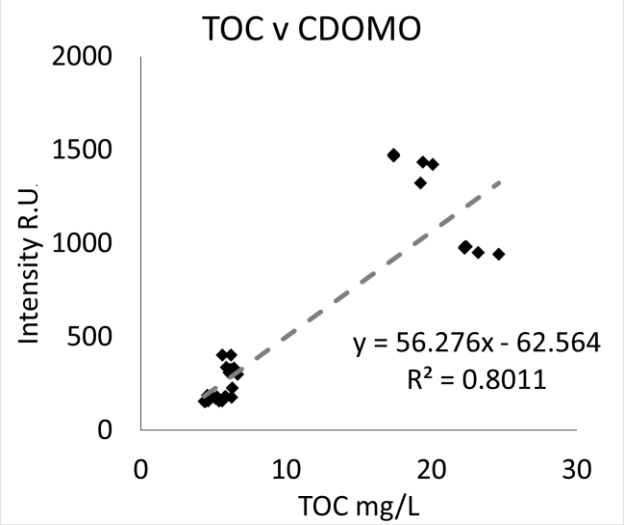

TOC v Peak C
Intensity R.U.
TOC mg/L
y = 0.0285x + 1.1195
R² = 0.2573

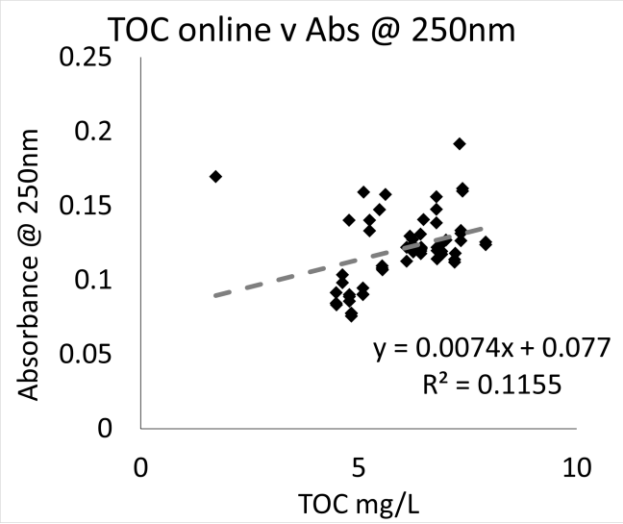

TOC v Peak M
Intensity R.U.
TOC mg/L
y = 0.011x + 1.275
R² = 0.0515

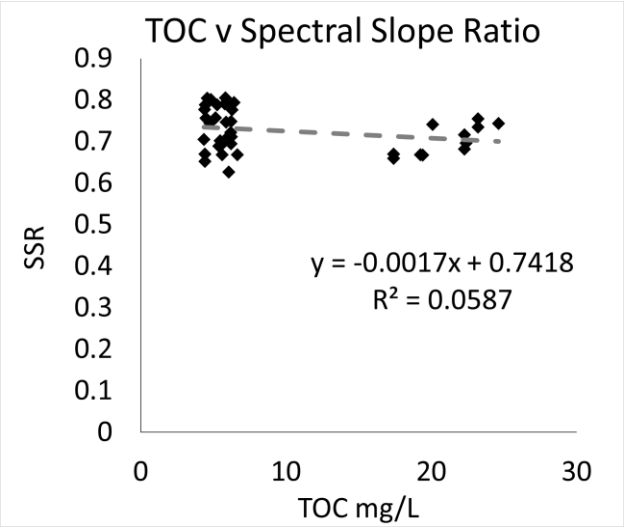

TOC v TrypEEM
Intensity R.U.
TOC mg/L
y = 0.0066x + 0.9633
R² = 0.0225


TOC v CDOM-EEM
Intensity R.U.
TOC mg/L
y = 0.0114x + 0.8467
R² = 0.1147

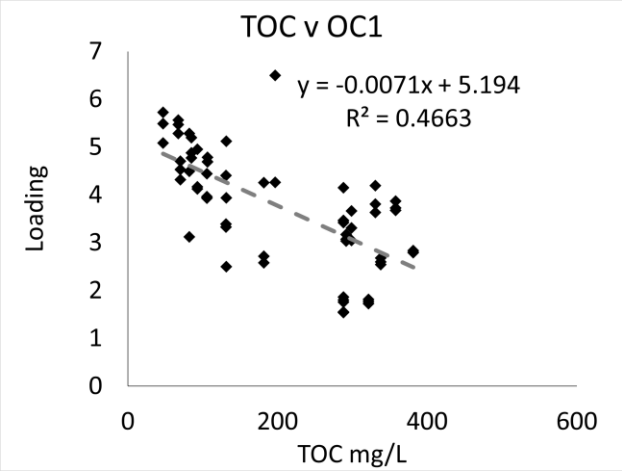

TOC v TrypO
Intensity R.U.
TOC mg/L
y = -0.0288x + 43.59
R² = 0.0323

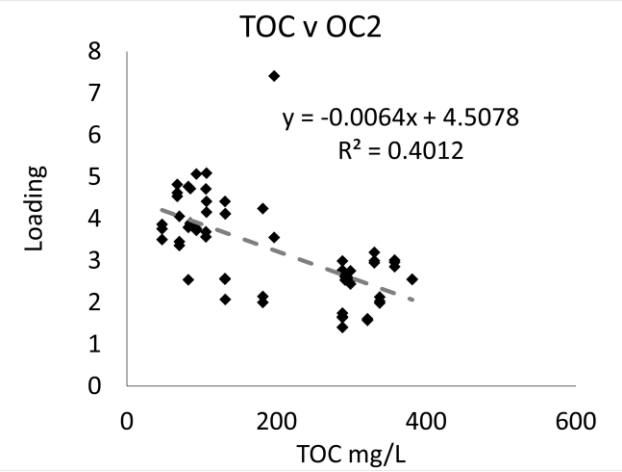

TOC v CDOMO
Intensity R.U.
2000
1500
1000
500
0
0
10
20
30
TOC mg/L
y = 56.276x - 62.564
R² = 0.8011

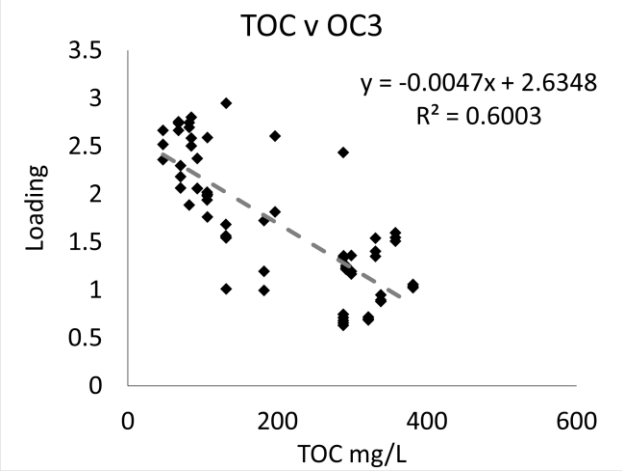

TOC online v Abs @ 250nm
Absorbance @ 250nm
0.25
0.2
0.15
0.1
0.05
0
0
5
10
TOC mg/L
y = 0.0074x + 0.077
R² = 0.1155

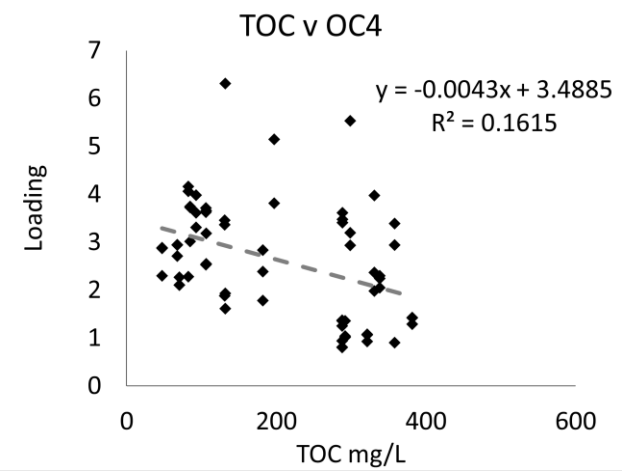

TOC v Spectral Slope Ratio
SSR
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
10
20
30
TOC mg/L
y = -0.0017x + 0.7418
R² = 0.0587

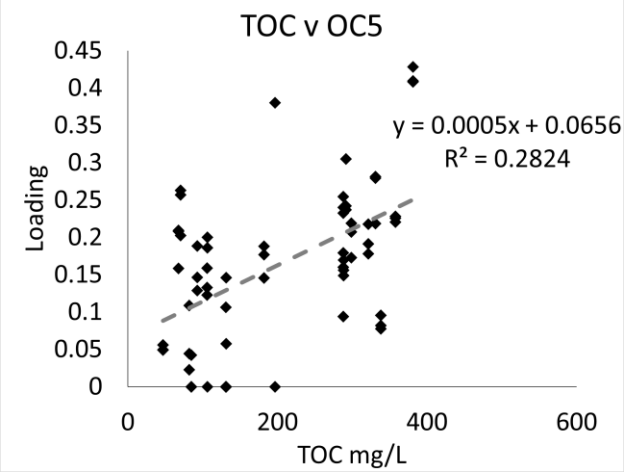
Oxic Tank

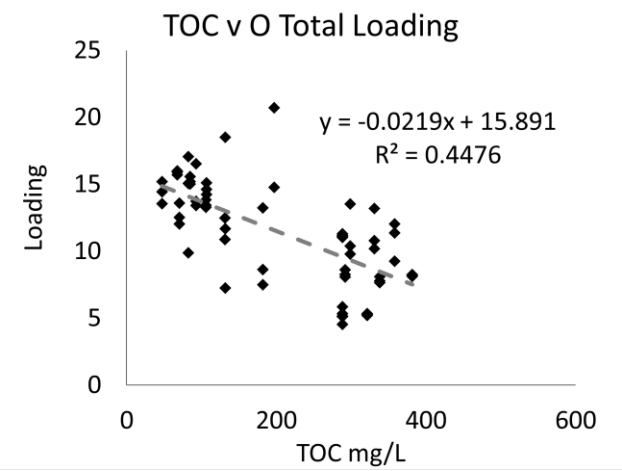

TOC v OC1
y = -0.0071x + 5.194
R² = 0.4663
Loading
TOC mg/L
0
1
2
3
4
5
6
7
0
200
400
600

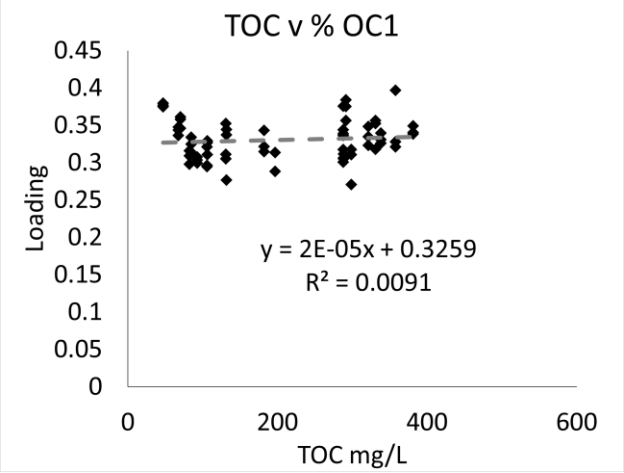

TOC v OC2
y = -0.0064x + 4.5078
R² = 0.4012
Loading
TOC mg/L
0
1
2
3
4
5
6
7
8
0
200
400
600

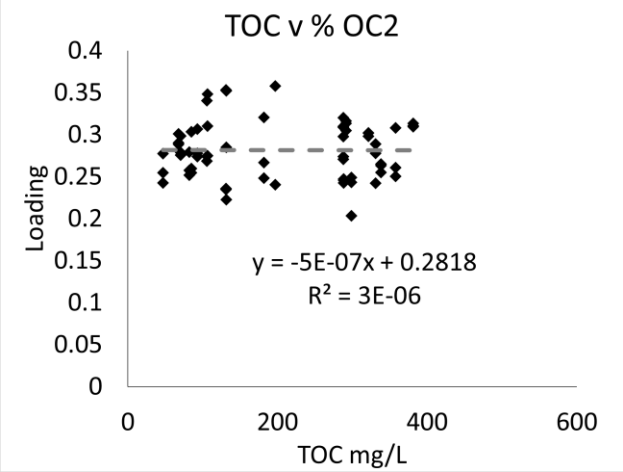

TOC v OC3
y = -0.0047x + 2.6348
R² = 0.6003
Loading
TOC mg/L
0
0.5
1
1.5
2
2.5
3
3.5
0
200
400
600

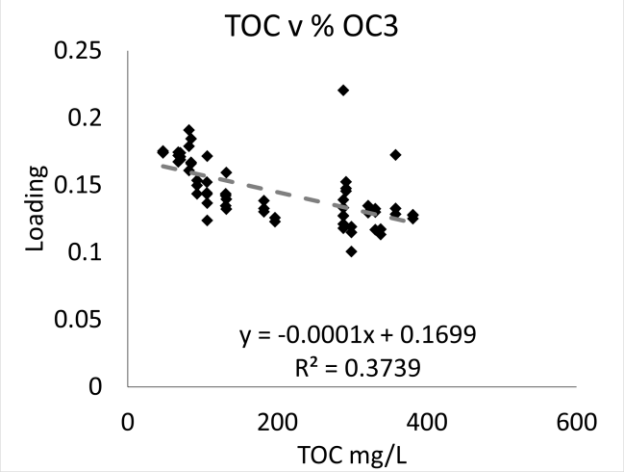

TOC v OC4
y = -0.0043x + 3.4885
R² = 0.1615
Loading
TOC mg/L
0
1
2
3
4
5
6
7
0
200
400
600

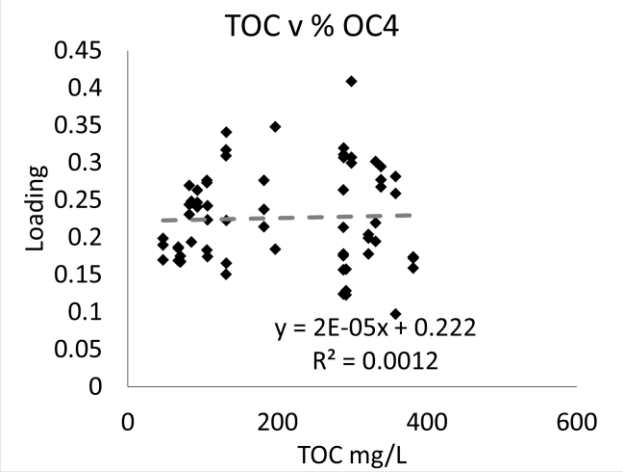

TOC v OC5
y = 0.0005x + 0.0656
R² = 0.2824
Loading
TOC mg/L
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0
200
400
600

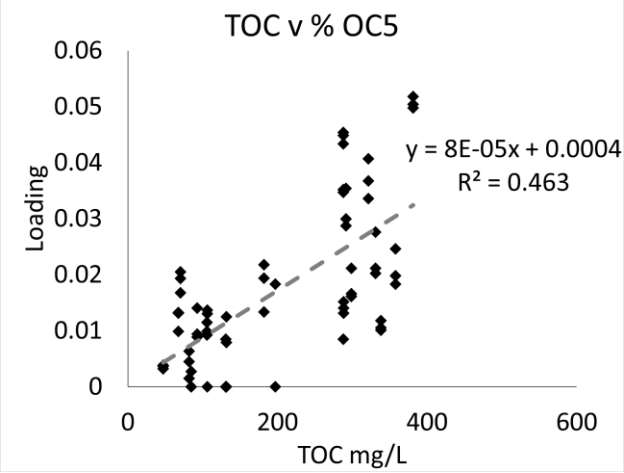

TOC v O Total Loading
y = -0.0219x + 15.891
R² = 0.4476
Loading
TOC mg/L
0
5
10
15
20
25
0
200
400
600

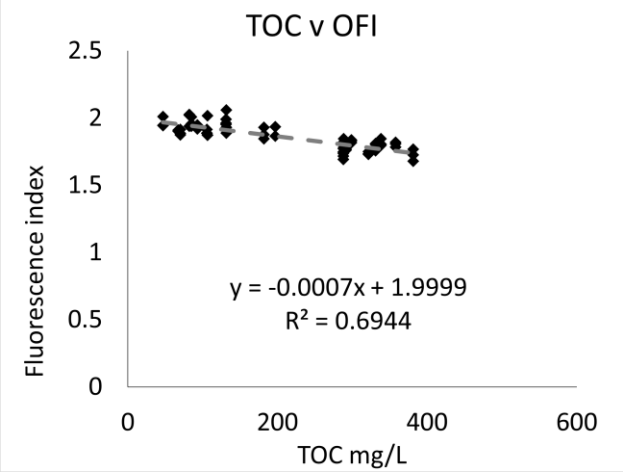

TOC v % OC1
Loading
TOC mg/L
y = 2E-05x + 0.3259
R² = 0.0091
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
200
400
600

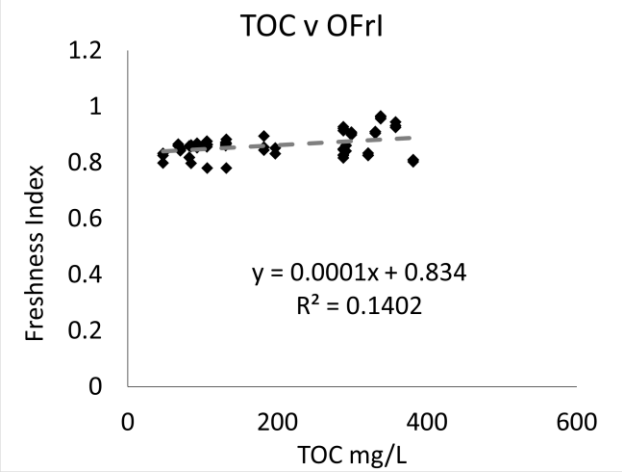

TOC v % OC2
Loading
TOC mg/L
y = -5E-07x + 0.2818
R² = 3E-06
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
200
400
600

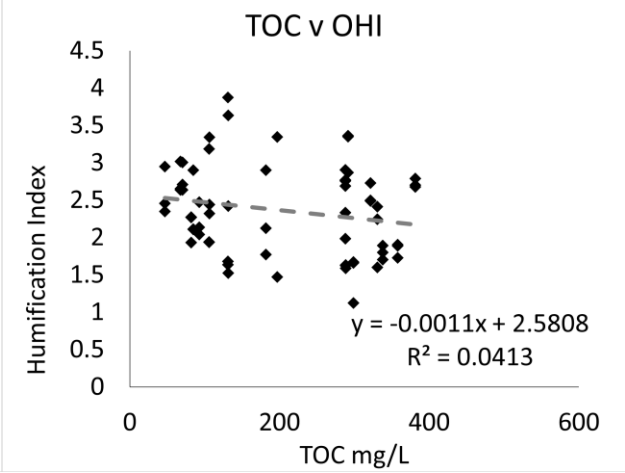

TOC v % OC3
Loading
TOC mg/L
y = -0.0001x + 0.1699
R² = 0.3739
0.25
0.2
0.15
0.1
0.05
0
0
200
400
600

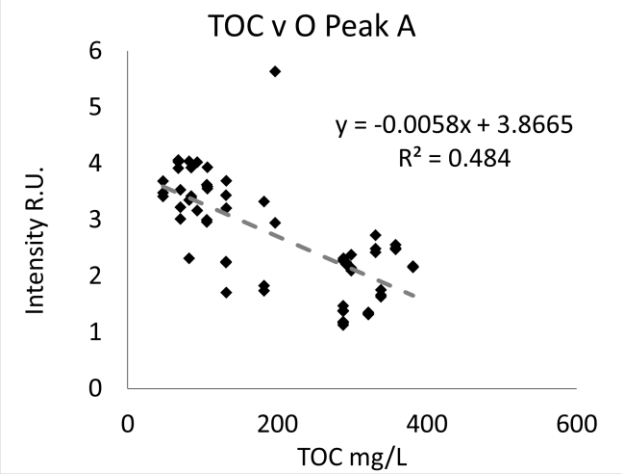

TOC v % OC4
Loading
TOC mg/L
y = 2E-05x + 0.222
R² = 0.0012
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
200
400
600

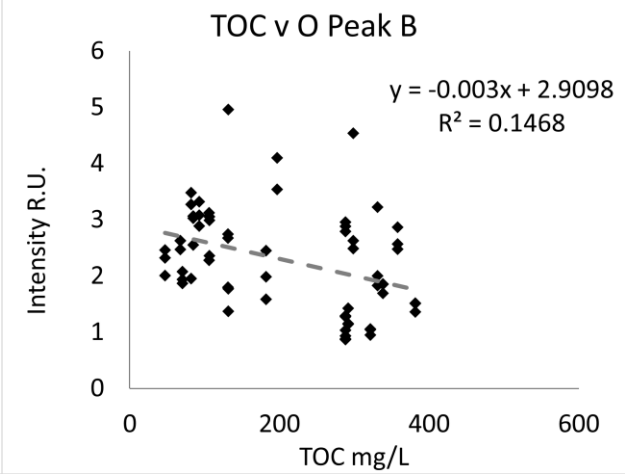

TOC v % OC5
Loading
TOC mg/L
y = 8E-05x + 0.0004
R² = 0.463
0.06
0.05
0.04
0.03
0.02
0.01
0
0
200
400
600

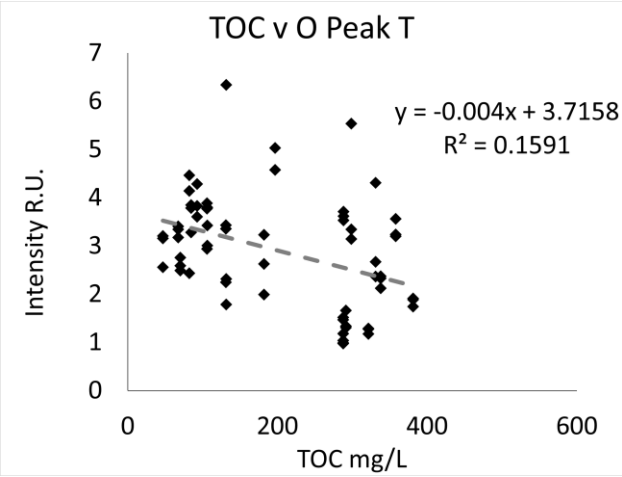

TOC v OFI
Fluorescence index
TOC mg/L
y = -0.0007x + 1.9999
R² = 0.6944
2.5
2
1.5
1
0.5
0
0
200
400
600

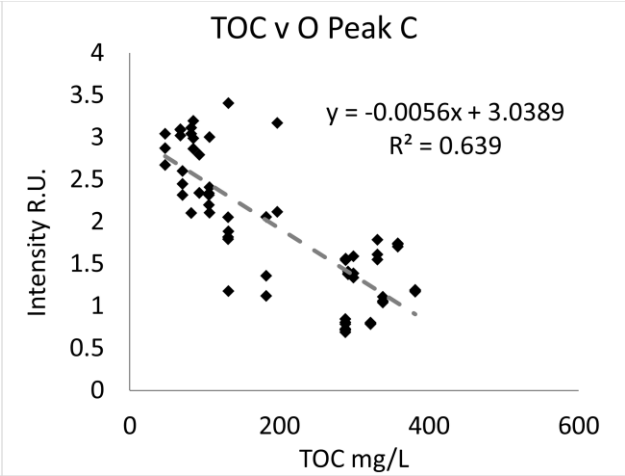

TOC v OFrI
Freshness Index
TOC mg/L
y = 0.0001x + 0.834
R² = 0.1402
0
0.2
0.4
0.6
0.8
1
1.2
0
200
400
600

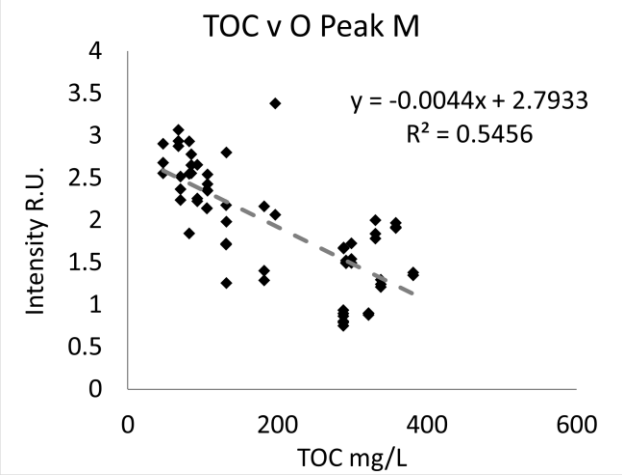

TOC v OHI
Humification Index
TOC mg/L
y = -0.0011x + 2.5808
R² = 0.0413
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
0
200
400
600

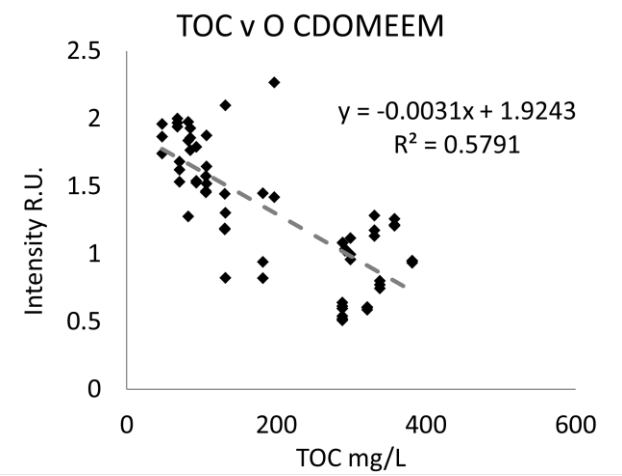

TOC v O Peak A
Intensity R.U.
TOC mg/L
y = -0.0058x + 3.8665
R² = 0.484
0
1
2
3
4
5
6
0
200
400
600

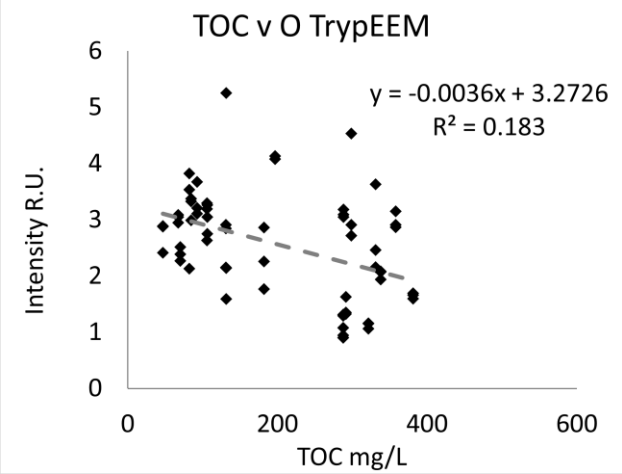

TOC v O Peak B
Intensity R.U.
TOC mg/L
y = -0.003x + 2.9098
R² = 0.1468
0
1
2
3
4
5
6
0
200
400
600

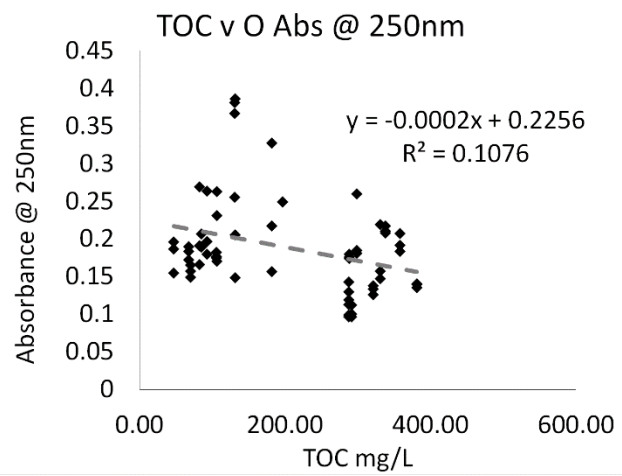

TOC v O Peak T
Intensity R.U.
TOC mg/L
y = -0.004x + 3.7158
R² = 0.1591
0
1
2
3
4
5
6
7
0
200
400
600

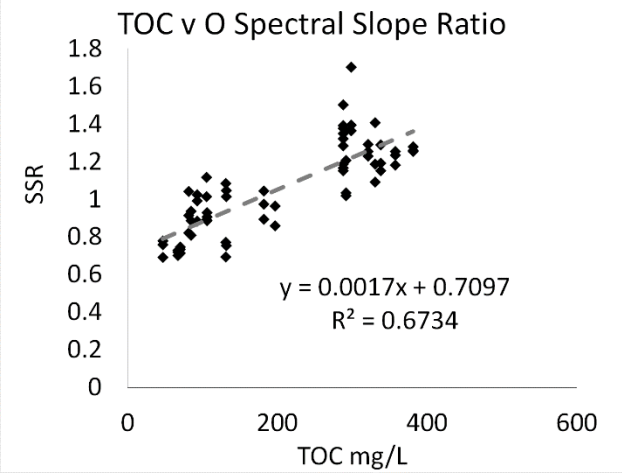

TOC v O Peak C
Intensity R.U.
TOC mg/L
y = -0.0056x + 3.0389
R² = 0.639
0
0.5
1
1.5
2
2.5
3
3.5
4
0
200
400
600


TOC v O Peak M
y = -0.0044x + 2.7933
R² = 0.5456
Intensity R.U.
TOC mg/L

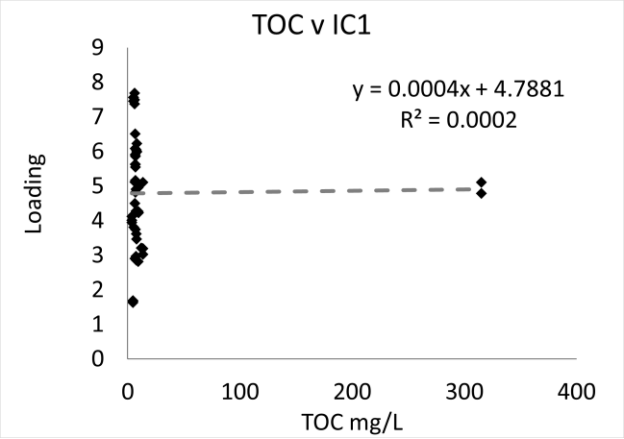

TOC v O CDOMEEM
y = -0.0031x + 1.9243
R² = 0.5791
Intensity R.U.
TOC mg/L

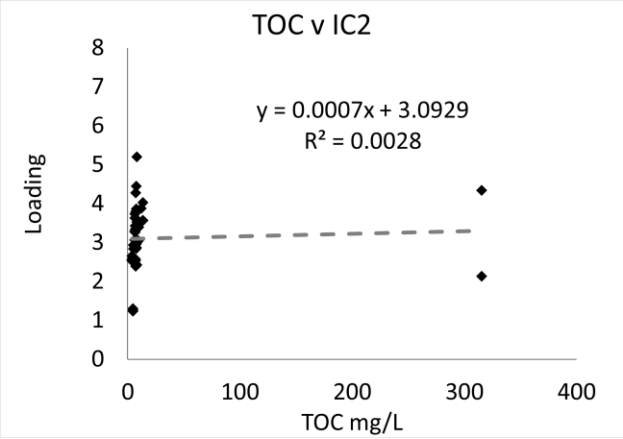

TOC v O TrypEEM
y = -0.0036x + 3.2726
R² = 0.183
Intensity R.U.
TOC mg/L

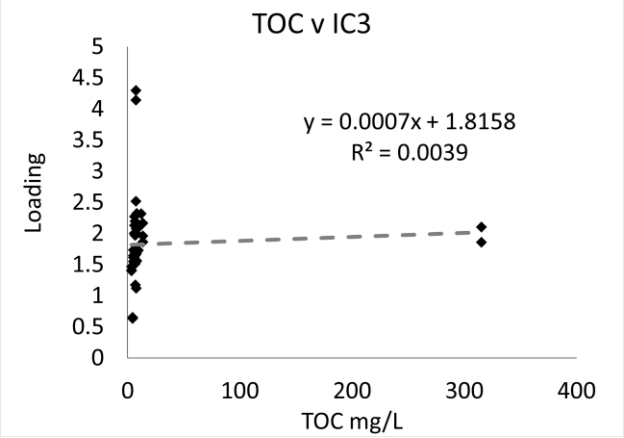

TOC v O Abs @ 250nm
y = -0.0002x + 0.2256
R² = 0.1076
Absorbance @ 250nm
TOC mg/L

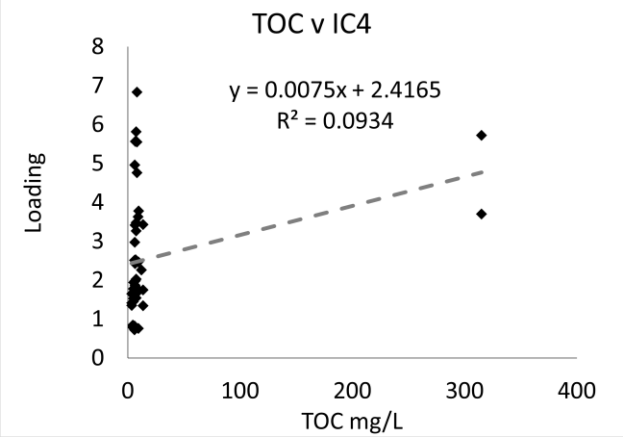

TOC v O Spectral Slope Ratio
y = 0.0017x + 0.7097
R² = 0.6734
SSR
TOC mg/L

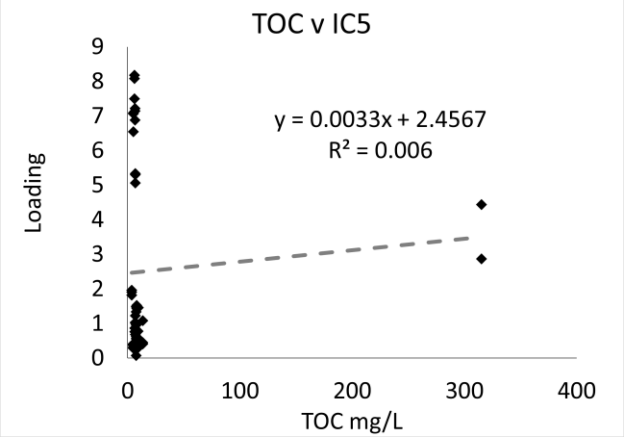
Influent

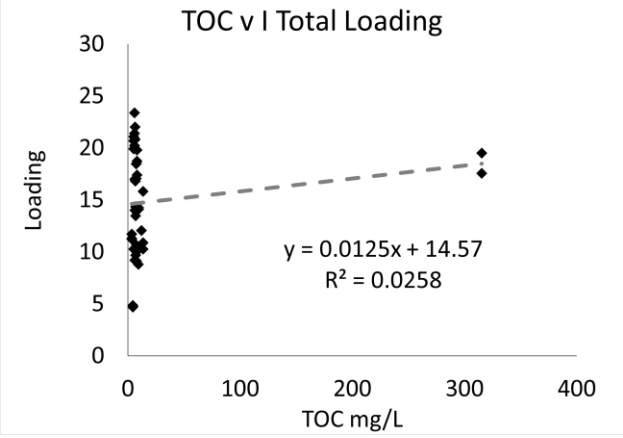

TOC v IC1
y = 0.0004x + 4.7881
R² = 0.0002
Loading
TOC mg/L

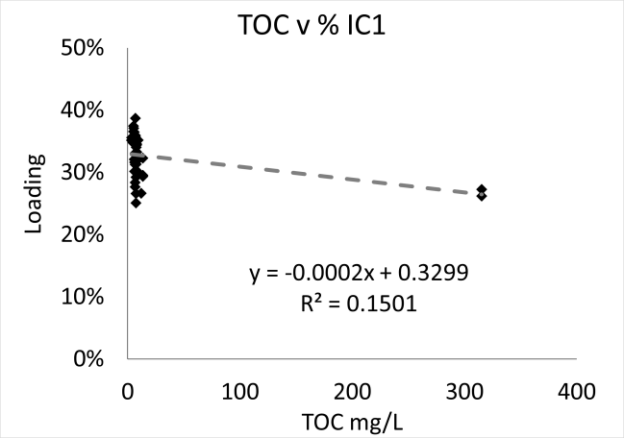

TOC v IC2
y = 0.0007x + 3.0929
R² = 0.0028
Loading
TOC mg/L

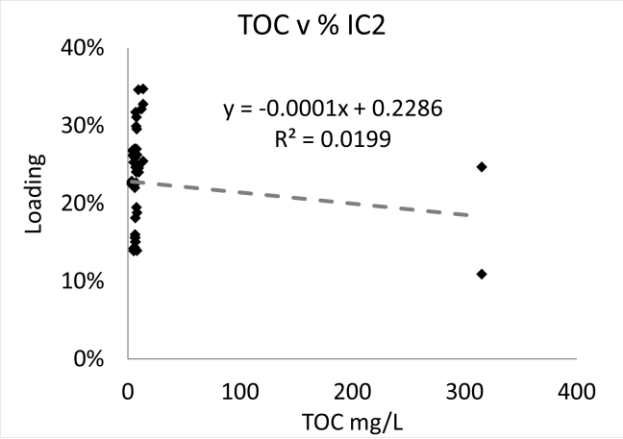

TOC v IC3
y = 0.0007x + 1.8158
R² = 0.0039
Loading
TOC mg/L

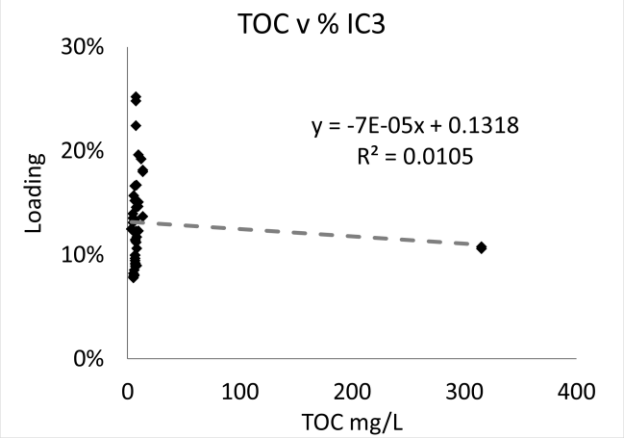

TOC v IC4
y = 0.0075x + 2.4165
R² = 0.0934
Loading
TOC mg/L

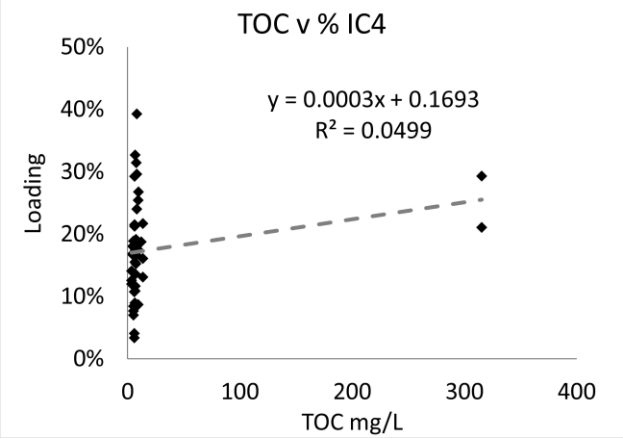

TOC v IC5
y = 0.0033x + 2.4567
R² = 0.006
Loading
TOC mg/L

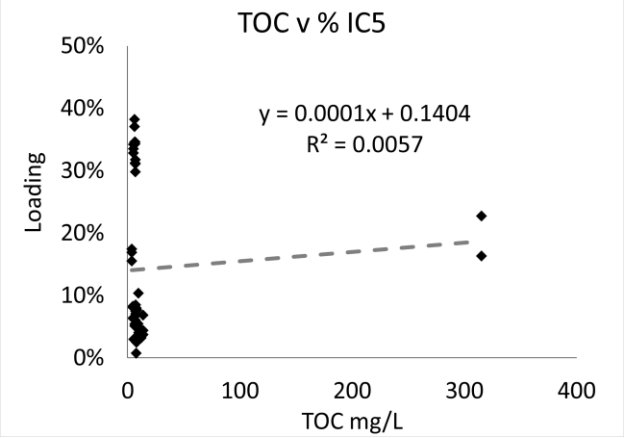

TOC v I Total Loading
y = 0.0125x + 14.57
R² = 0.0258
Loading
TOC mg/L

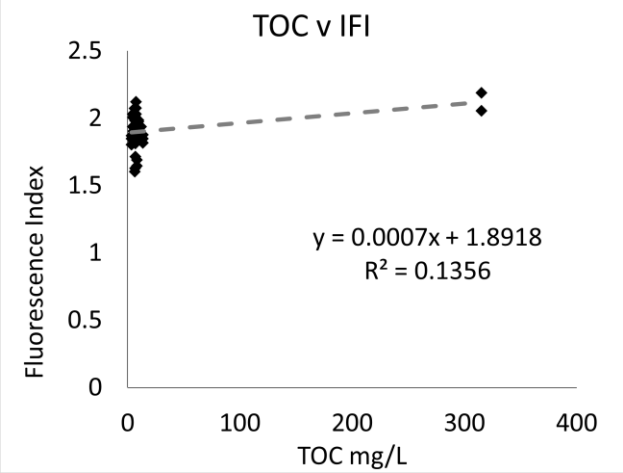

TOC v % IC1
Loading
50%
40%
30%
20%
10%
0%
y = -0.0002x + 0.3299
R² = 0.1501
0
100
200
300
400
TOC mg/L

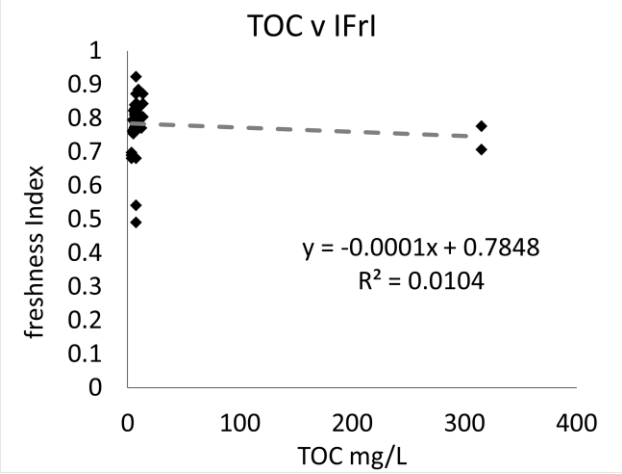

TOC v % IC2
Loading
40%
30%
20%
10%
0%
y = -0.0001x + 0.2286
R² = 0.0199
0
100
200
300
400
TOC mg/L

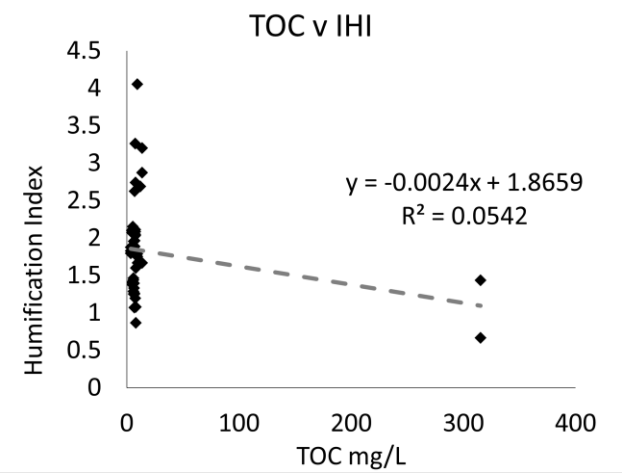

TOC v % IC3
Loading
30%
20%
10%
0%
y = -7E-05x + 0.1318
R² = 0.0105
0
100
200
300
400
TOC mg/L

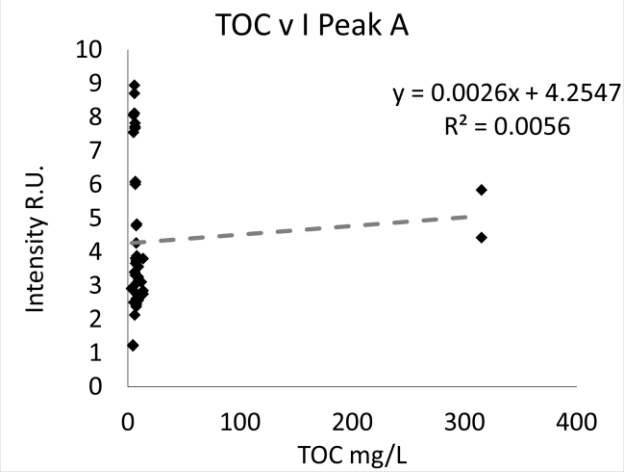

TOC v % IC4
Loading
50%
40%
30%
20%
10%
0%
y = 0.0003x + 0.1693
R² = 0.0499
0
100
200
300
400
TOC mg/L

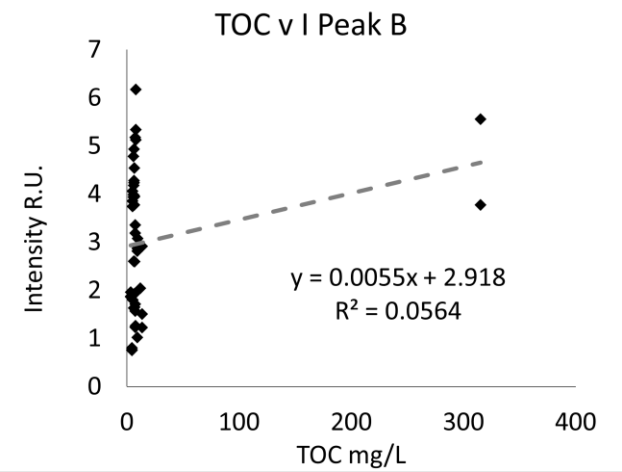

TOC v % IC5
Loading
50%
40%
30%
20%
10%
0%
y = 0.0001x + 0.1404
R² = 0.0057
0
100
200
300
400
TOC mg/L

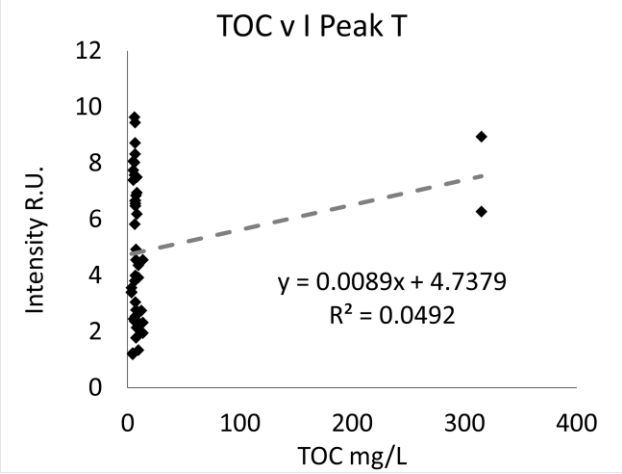

TOC v IFI
Fluorescence Index
2.5
2
1.5
1
0.5
0
y = 0.0007x + 1.8918
R² = 0.1356
0
100
200
300
400
TOC mg/L

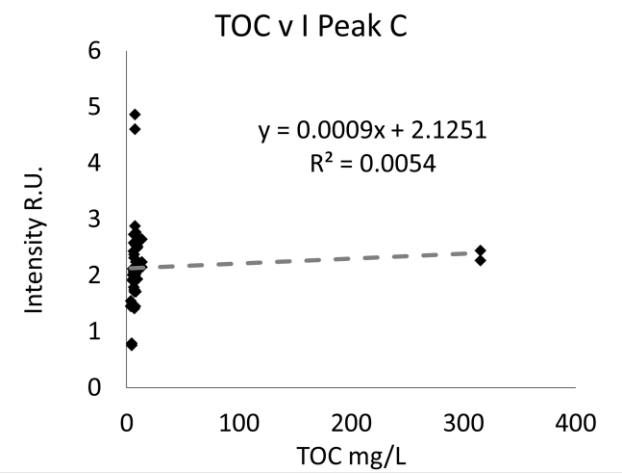

TOC v IFrI
freshness Index
y = -0.0001x + 0.7848
R² = 0.0104
TOC mg/L

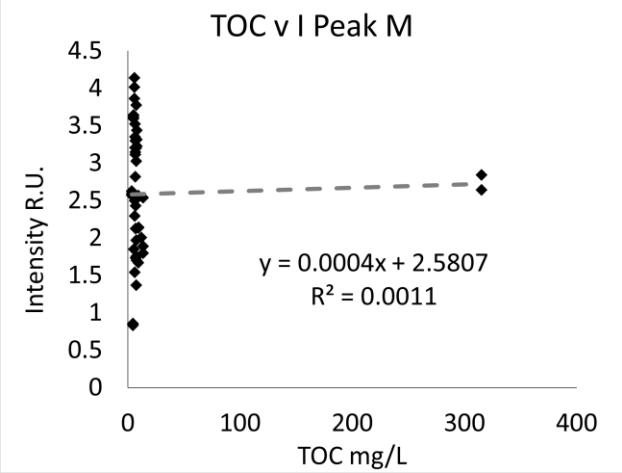

TOC v IHI
Humification Index
y = -0.0024x + 1.8659
R² = 0.0542
TOC mg/L

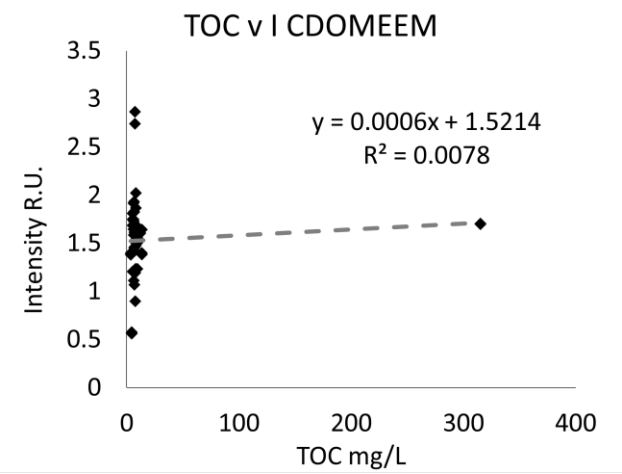

TOC v I Peak A
Intensity R.U.
y = 0.0026x + 4.2547
R² = 0.0056
TOC mg/L

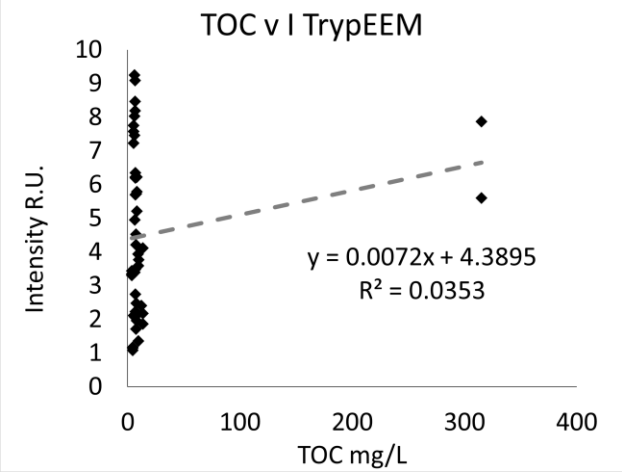

TOC v I Peak B
Intensity R.U.
y = 0.0055x + 2.918
R² = 0.0564
TOC mg/L

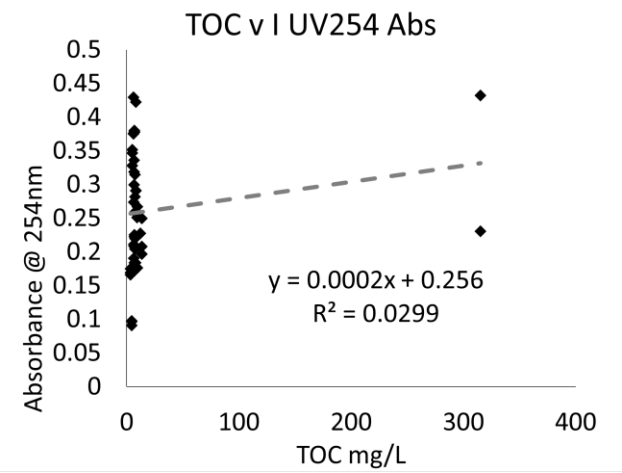

TOC v I Peak T
Intensity R.U.
y = 0.0089x + 4.7379
R² = 0.0492
TOC mg/L

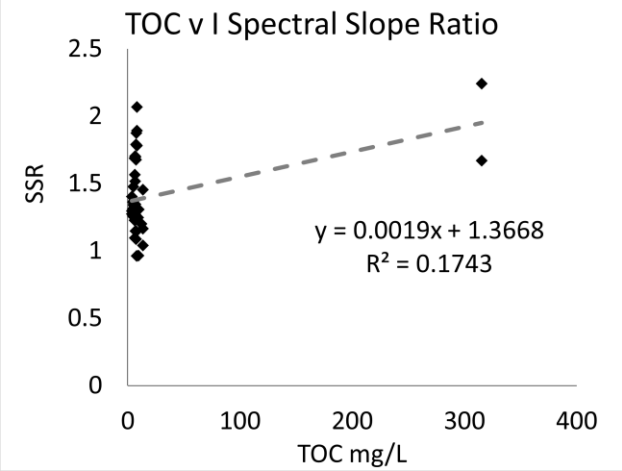

TOC v I Peak C
Intensity R.U.
y = 0.0009x + 2.1251
R² = 0.0054
TOC mg/L





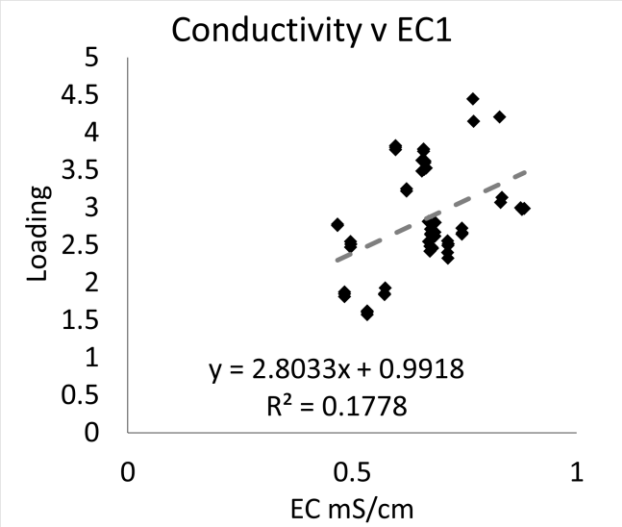


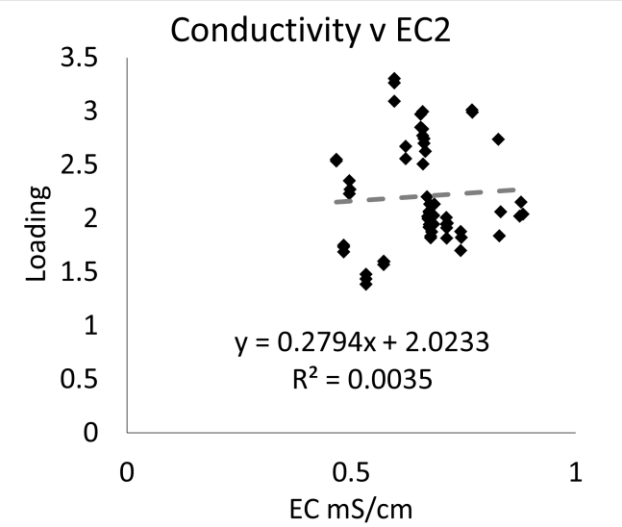


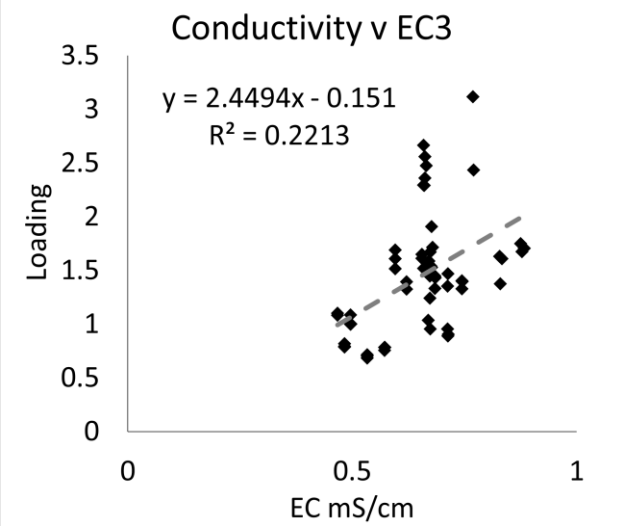


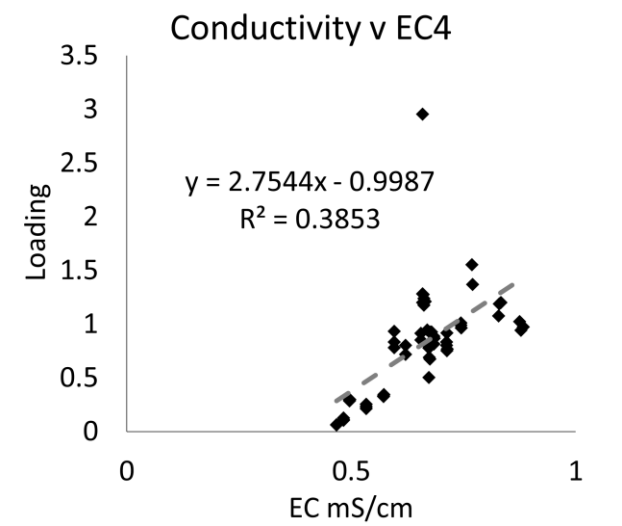
Electrical conductivity - online

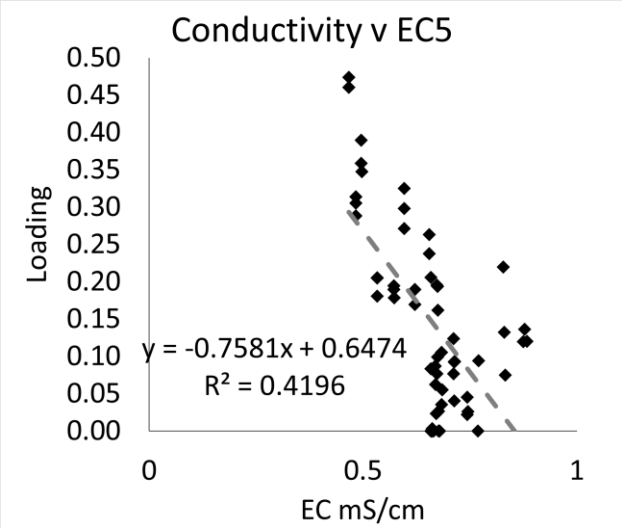
Effluent

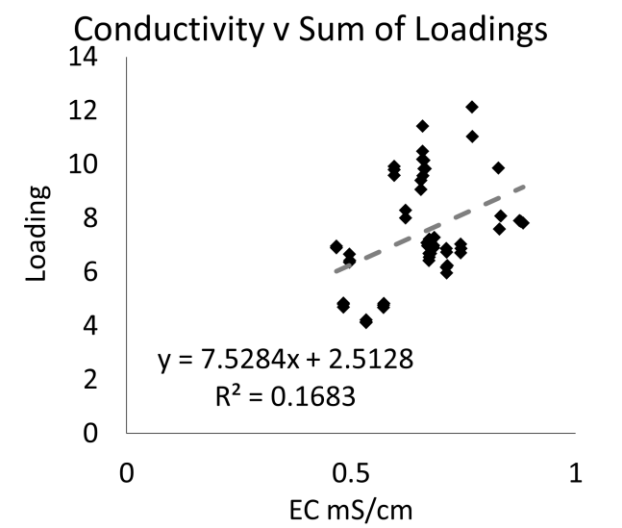

Conductivity v EC1
Loading
EC mS/cm
y = 2.8033x + 0.9918
R² = 0.1778

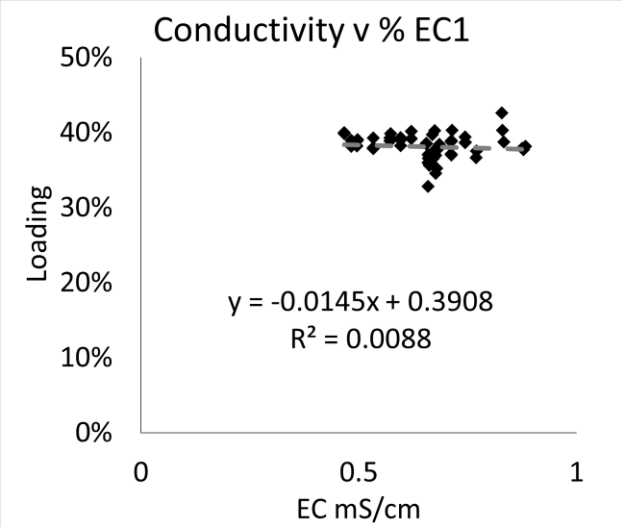

Conductivity v EC2
Loading
EC mS/cm
y = 0.2794x + 2.0233
R² = 0.0035

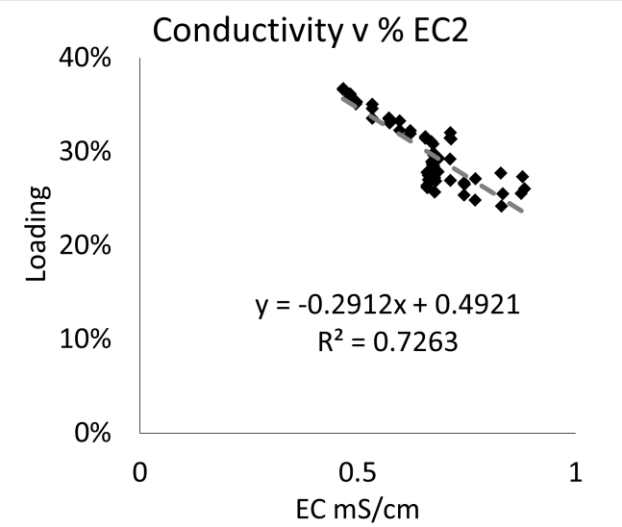

Conductivity v EC3
Loading
EC mS/cm
y = 2.4494x - 0.151
R² = 0.2213

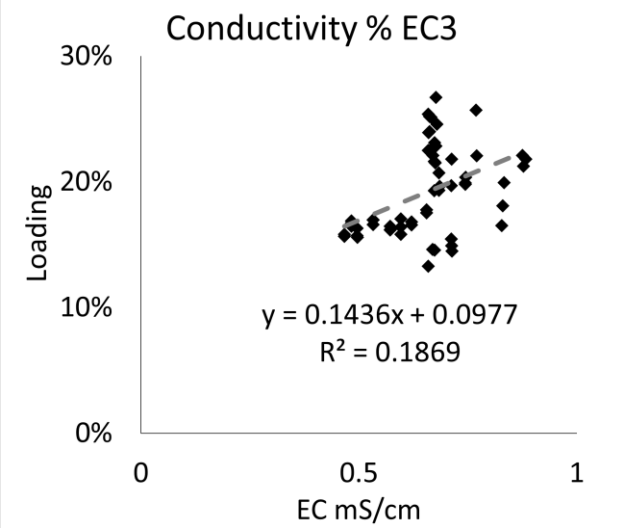

Conductivity v EC4
Loading
EC mS/cm
y = 2.7544x - 0.9987
R² = 0.3853

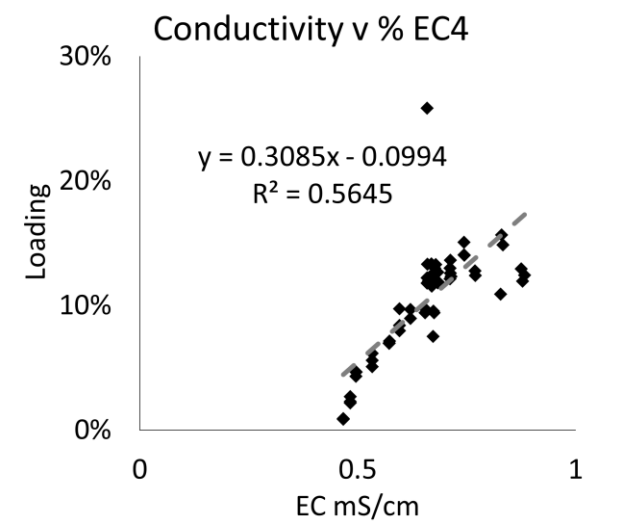

Conductivity v EC5
Loading
EC mS/cm
y = -0.7581x + 0.6474
R² = 0.4196

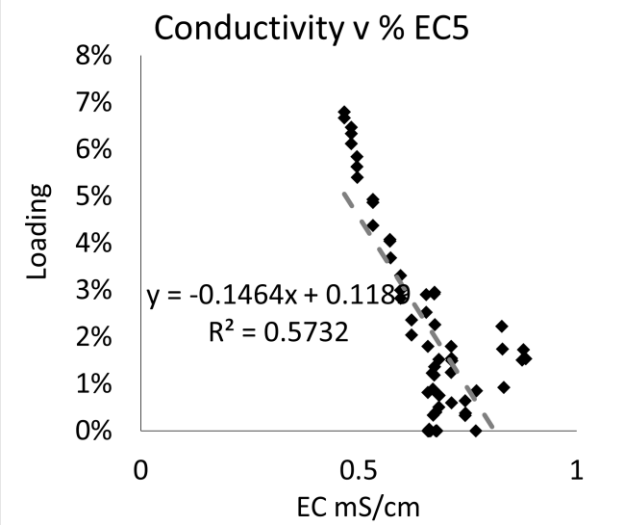

Conductivity v Sum of Loadings
Loading
EC mS/cm
y = 7.5284x + 2.5128
R² = 0.1683

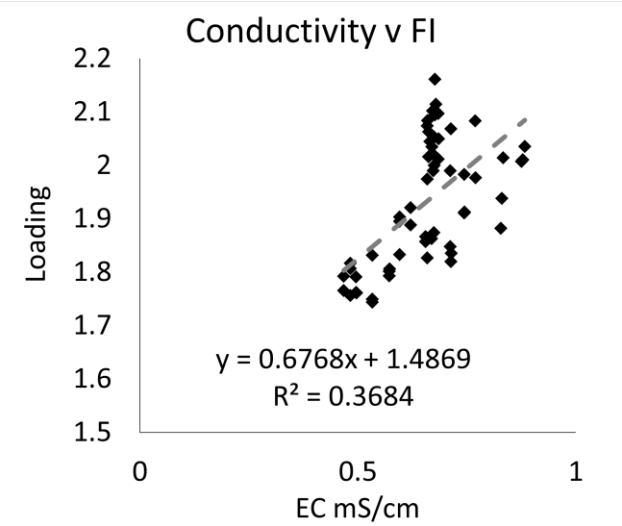

Conductivity v % EC1
50%
40%
30%
20%
10%
0%
Loading
y = -0.0145x + 0.3908
R² = 0.0088
0
0.5
1
EC mS/cm

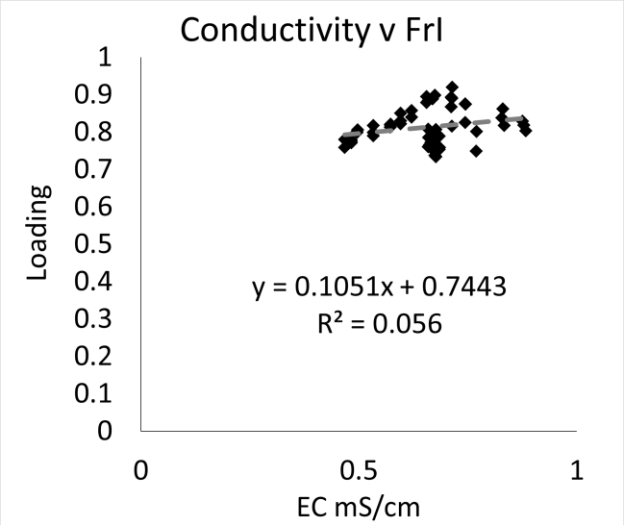

Conductivity v % EC2
40%
30%
20%
10%
0%
Loading
y = -0.2912x + 0.4921
R² = 0.7263
0
0.5
1
EC mS/cm

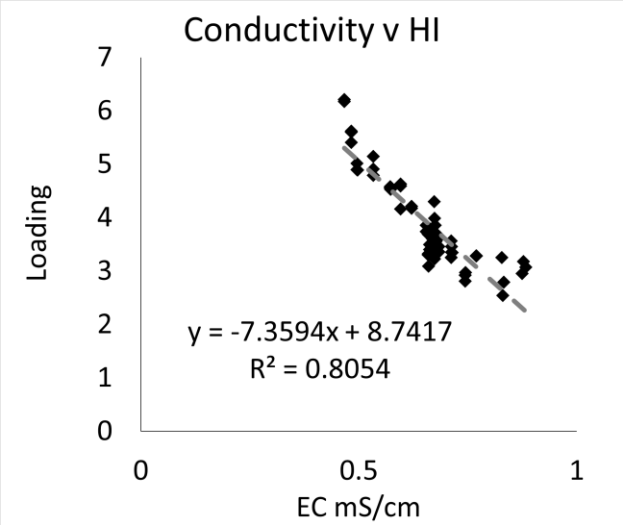

Conductivity % EC3
30%
20%
10%
0%
Loading
y = 0.1436x + 0.0977
R² = 0.1869
0
0.5
1
EC mS/cm

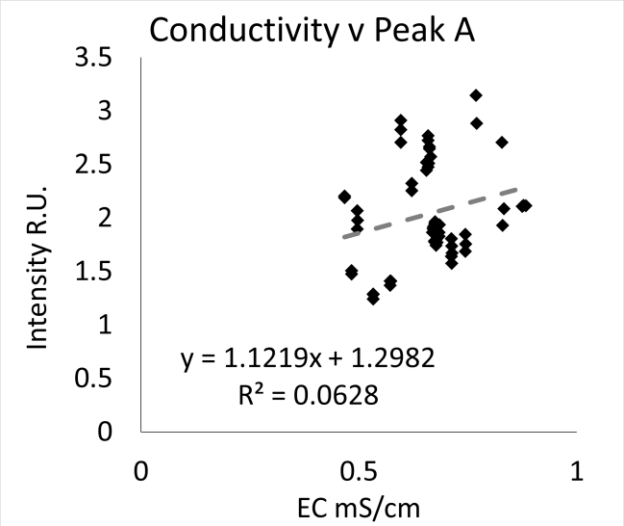

Conductivity v % EC4
30%
20%
10%
0%
Loading
y = 0.3085x - 0.0994
R² = 0.5645
0
0.5
1
EC mS/cm

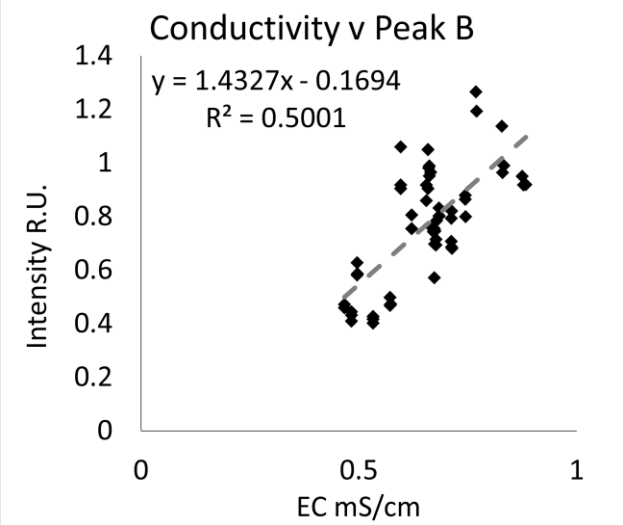

Conductivity v % EC5
8%
7%
6%
5%
4%
3%
2%
1%
0%
Loading
y = -0.1464x + 0.1183
R² = 0.5732
0
0.5
1
EC mS/cm

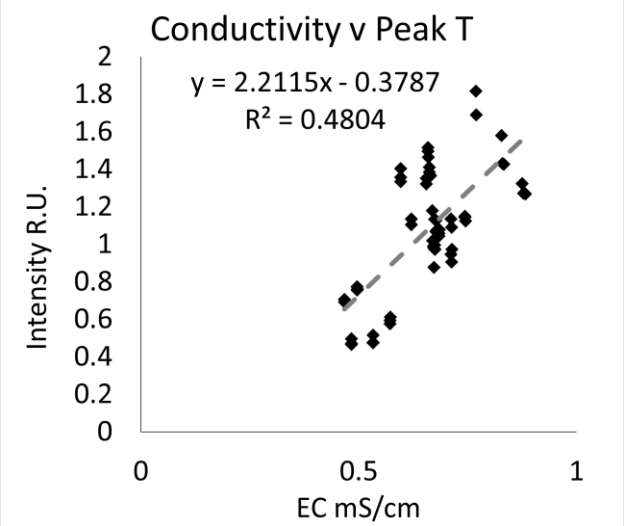

Conductivity v FI
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
Loading
y = 0.6768x + 1.4869
R² = 0.3684
0
0.5
1
EC mS/cm

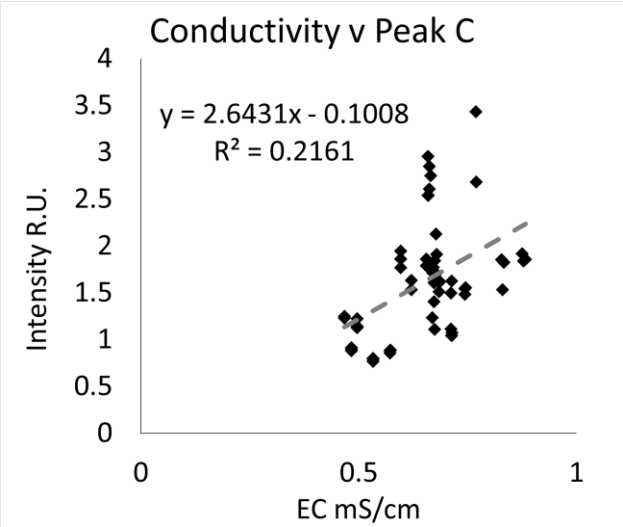

Conductivity v FrI
Loading
EC mS/cm
y = 0.1051x + 0.7443
R² = 0.056

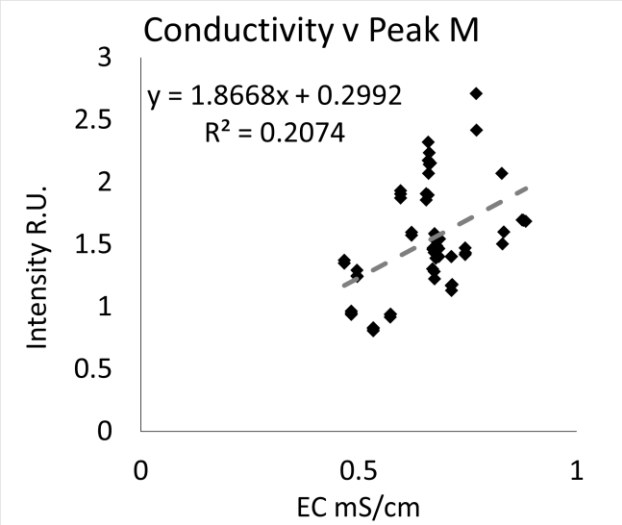

Conductivity v HI
Loading
EC mS/cm
y = -7.3594x + 8.7417
R² = 0.8054

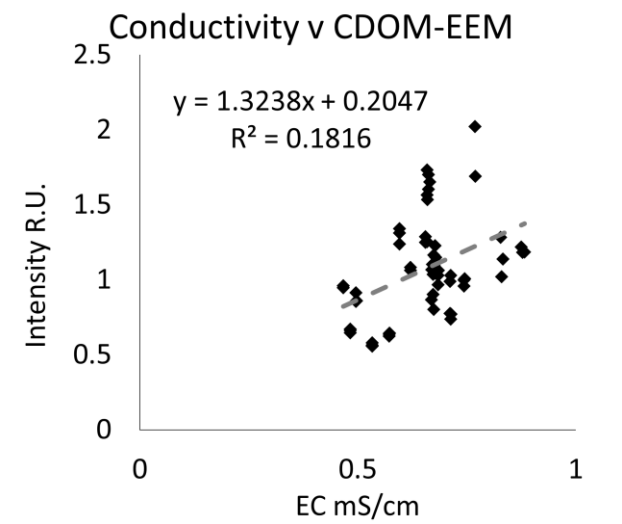

Conductivity v Peak A
Intensity R.U.
EC mS/cm
y = 1.1219x + 1.2982
R² = 0.0628

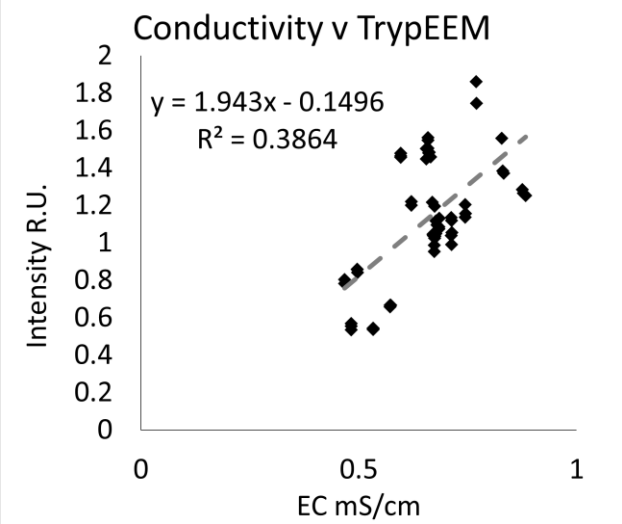

Conductivity v Peak B
Intensity R.U.
EC mS/cm
y = 1.4327x - 0.1694
R² = 0.5001

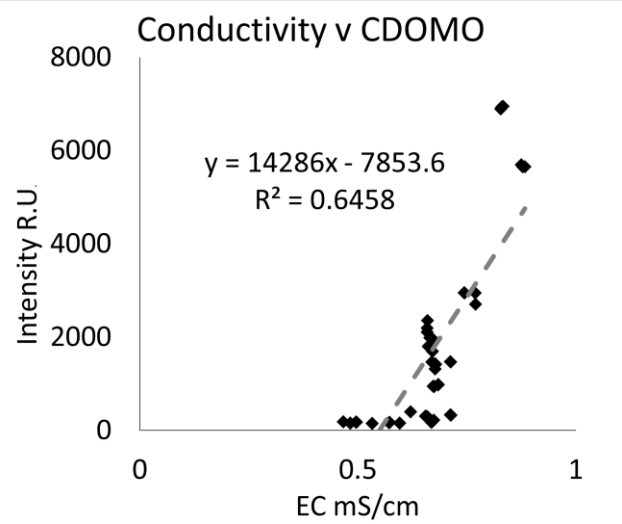

Conductivity v Peak T
Intensity R.U.
EC mS/cm
y = 2.2115x - 0.3787
R² = 0.4804

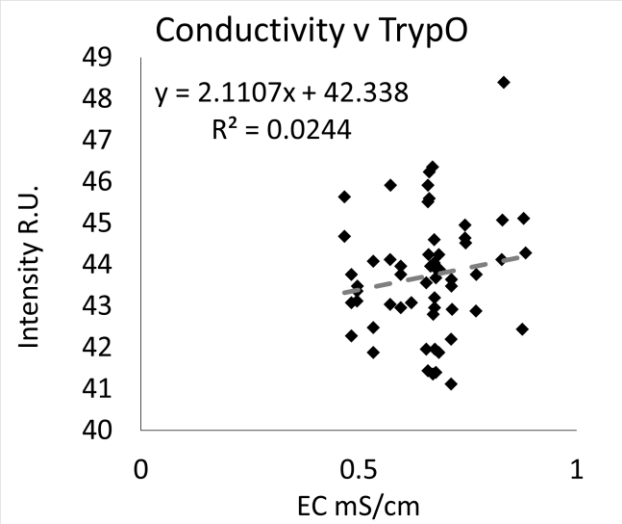

Conductivity v Peak C
Intensity R.U.
EC mS/cm
y = 2.6431x - 0.1008
R² = 0.2161

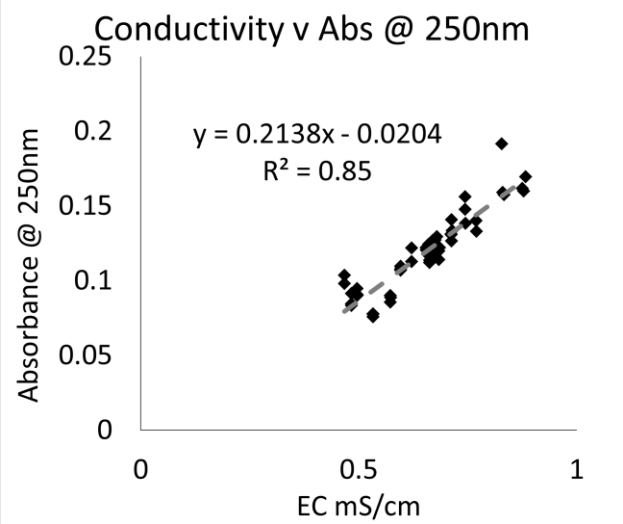

Conductivity v Peak M
y = 1.8668x + 0.2992
R² = 0.2074
Intensity R.U.
EC mS/cm
0
0.5
1
1.5
2
2.5
3

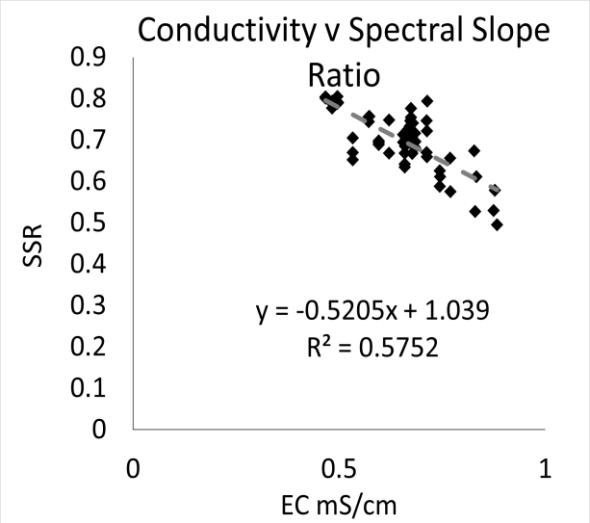

Conductivity v CDOM-EEM
y = 1.3238x + 0.2047
R² = 0.1816
Intensity R.U.
EC mS/cm
0
0.5
1
1.5
2
2.5


Conductivity v TrypEEM
y = 1.943x - 0.1496
R² = 0.3864
Intensity R.U.
EC mS/cm
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2


Conductivity v CDOMO
y = 14286x - 7853.6
R² = 0.6458
Intensity R.U
EC mS/cm
0
2000
4000
6000
8000

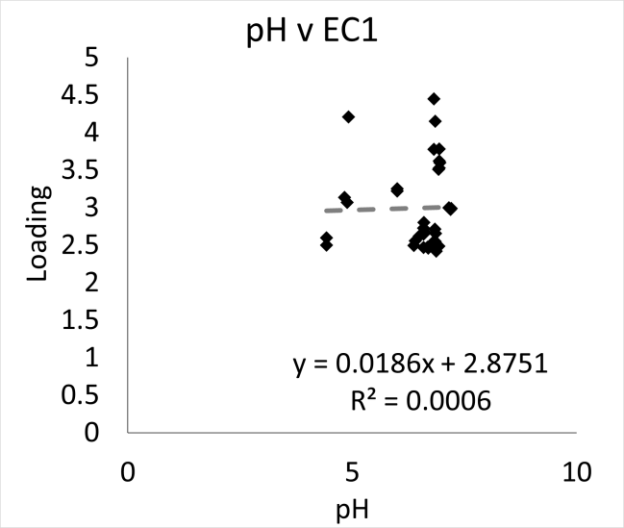


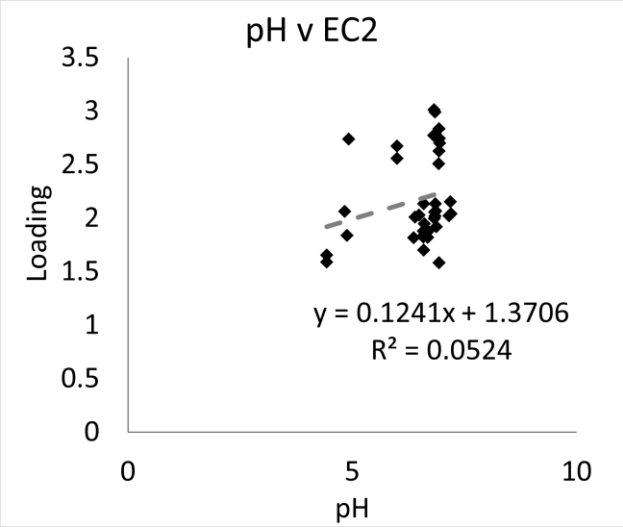


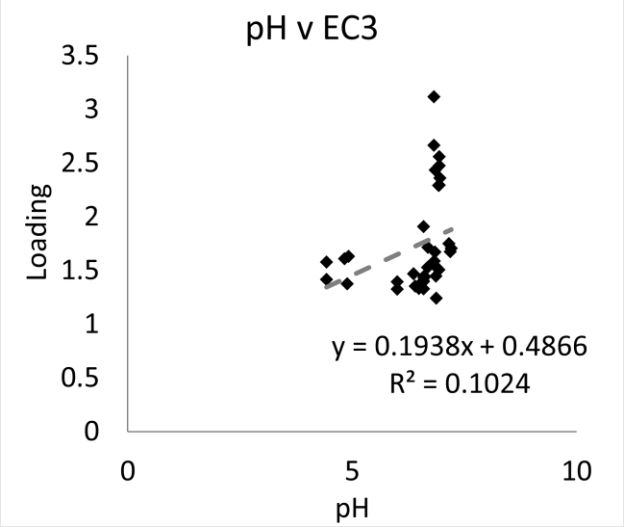


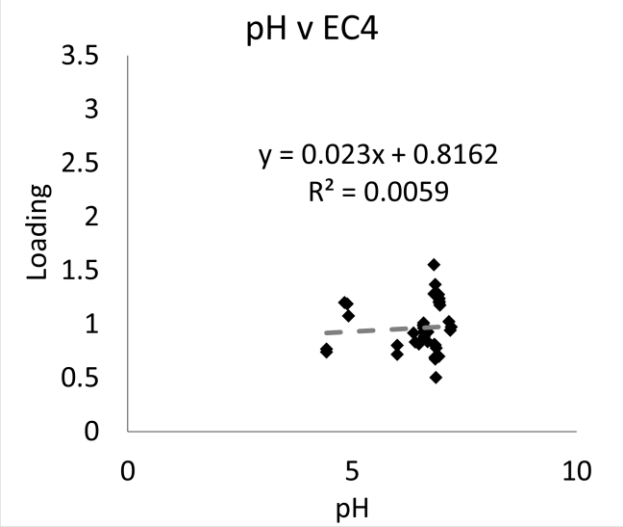
pH – online

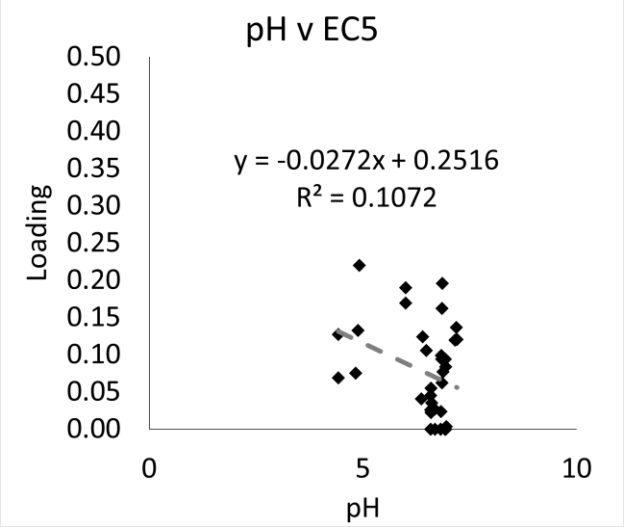
Effluent

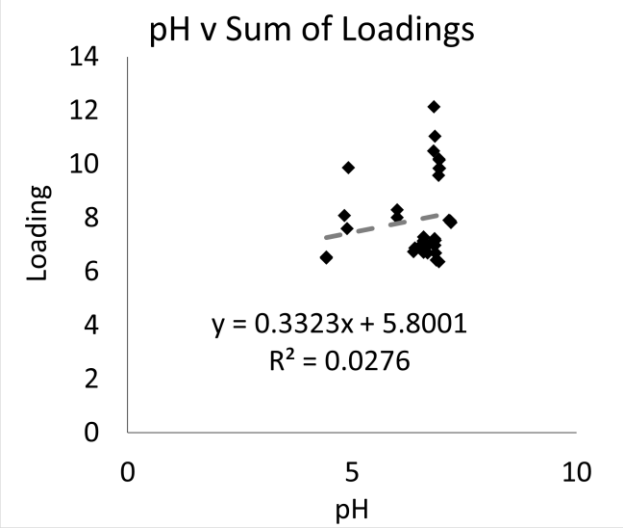

pH v EC1
Loading
pH
y = 0.0186x + 2.8751
R² = 0.0006

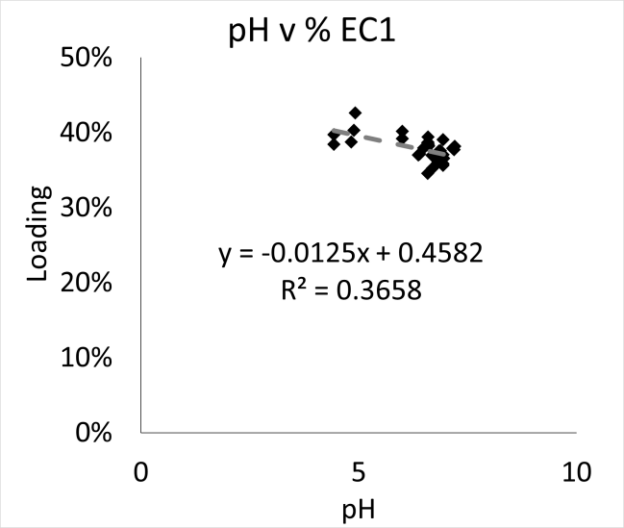

pH v EC2
Loading
pH
y = 0.1241x + 1.3706
R² = 0.0524

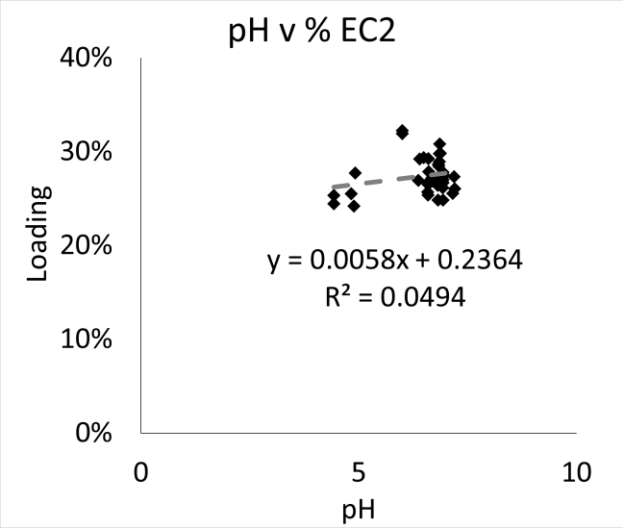

pH v EC3
Loading
pH
y = 0.1938x + 0.4866
R² = 0.1024

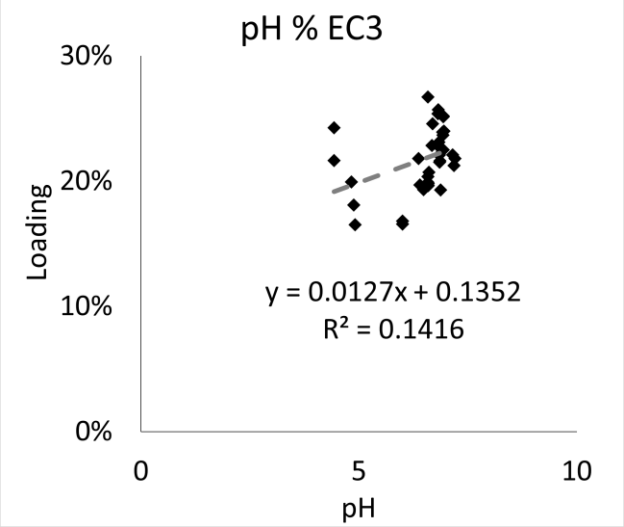

pH v EC4
Loading
pH
y = 0.023x + 0.8162
R² = 0.0059

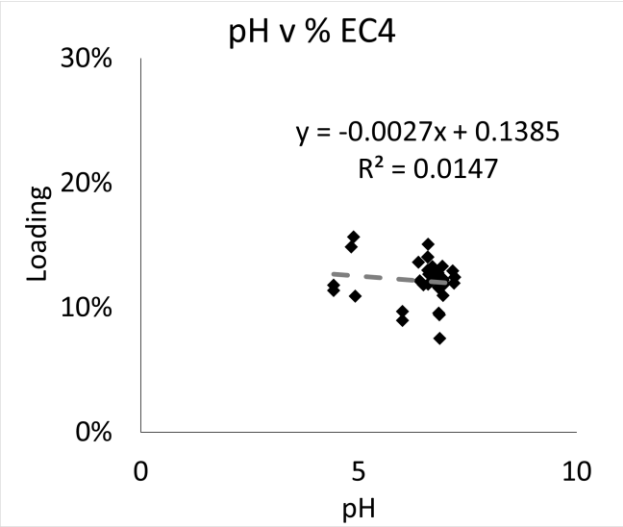

pH v EC5
Loading
pH
y = -0.0272x + 0.2516
R² = 0.1072

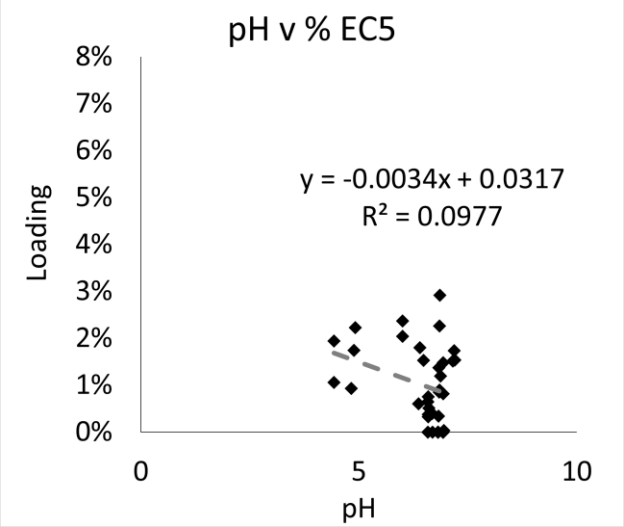

pH v Sum of Loadings
Loading
pH
y = 0.3323x + 5.8001
R² = 0.0276

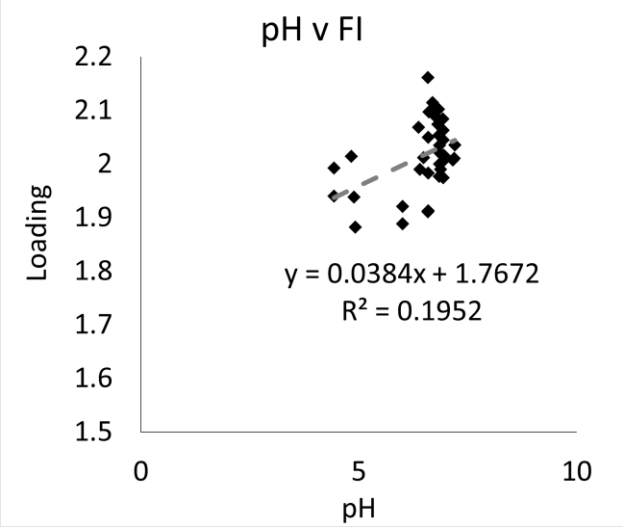

pH v % EC1
50%
40%
30%
20%
10%
0%
Loading
y = -0.0125x + 0.4582
R² = 0.3658
0
5
10
pH

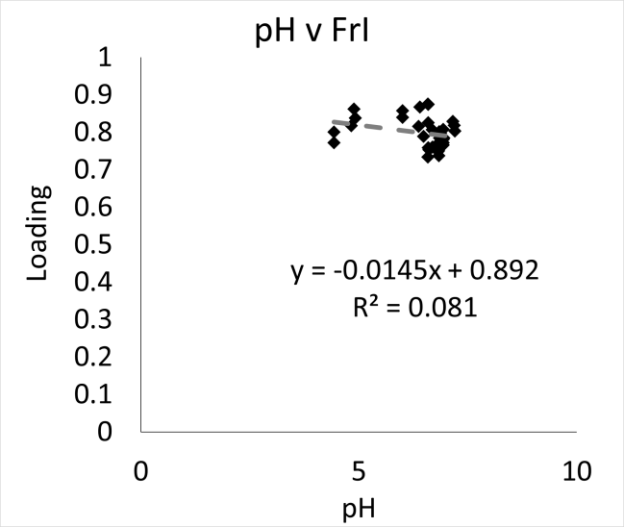

pH v % EC2
40%
30%
20%
10%
0%
Loading
y = 0.0058x + 0.2364
R² = 0.0494
0
5
10
pH

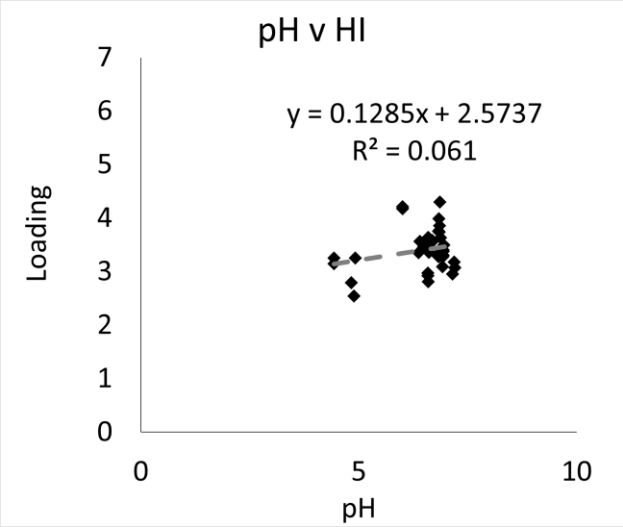

pH % EC3
30%
20%
10%
0%
Loading
y = 0.0127x + 0.1352
R² = 0.1416
0
5
10
pH

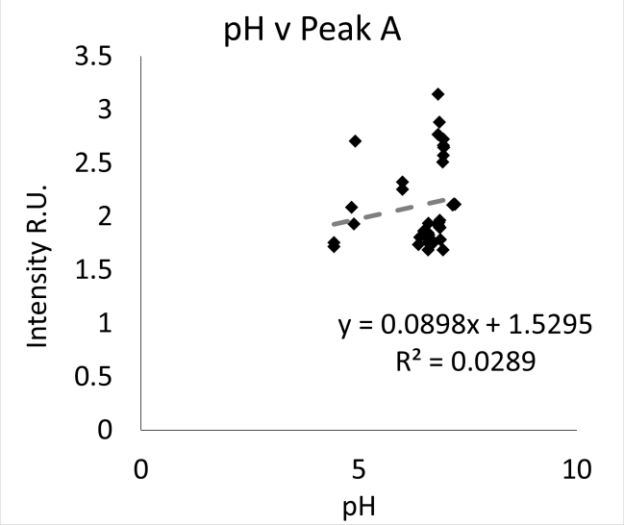

pH v % EC4
30%
20%
10%
0%
Loading
y = -0.0027x + 0.1385
R² = 0.0147
0
5
10
pH

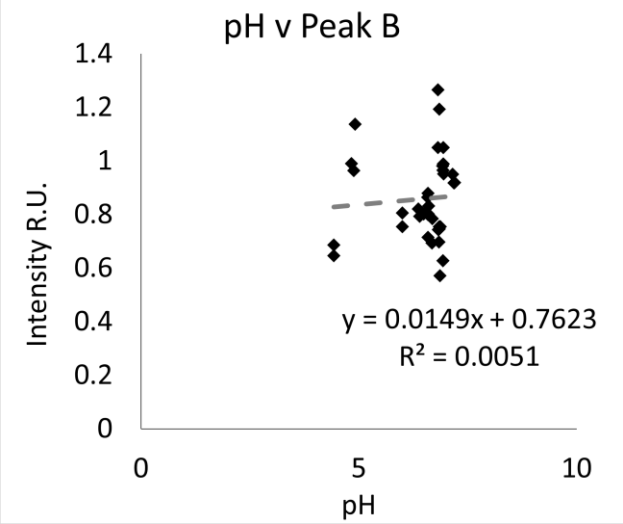

pH v % EC5
8%
7%
6%
5%
4%
3%
2%
1%
0%
Loading
y = -0.0034x + 0.0317
R² = 0.0977
0
5
10
pH

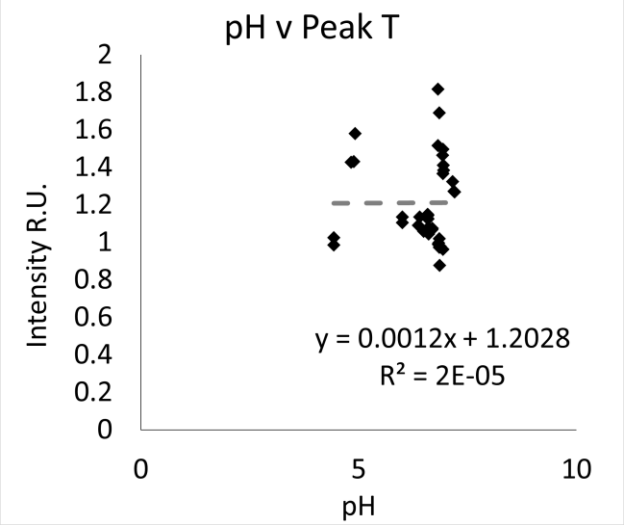

pH v FI
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
Loading
y = 0.0384x + 1.7672
R² = 0.1952
0
5
10
pH

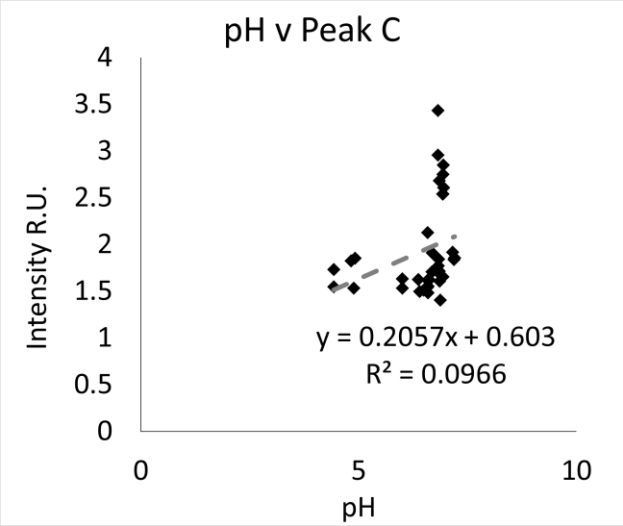

pH v FrI
Loading
pH
y = -0.0145x + 0.892
R² = 0.081

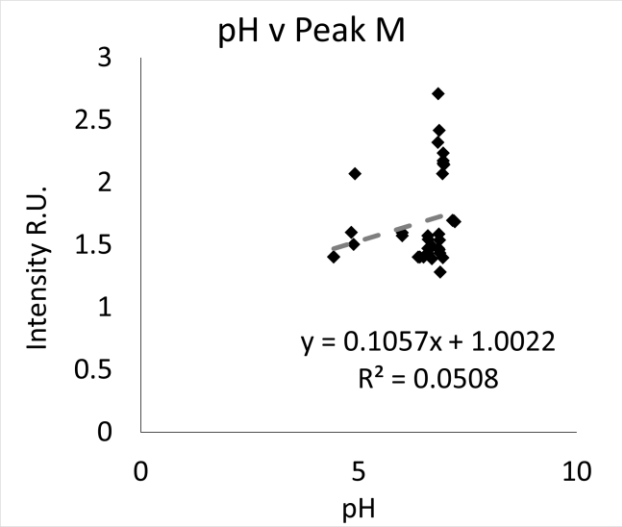

pH v HI
Loading
pH
y = 0.1285x + 2.5737
R² = 0.061

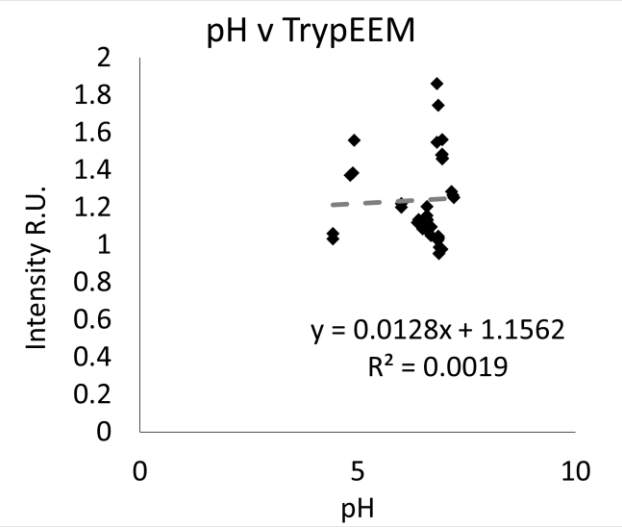

pH v Peak A
Intensity R.U.
pH
y = 0.0898x + 1.5295
R² = 0.0289

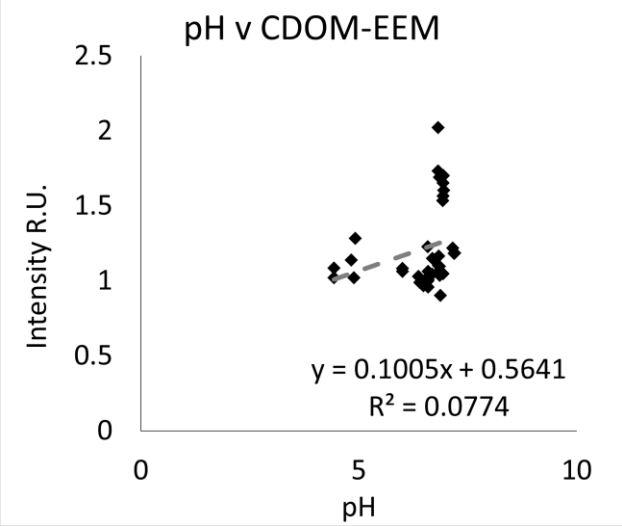

pH v Peak B
Intensity R.U.
pH
y = 0.0149x + 0.7623
R² = 0.0051

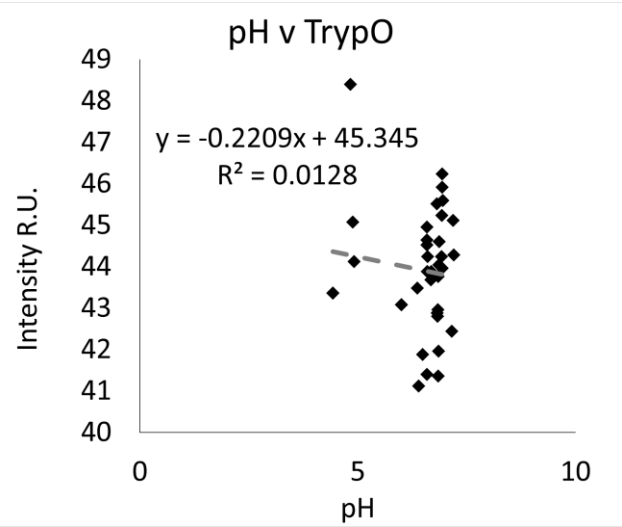

pH v Peak T
Intensity R.U.
pH
y = 0.0012x + 1.2028
R² = 2E-05

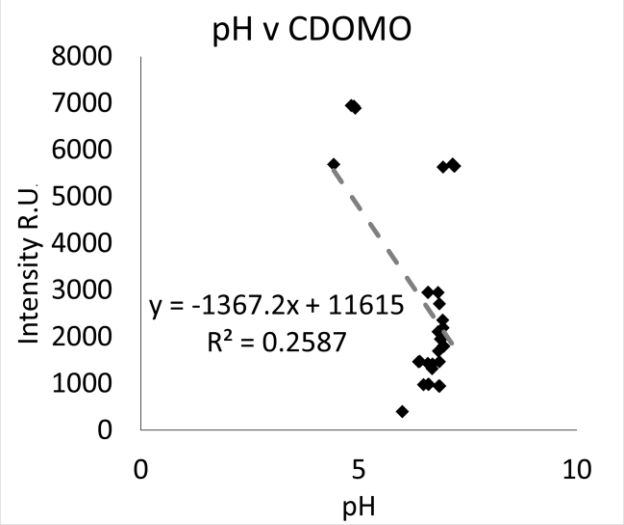

pH v Peak C
Intensity R.U.
pH
y = 0.2057x + 0.603
R² = 0.0966

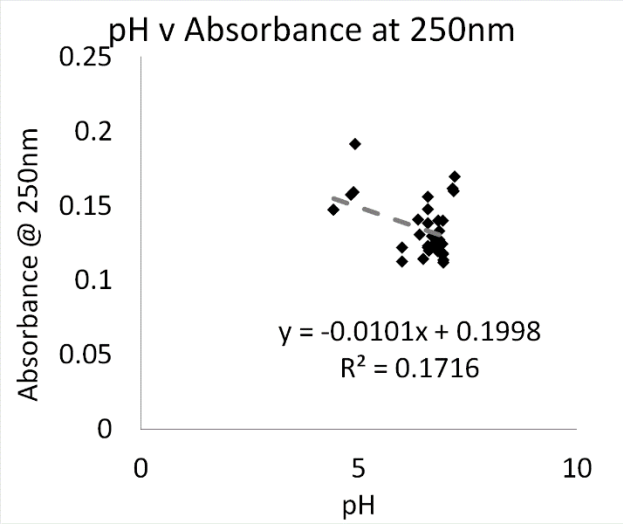

pH v Peak M
Intensity R.U.
pH
y = 0.1057x + 1.0022
R² = 0.0508
0
0.5
1
1.5
2
2.5
3
0
5
10

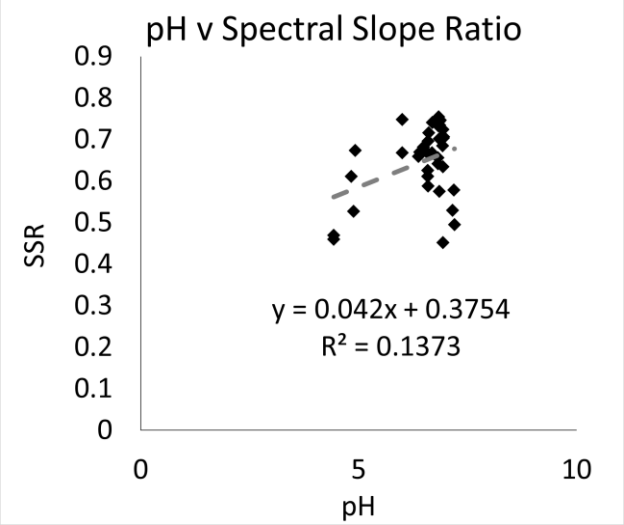

pH v TrypEEM
Intensity R.U.
pH
y = 0.0128x + 1.1562
R² = 0.0019
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0
5
10


pH v CDOM-EEM
Intensity R.U.
pH
y = 0.1005x + 0.5641
R² = 0.0774
0
0.5
1
1.5
2
2.5
0
5
10


pH v TrypO
Intensity R.U.
pH
y = -0.2209x + 45.345
R² = 0.0128
40
41
42
43
44
45
46
47
48
49
0
5
10

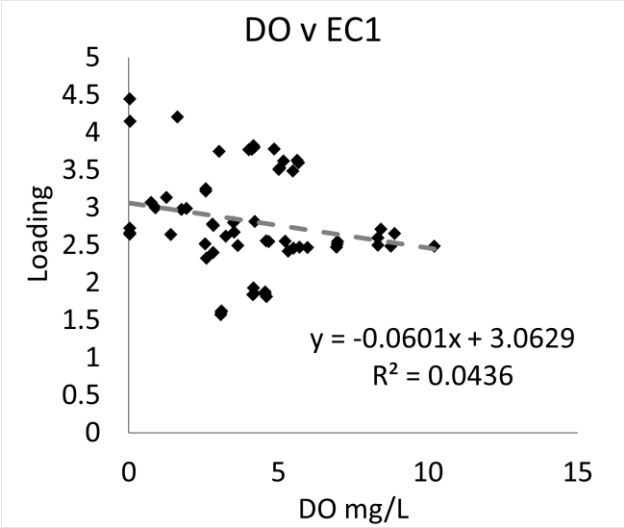


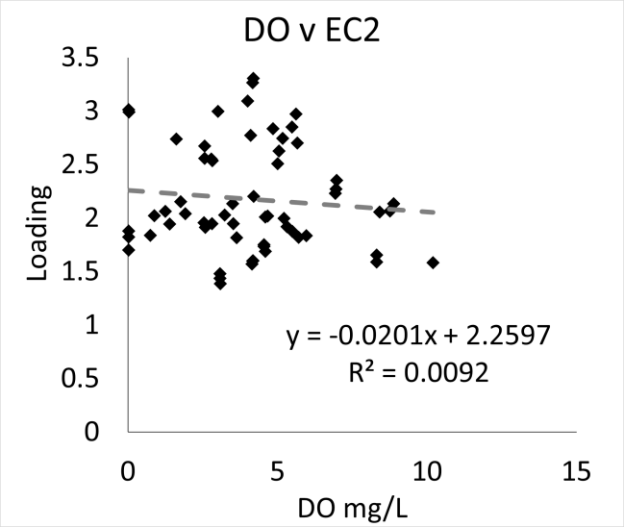


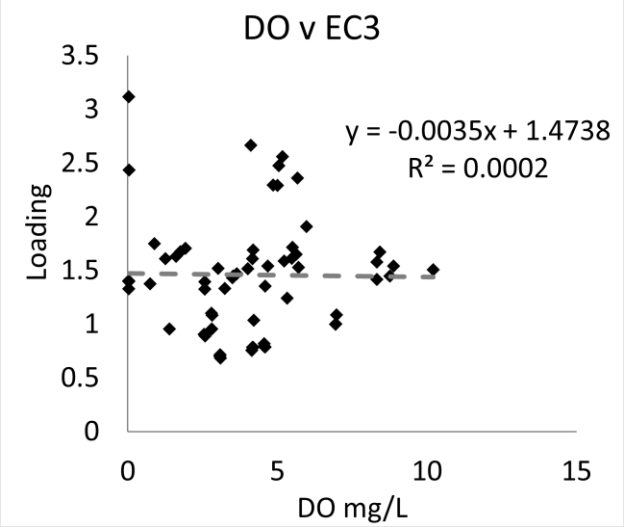


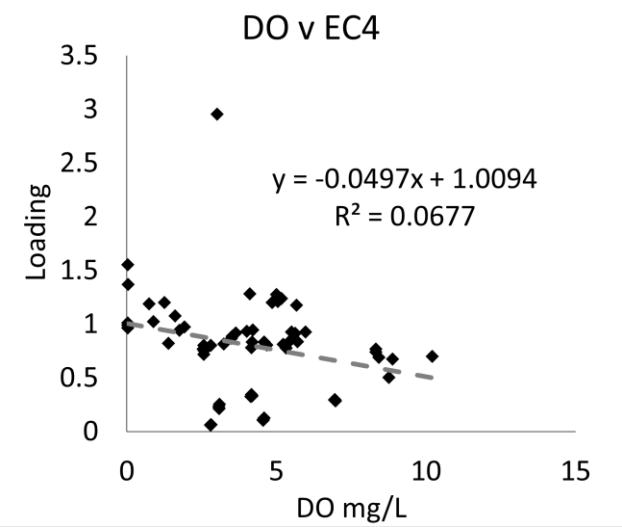
Dissolved oxygen – online

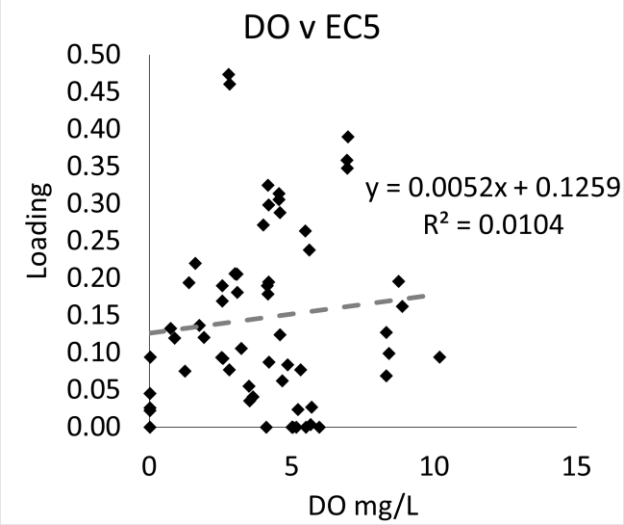
Effluent

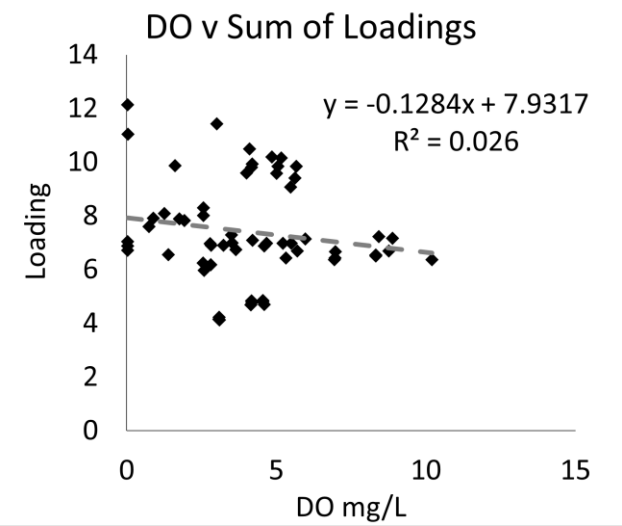

DO v EC1
Loading
DO mg/L
y = -0.0601x + 3.0629
R² = 0.0436

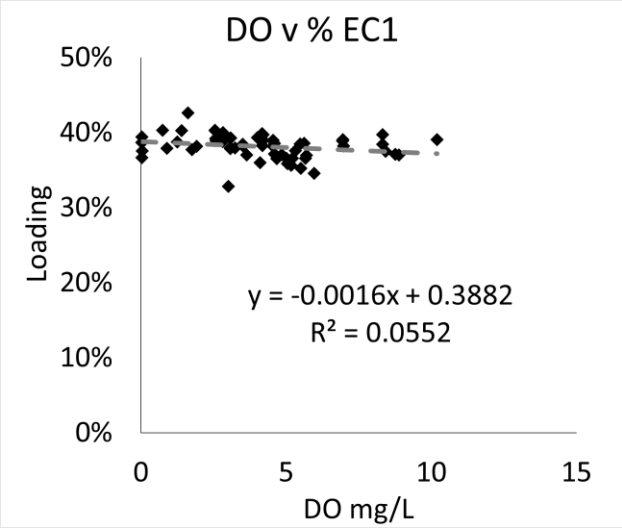

DO v EC2
Loading
DO mg/L
y = -0.0201x + 2.2597
R² = 0.0092

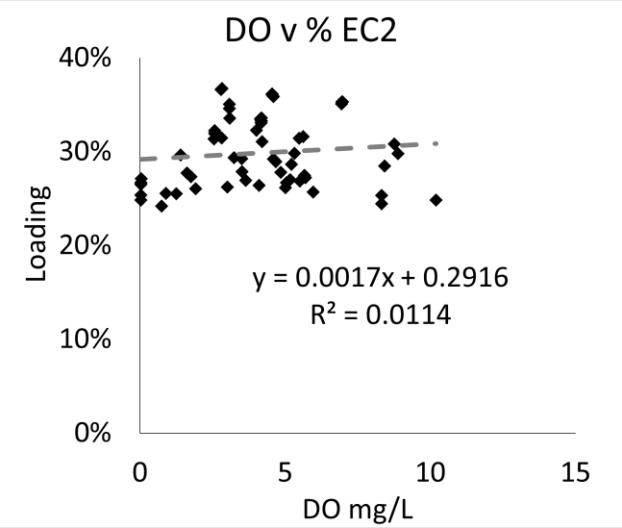

DO v EC3
Loading
DO mg/L
y = -0.0035x + 1.4738
R² = 0.0002

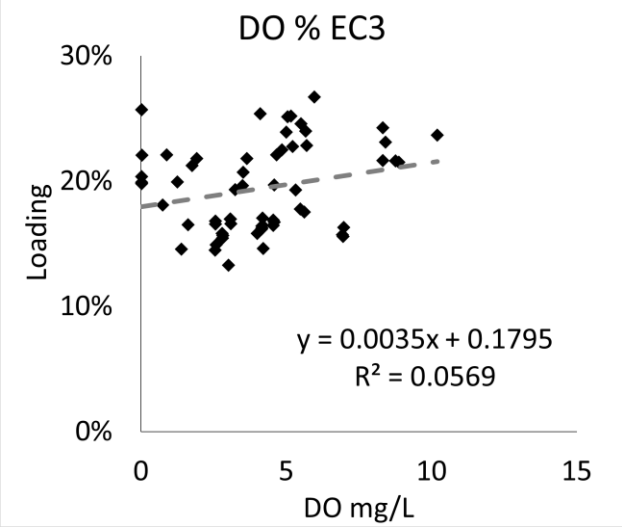

DO v EC4
Loading
DO mg/L
y = -0.0497x + 1.0094
R² = 0.0677

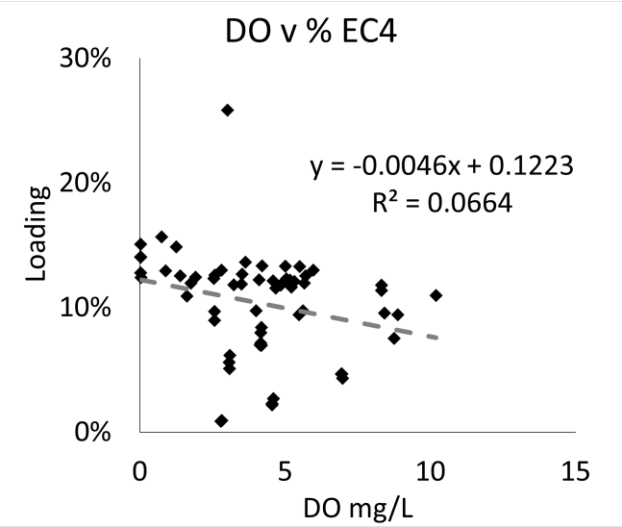

DO v EC5
Loading
DO mg/L
y = 0.0052x + 0.1259
R² = 0.0104

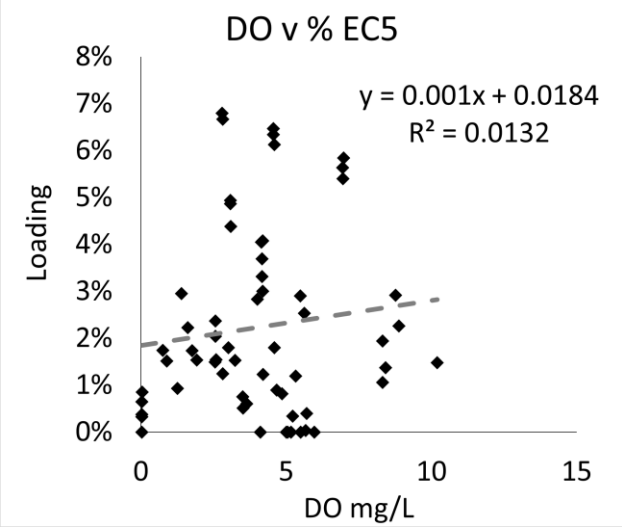

DO v Sum of Loadings
Loading
DO mg/L
y = -0.1284x + 7.9317
R² = 0.026

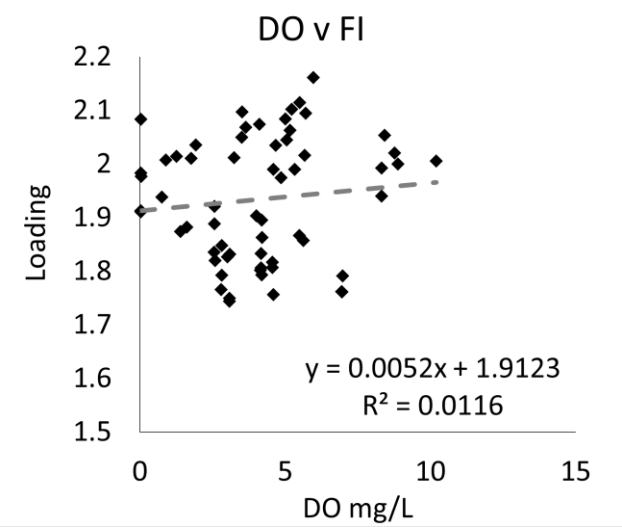

DO v % EC1
Loading
50%
40%
30%
20%
10%
0%
0
5
10
15
DO mg/L
y = -0.0016x + 0.3882
R² = 0.0552

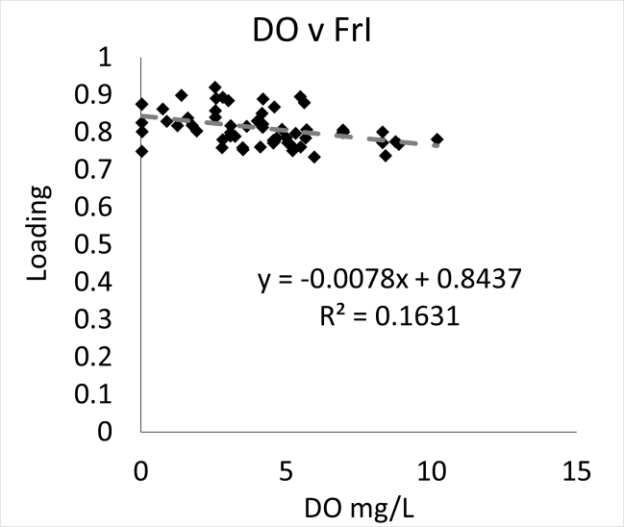

DO v % EC2
Loading
40%
30%
20%
10%
0%
0
5
10
15
DO mg/L
y = 0.0017x + 0.2916
R² = 0.0114

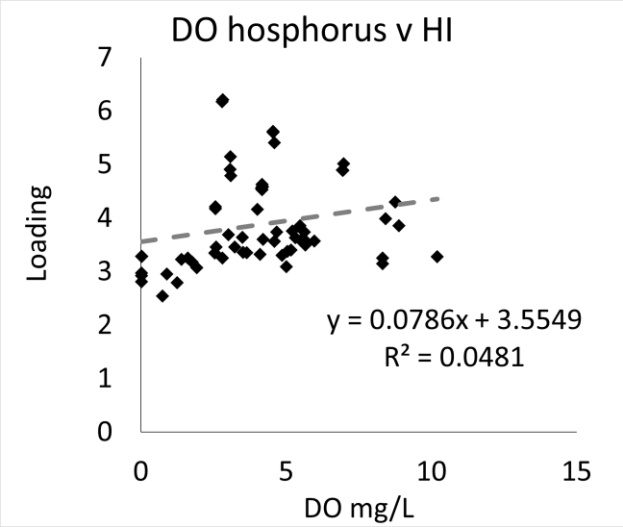

DO % EC3
Loading
30%
20%
10%
0%
0
5
10
15
DO mg/L
y = 0.0035x + 0.1795
R² = 0.0569

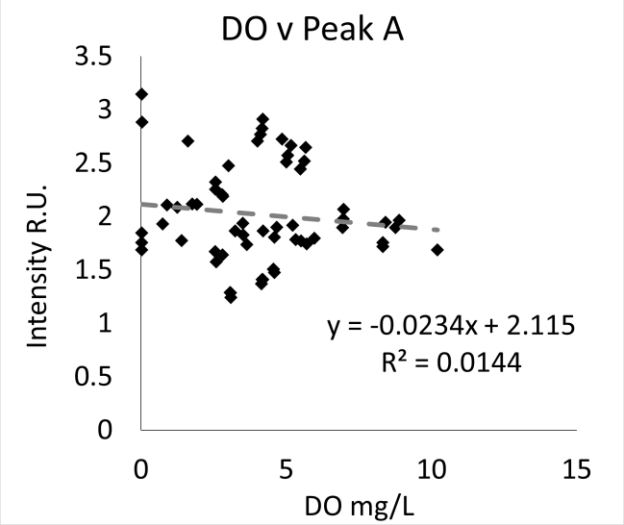

DO v % EC4
Loading
30%
20%
10%
0%
0
5
10
15
DO mg/L
y = -0.0046x + 0.1223
R² = 0.0664

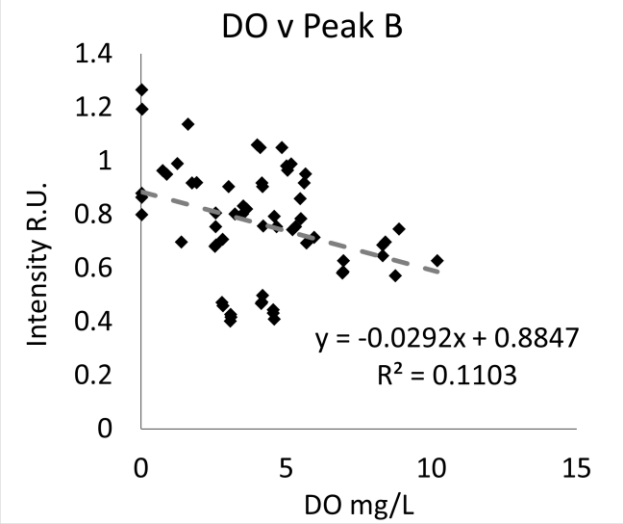

DO v % EC5
Loading
8%
7%
6%
5%
4%
3%
2%
1%
0%
0
5
10
15
DO mg/L
y = 0.001x + 0.0184
R² = 0.0132

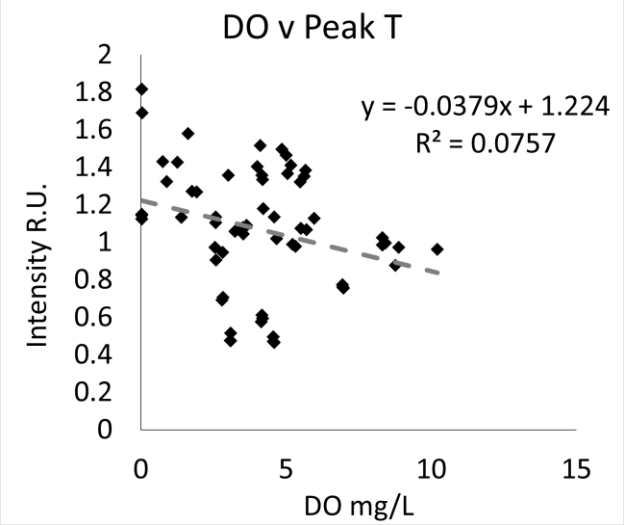

DO v FI
Loading
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
0
5
10
15
DO mg/L
y = 0.0052x + 1.9123
R² = 0.0116

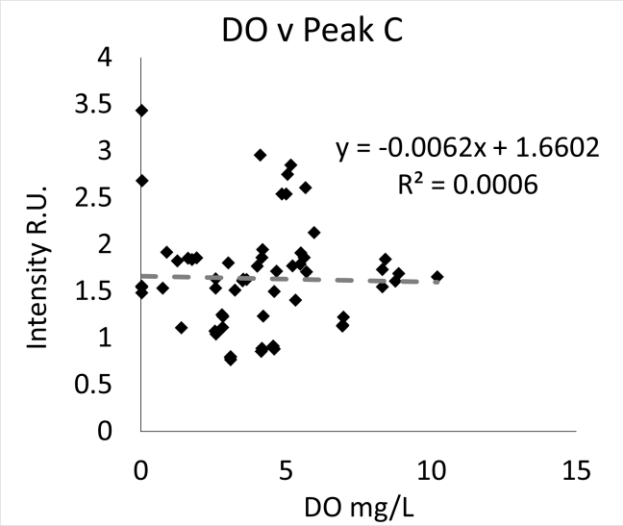

DO v FrI
Loading
DO mg/L
y = -0.0078x + 0.8437
R² = 0.1631

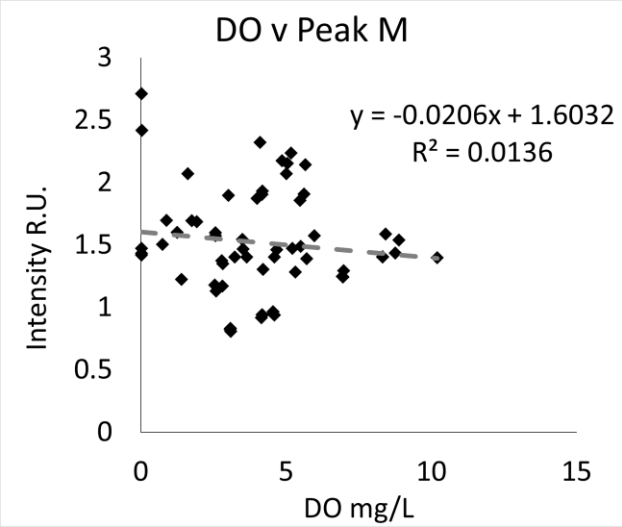

DO hosphorus v HI
Loading
DO mg/L
y = 0.0786x + 3.5549
R² = 0.0481

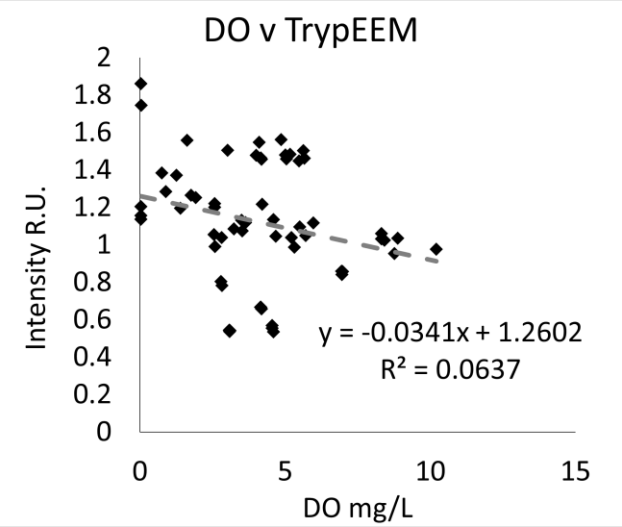

DO v Peak A
Intensity R.U.
DO mg/L
y = -0.0234x + 2.115
R² = 0.0144

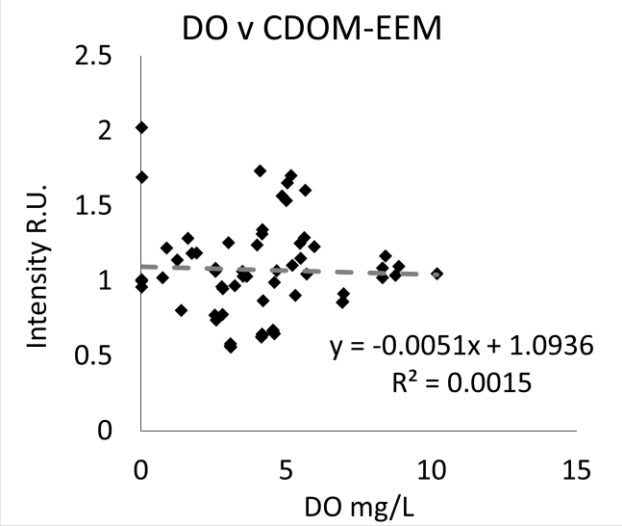

DO v Peak B
Intensity R.U.
DO mg/L
y = -0.0292x + 0.8847
R² = 0.1103

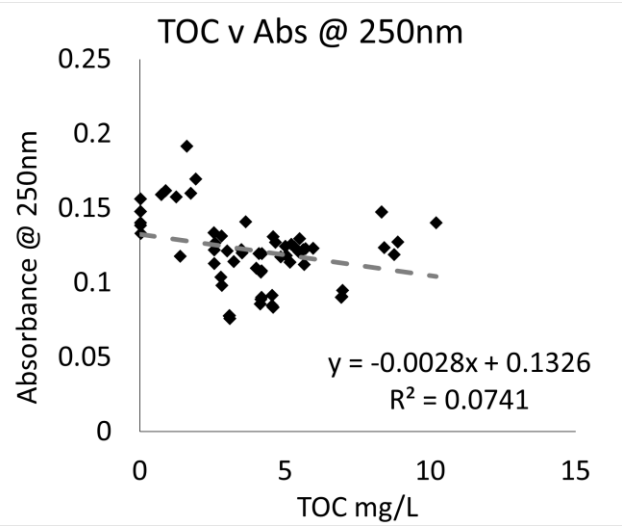

DO v Peak T
Intensity R.U.
DO mg/L
y = -0.0379x + 1.224
R² = 0.0757

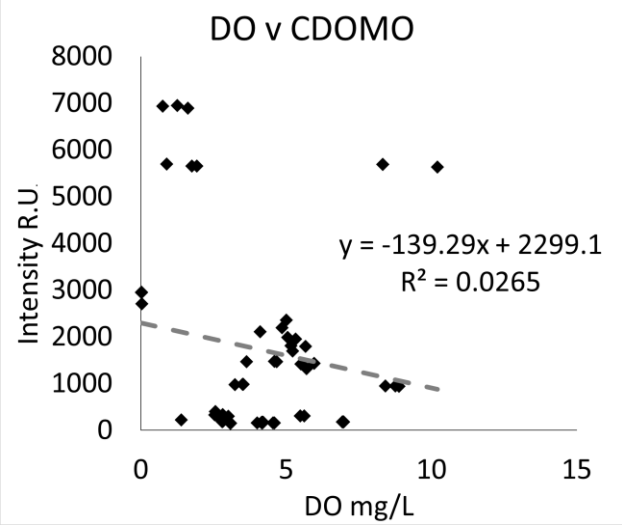

DO v Peak C
Intensity R.U.
DO mg/L
y = -0.0062x + 1.6602
R² = 0.0006

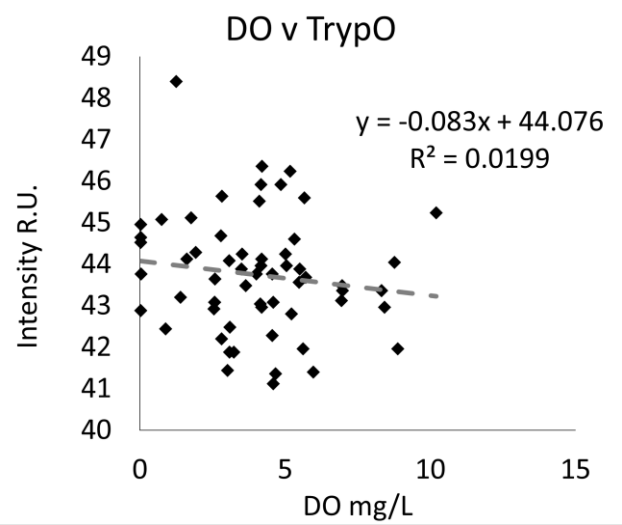

DO v Peak M
y = -0.0206x + 1.6032
R² = 0.0136
Intensity R.U.
DO mg/L
0
0.5
1
1.5
2
2.5
3
0
5
10
15

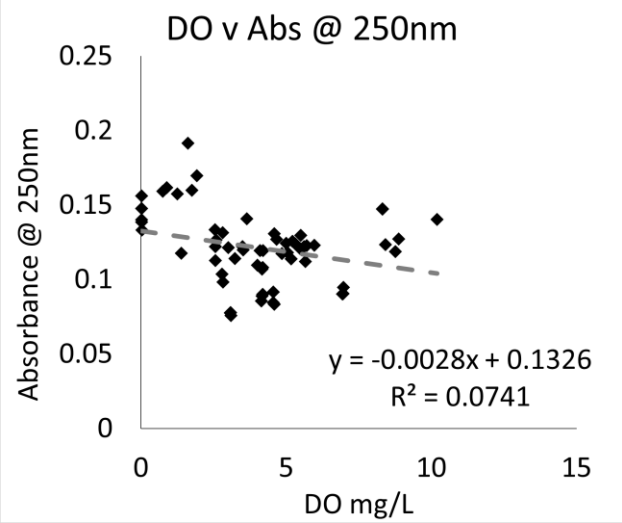

DO v TrypEEM
y = -0.0341x + 1.2602
R² = 0.0637
Intensity R.U.
DO mg/L
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0
5
10
15

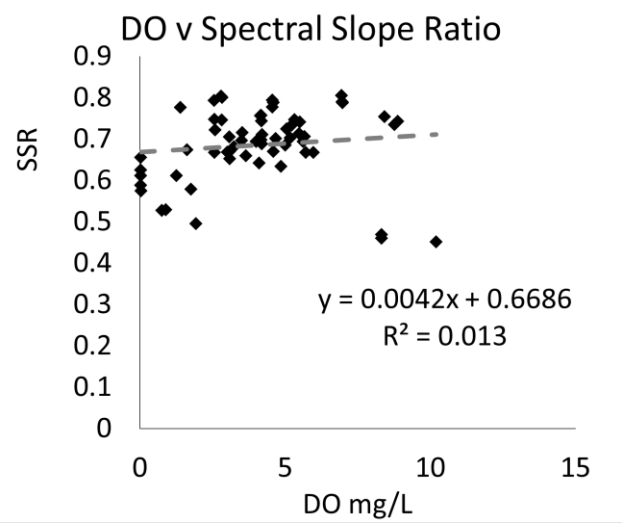

DO v CDOM-EEM
y = -0.0051x + 1.0936
R² = 0.0015
Intensity R.U.
DO mg/L
0
0.5
1
1.5
2
2.5
0
5
10
15


TOC v Abs @ 250nm
y = -0.0028x + 0.1326
R² = 0.0741
Absorbance @ 250nm
TOC mg/L
0
0.05
0.1
0.15
0.2
0.25
0
5
10
15



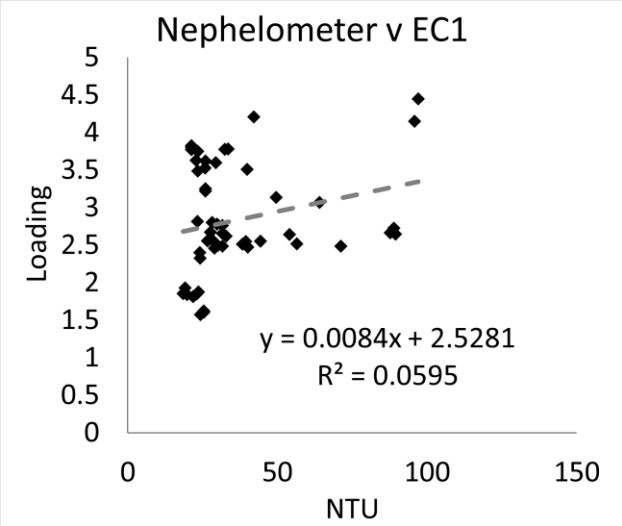


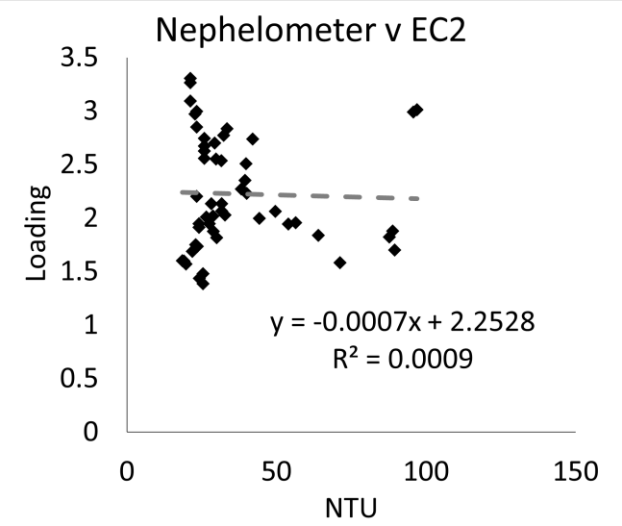


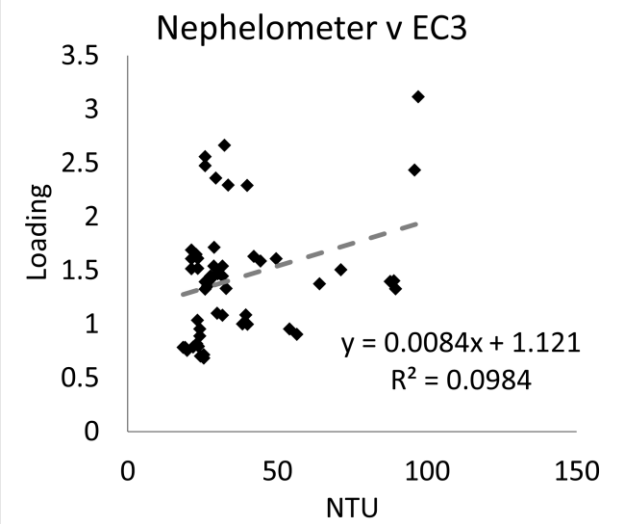


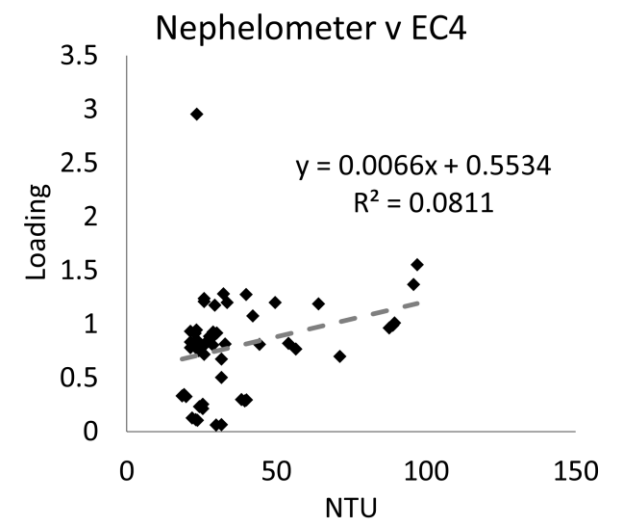
Turbidity (nephelometer) – online

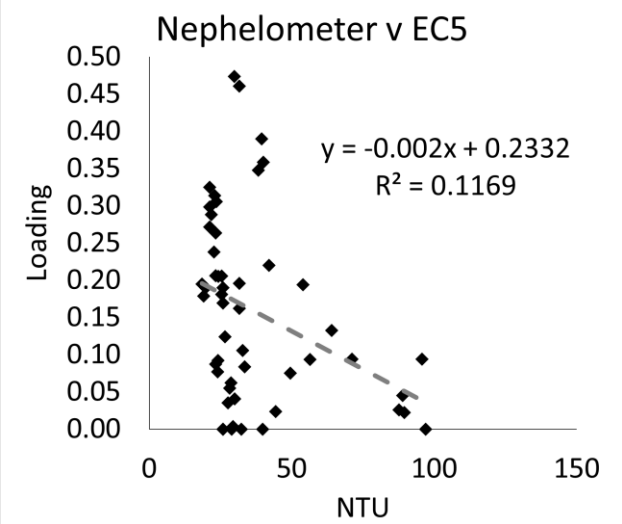
Effluent

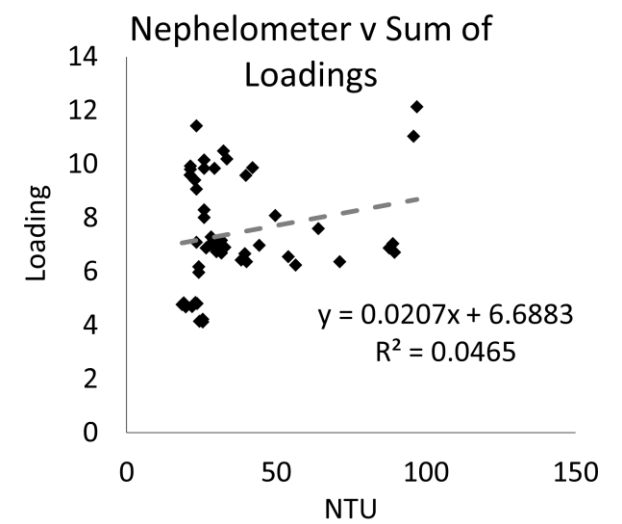

Nephelometer v EC1
Loading
NTU
y = 0.0084x + 2.5281
R² = 0.0595

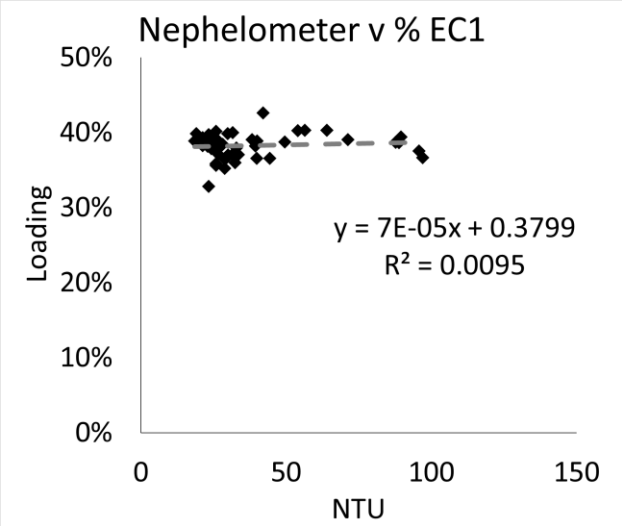

Nephelometer v EC2
Loading
NTU
y = -0.0007x + 2.2528
R² = 0.0009

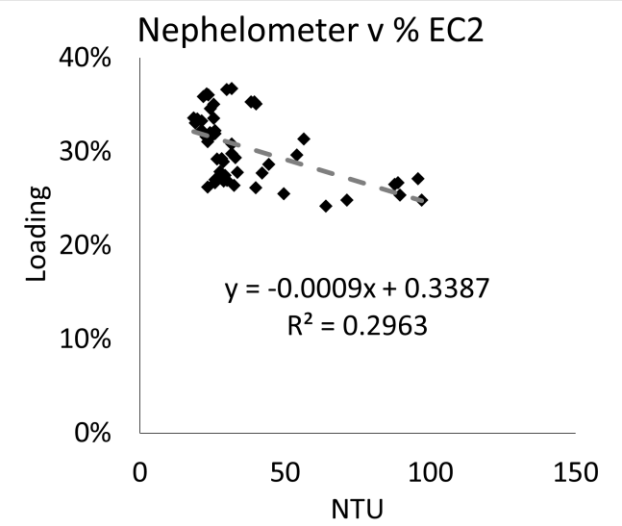

Nephelometer v EC3
Loading
NTU
y = 0.0084x + 1.121
R² = 0.0984

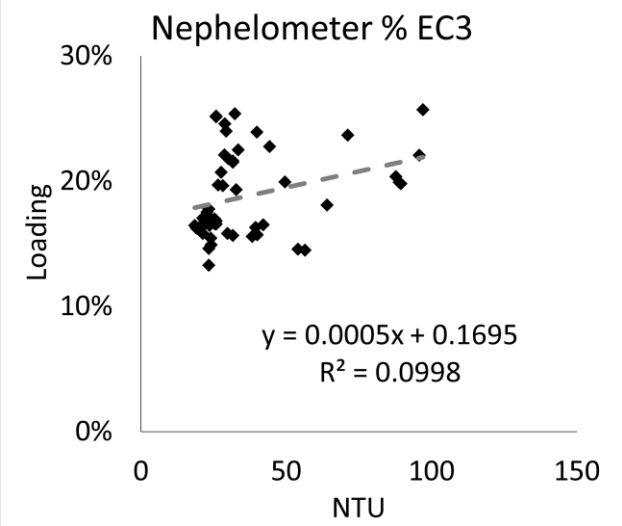

Nephelometer v EC4
Loading
NTU
y = 0.0066x + 0.5534
R² = 0.0811

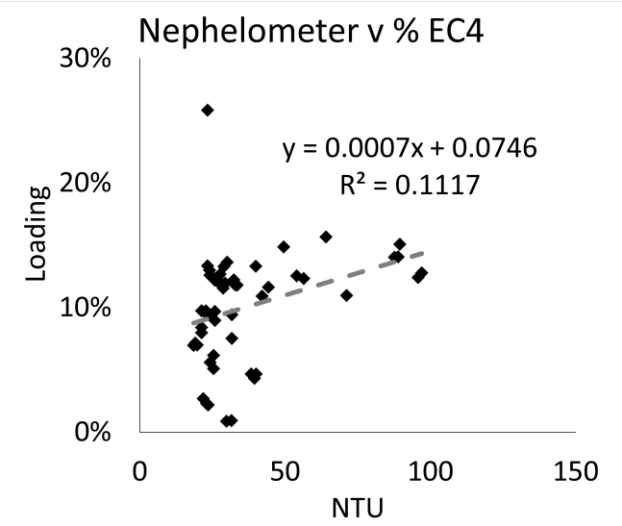

Nephelometer v EC5
Loading
NTU
y = -0.002x + 0.2332
R² = 0.1169

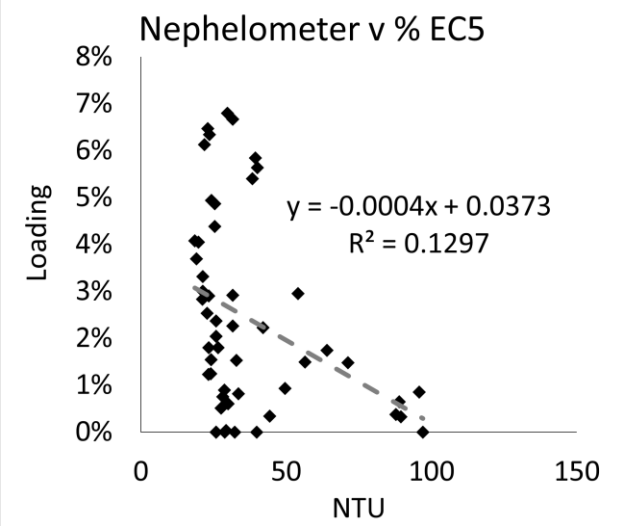

Nephelometer v Sum of Loadings
Loading
NTU
y = 0.0207x + 6.6883
R² = 0.0465

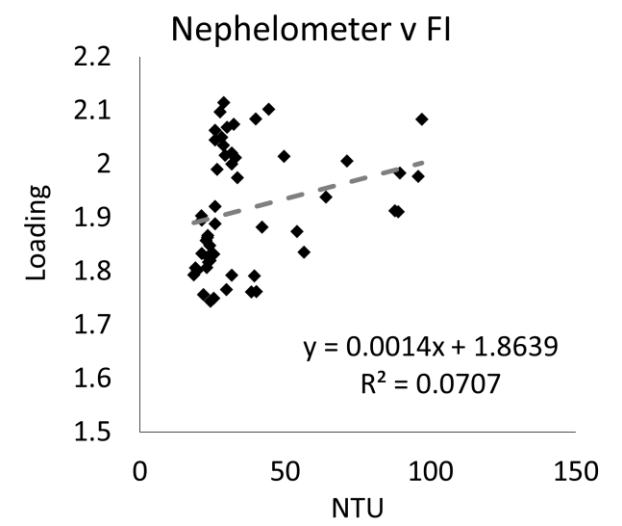

Nephelometer v % EC1
Loading
NTU
y = 7E-05x + 0.3799
R² = 0.0095
50%
40%
30%
20%
10%
0%
0
50
100
150

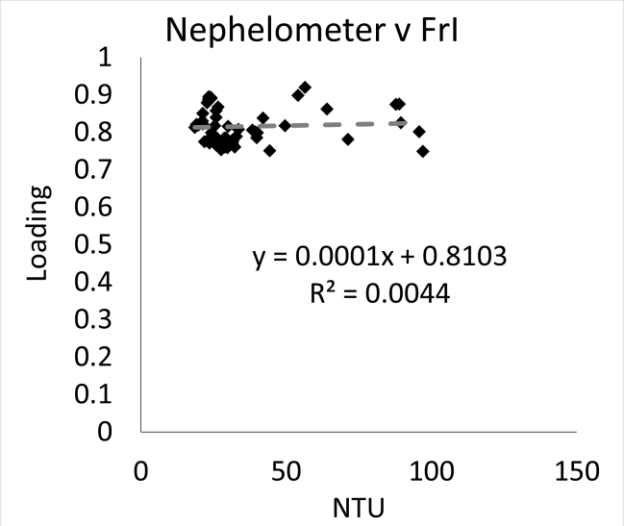

Nephelometer v % EC2
Loading
NTU
y = -0.0009x + 0.3387
R² = 0.2963
40%
30%
20%
10%
0%
0
50
100
150

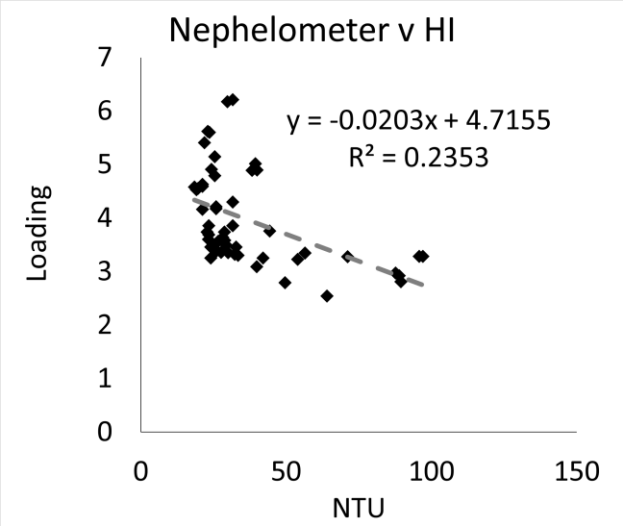

Nephelometer % EC3
Loading
NTU
y = 0.0005x + 0.1695
R² = 0.0998
30%
20%
10%
0%
0
50
100
150

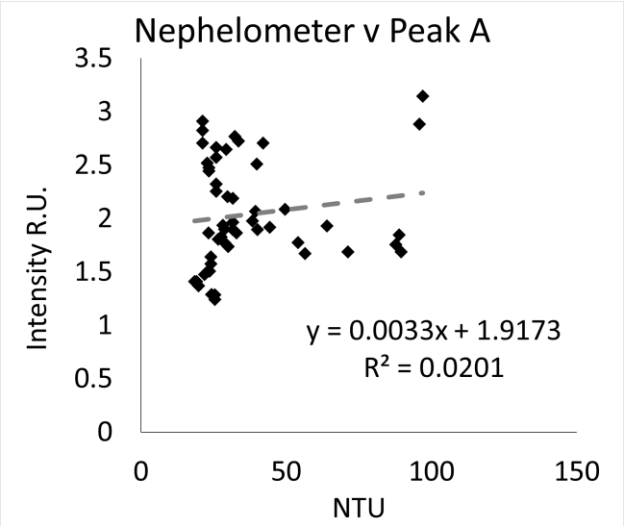

Nephelometer v % EC4
Loading
NTU
y = 0.0007x + 0.0746
R² = 0.1117
30%
20%
10%
0%
0
50
100
150

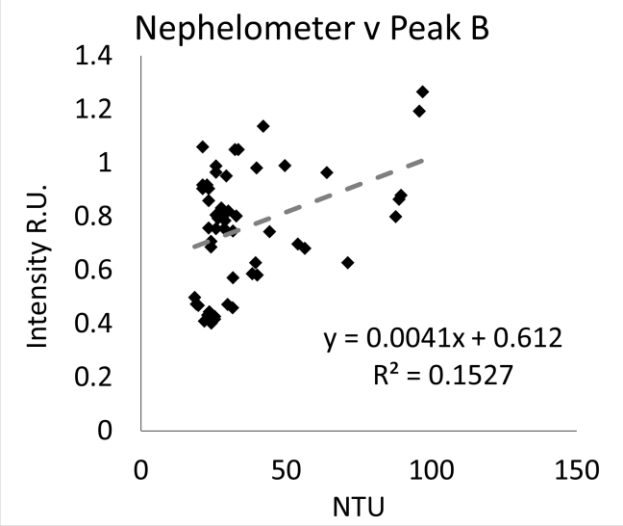

Nephelometer v % EC5
Loading
NTU
y = -0.0004x + 0.0373
R² = 0.1297
8%
7%
6%
5%
4%
3%
2%
1%
0%
0
50
100
150

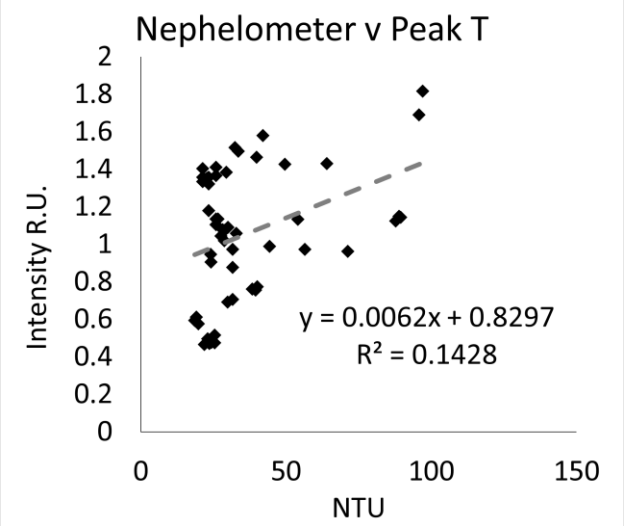

Nephelometer v FI
Loading
NTU
y = 0.0014x + 1.8639
R² = 0.0707
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
0
50
100
150

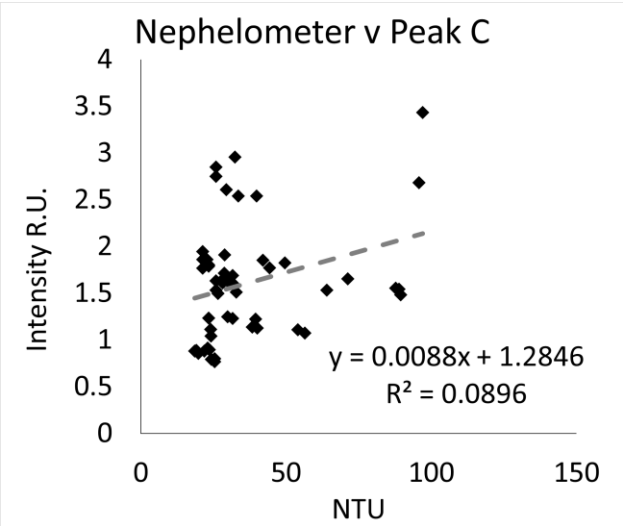

Nephelometer v FrI
Loading
NTU
y = 0.0001x + 0.8103
R² = 0.0044

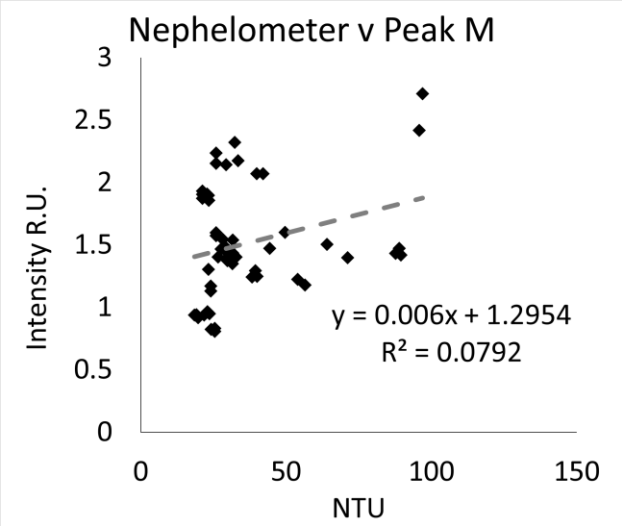

Nephelometer v HI
Loading
NTU
y = -0.0203x + 4.7155
R² = 0.2353

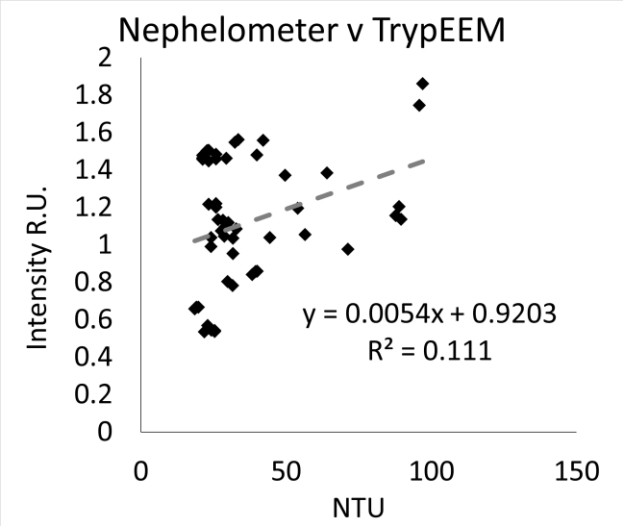

Nephelometer v Peak A
Intensity R.U.
NTU
y = 0.0033x + 1.9173
R² = 0.0201

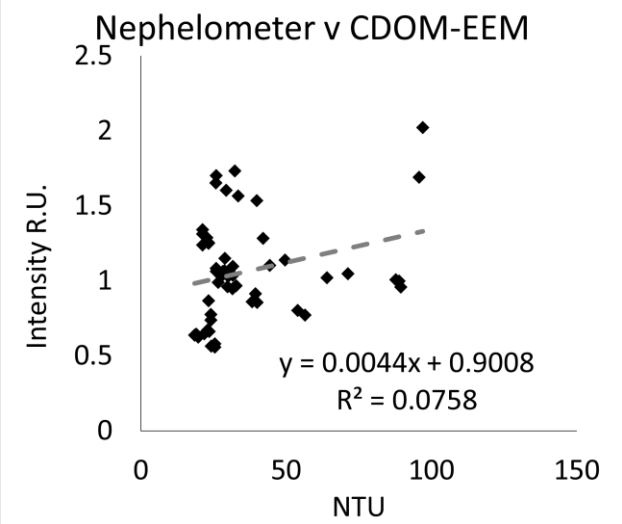

Nephelometer v Peak B
Intensity R.U.
NTU
y = 0.0041x + 0.612
R² = 0.1527

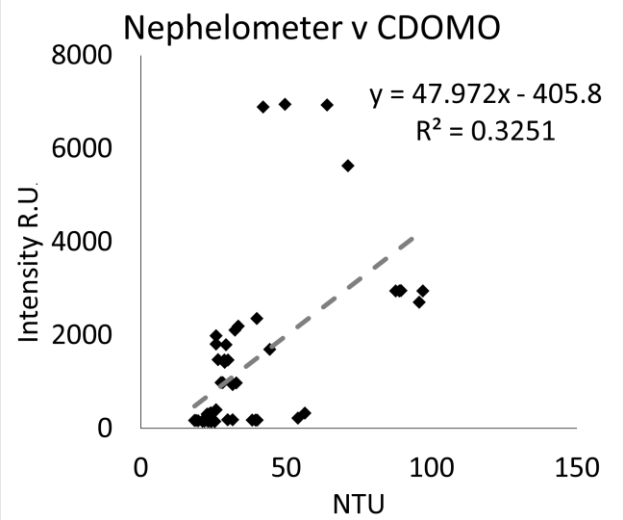

Nephelometer v Peak T
Intensity R.U.
NTU
y = 0.0062x + 0.8297
R² = 0.1428

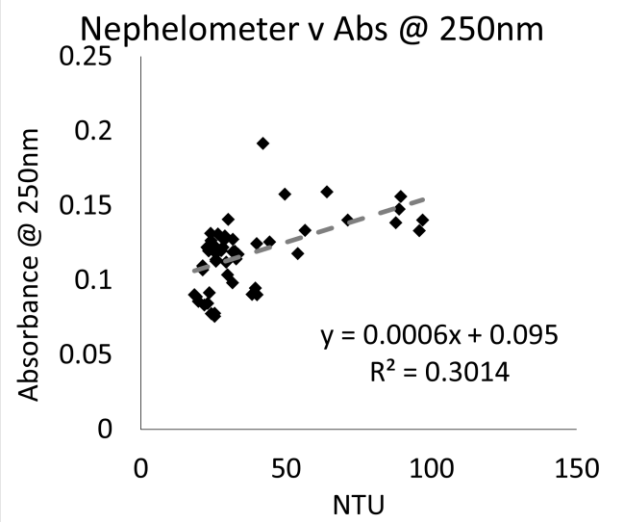

Nephelometer v Peak C
Intensity R.U.
NTU
y = 0.0088x + 1.2846
R² = 0.0896

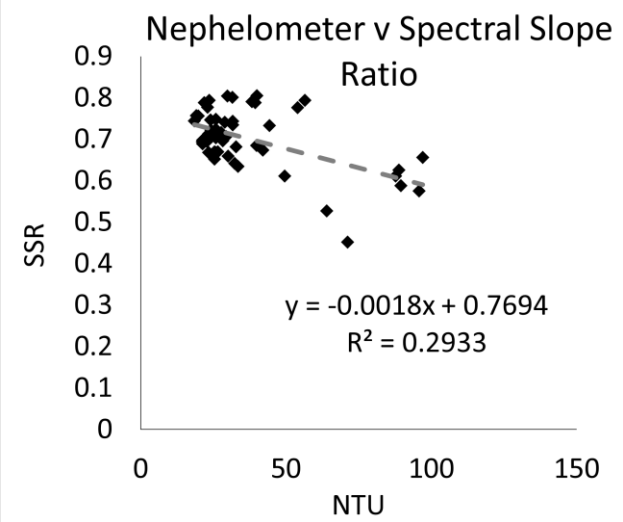

Nephelometer v Peak M
Intensity R.U.
NTU
y = 0.006x + 1.2954
R² = 0.0792


Nephelometer v TrypEEM
Intensity R.U.
NTU
y = 0.0054x + 0.9203
R² = 0.111


Nephelometer v CDOM-EEM
Intensity R.U.
NTU
y = 0.0044x + 0.9008
R² = 0.0758

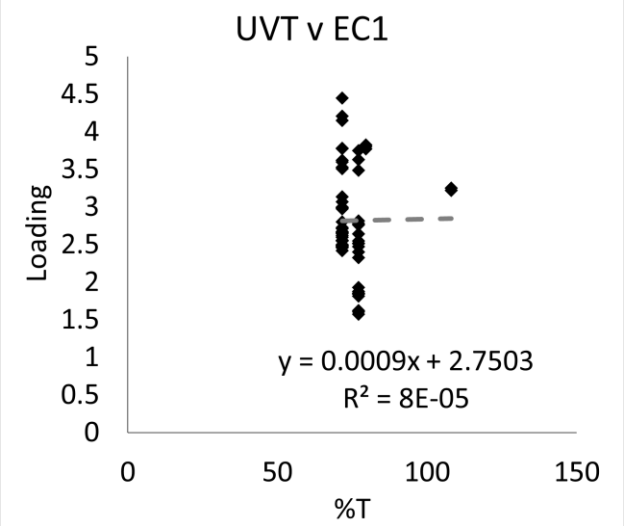

Nephelometer v CDOMO
Intensity R.U
NTU
y = 47.972x - 405.8
R² = 0.3251

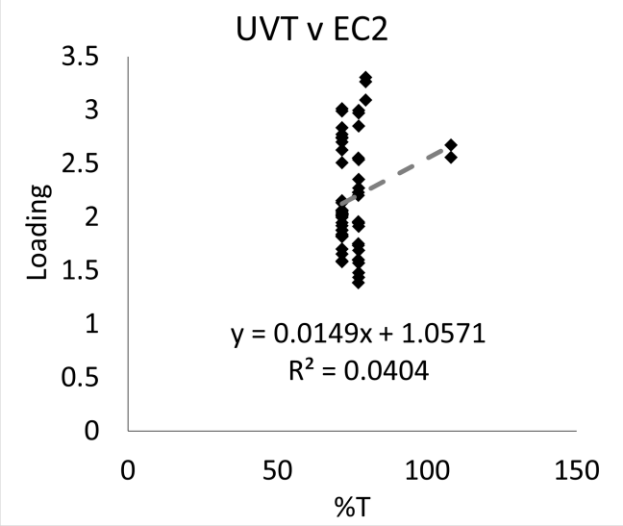

Nephelometer v Abs @ 250nm
Absorbance @ 250nm
NTU
y = 0.0006x + 0.095
R² = 0.3014

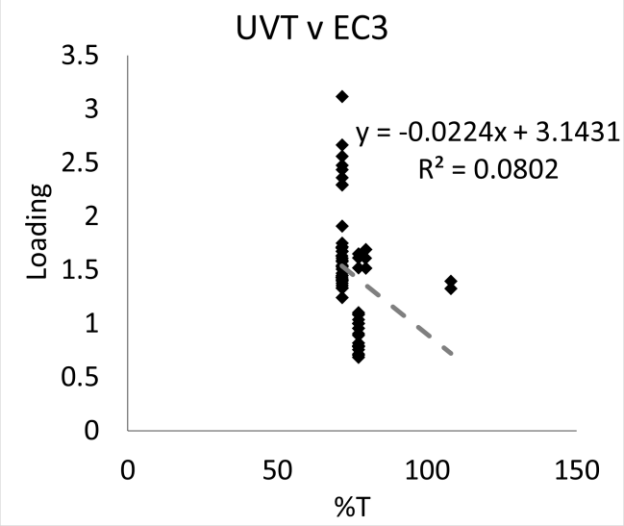

Nephelometer v Spectral Slope Ratio
SSR
NTU
y = -0.0018x + 0.7694
R² = 0.2933

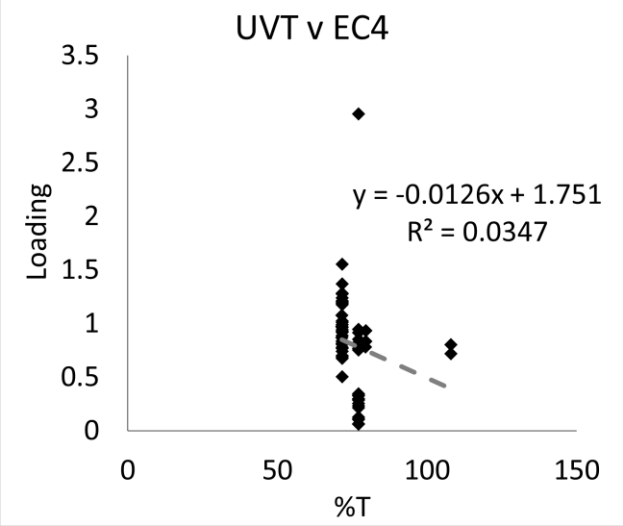
UV transmittance – online

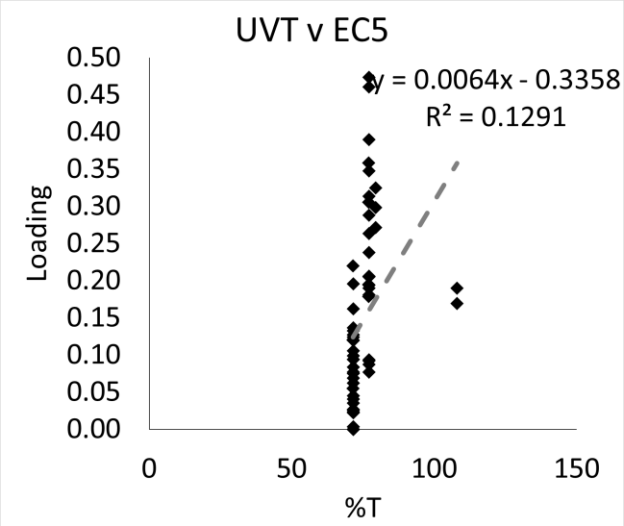
Effluent

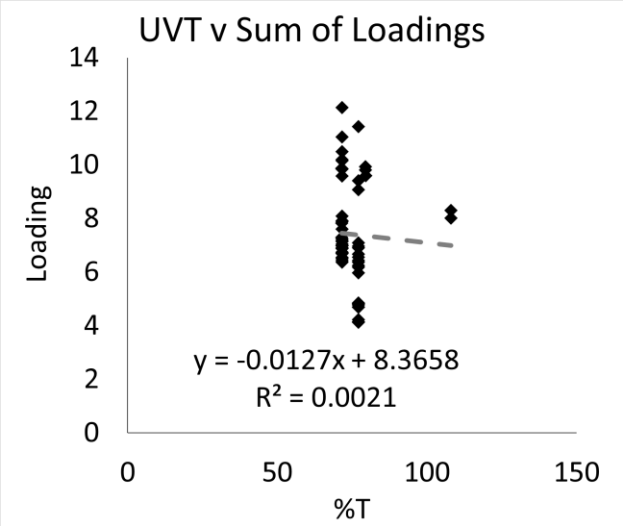


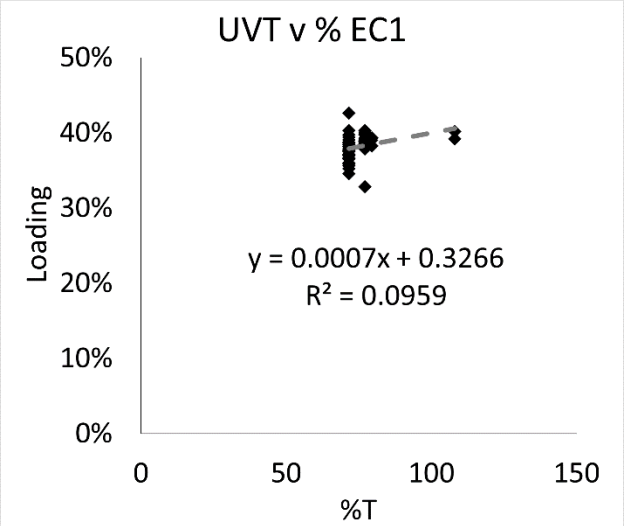


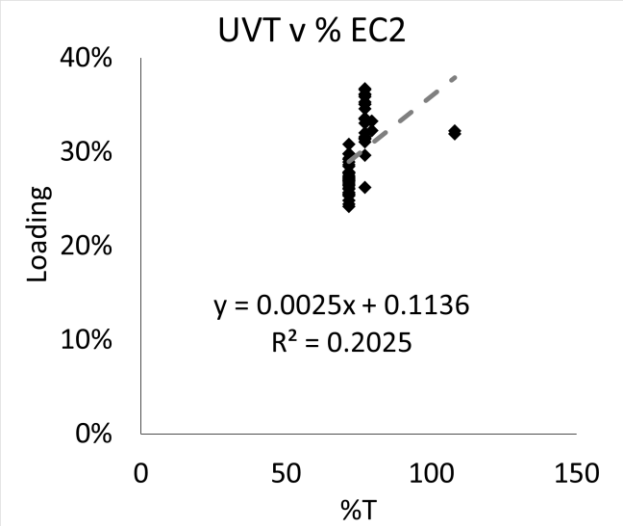


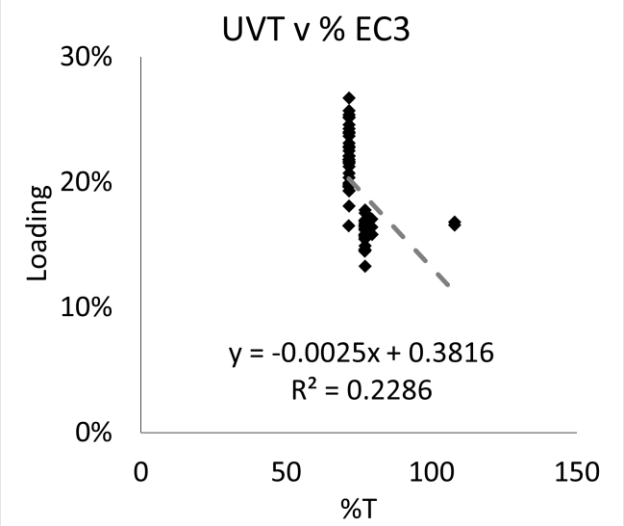


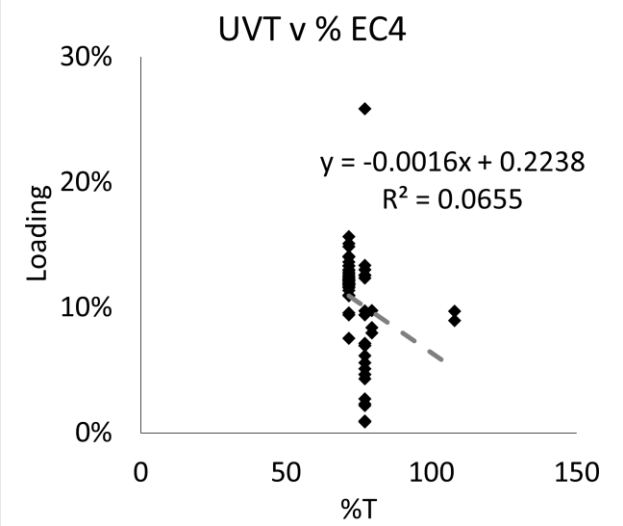

UVT v EC5
y = 0.0064x - 0.3358
R² = 0.1291
Loading
%T
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
50
100
150

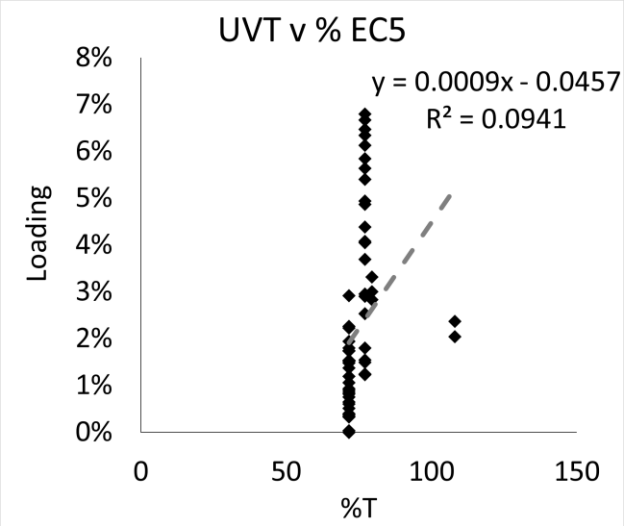

UVT v Sum of Loadings
y = -0.0127x + 8.3658
R² = 0.0021
Loading
%T
14
12
10
8
6
4
2
0
0
50
100
150

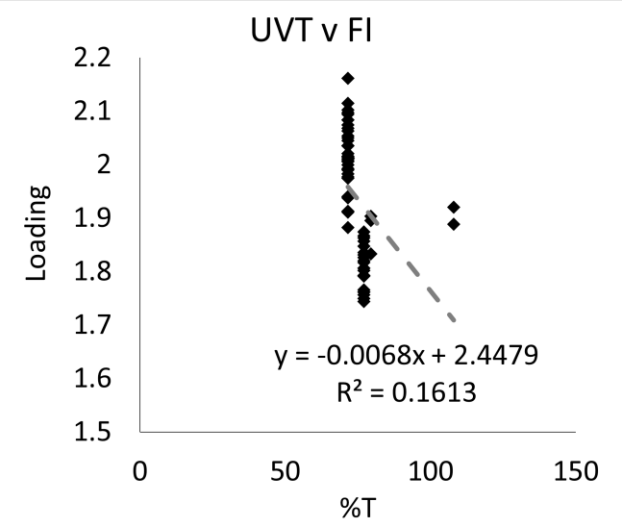

UVT v % EC1
y = 0.0007x + 0.3266
R² = 0.0959
Loading
%T
50%
40%
30%
20%
10%
0%
0
50
100
150

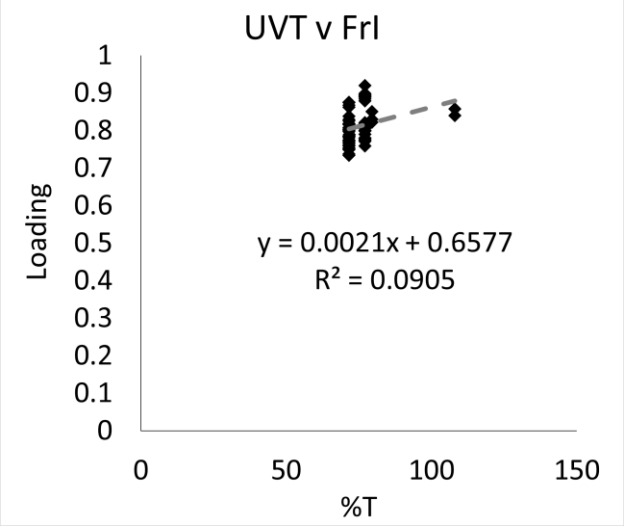

UVT v % EC2
y = 0.0025x + 0.1136
R² = 0.2025
Loading
%T
40%
30%
20%
10%
0%
0
50
100
150

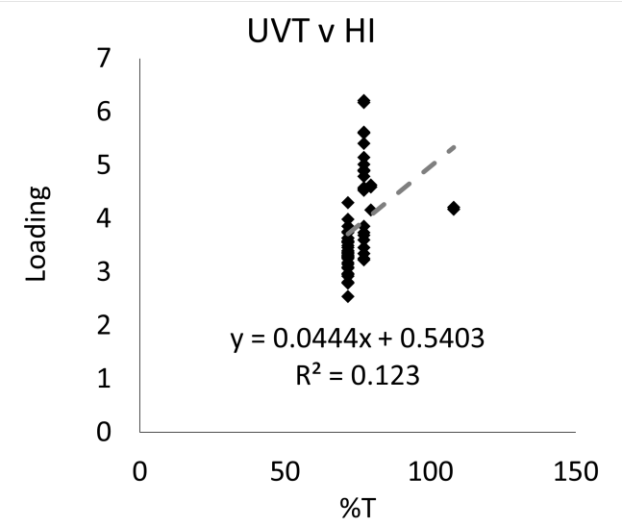

UVT v % EC3
y = -0.0025x + 0.3816
R² = 0.2286
Loading
%T
30%
20%
10%
0%
0
50
100
150

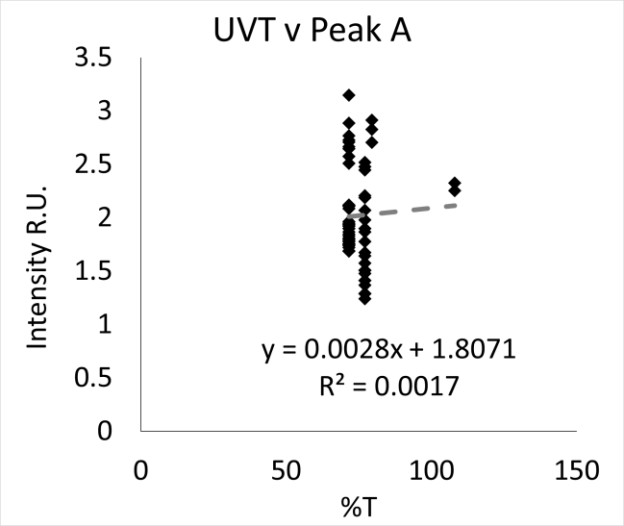

UVT v % EC4
y = -0.0016x + 0.2238
R² = 0.0655
Loading
%T
30%
20%
10%
0%
0
50
100
150

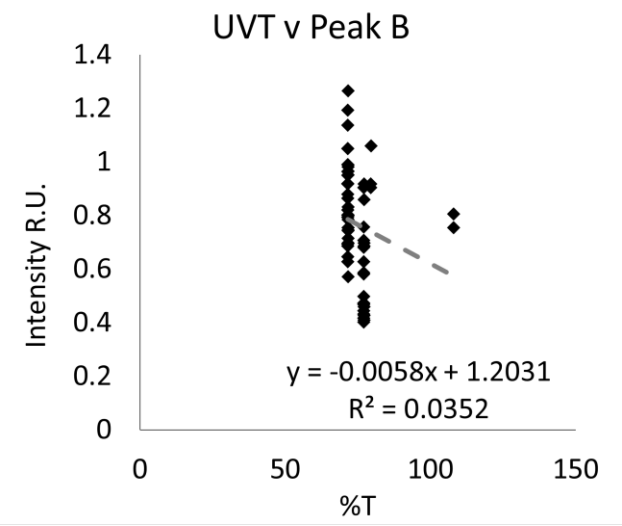

UVT v % EC5
y = 0.0009x - 0.0457
R² = 0.0941
Loading
%T
8%
7%
6%
5%
4%
3%
2%
1%
0%
0
50
100
150

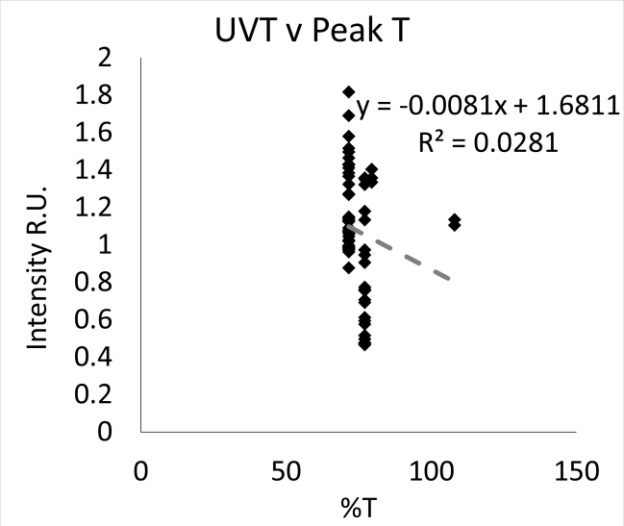

UVT v FI
y = -0.0068x + 2.4479
R² = 0.1613
Loading
%T
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
0
50
100
150

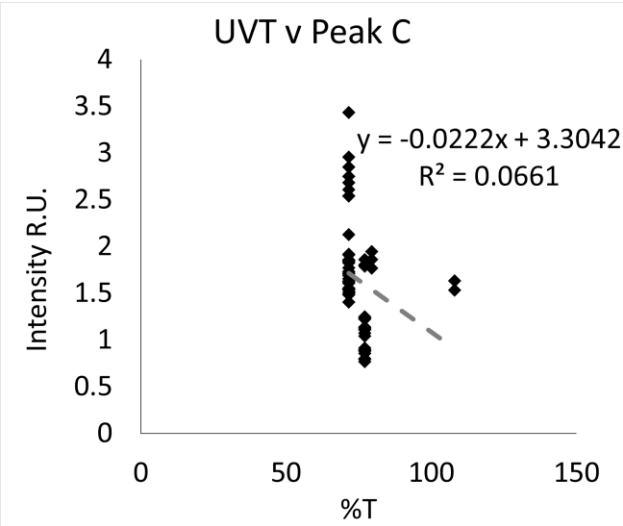

UVT v FrI
y = 0.0021x + 0.6577
R² = 0.0905
Loading
%T
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
50
100
150

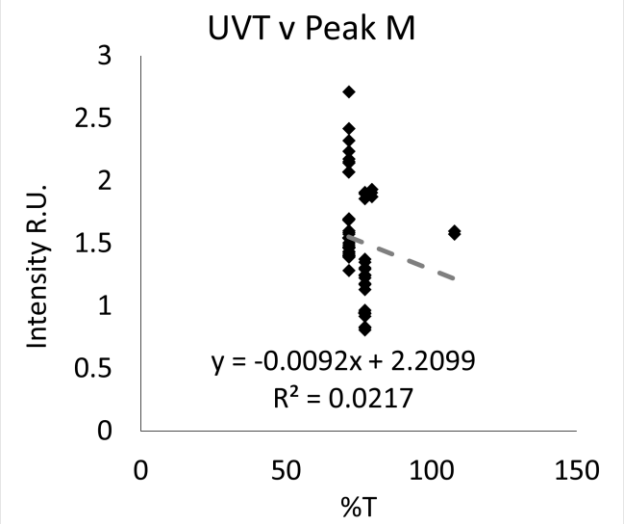

UVT v HI
y = 0.0444x + 0.5403
R² = 0.123
Loading
%T
7
6
5
4
3
2
1
0
0
50
100
150

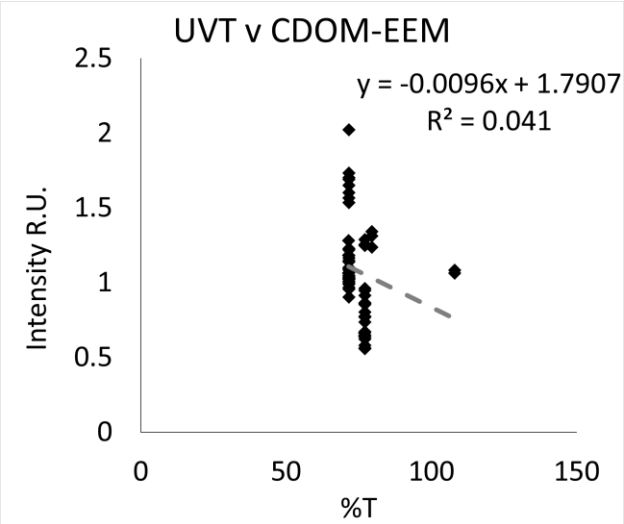

UVT v Peak A
y = 0.0028x + 1.8071
R² = 0.0017
Intensity R.U.
%T
3.5
3
2.5
2
1.5
1
0.5
0
0
50
100
150

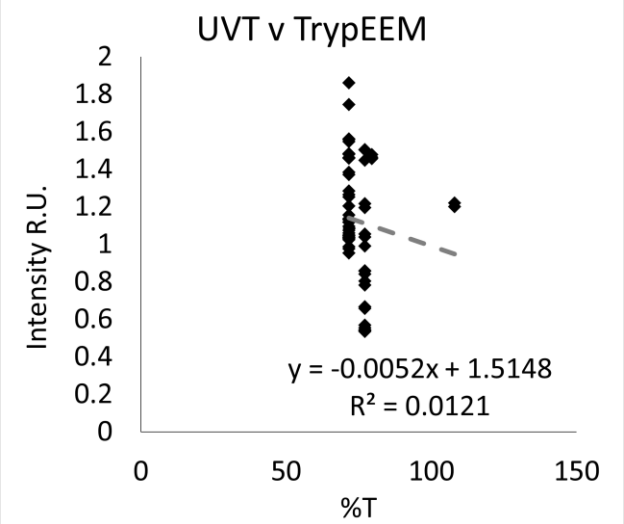

UVT v Peak B
y = -0.0058x + 1.2031
R² = 0.0352
Intensity R.U.
%T
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0
50
100
150

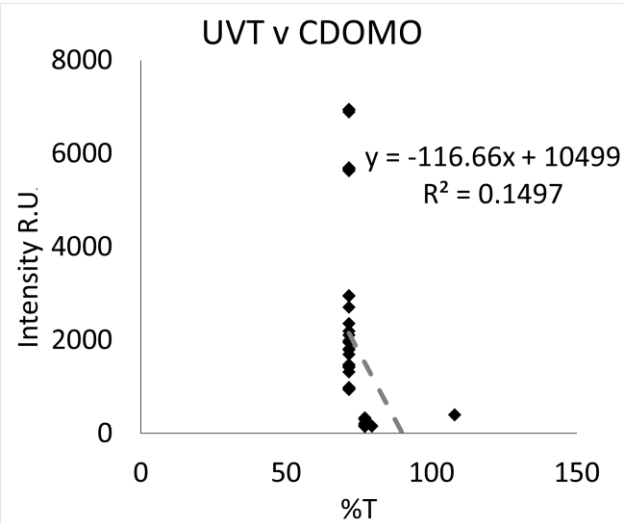

UVT v Peak T
y = -0.0081x + 1.6811
R² = 0.0281
Intensity R.U.
%T

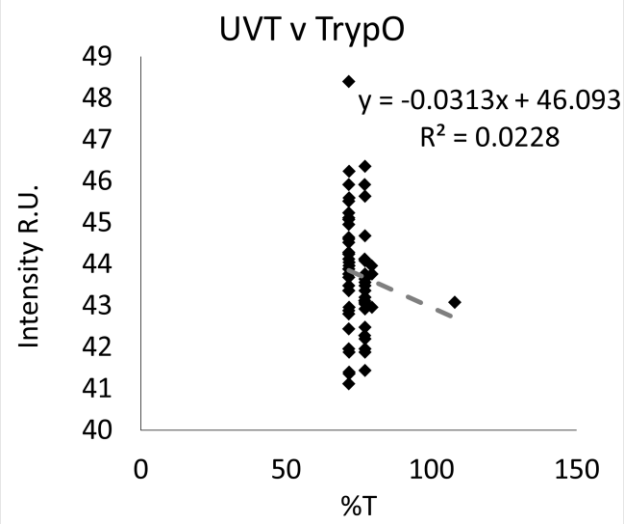

UVT v Peak C
y = -0.0222x + 3.3042
R² = 0.0661
Intensity R.U.
%T

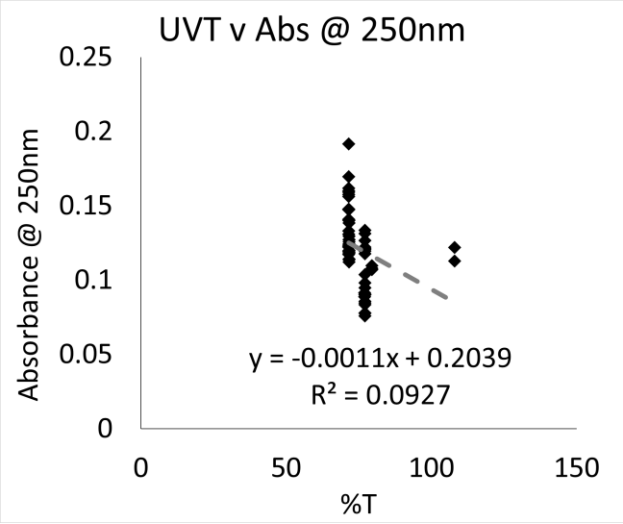

UVT v Peak M
y = -0.0092x + 2.2099
R² = 0.0217
Intensity R.U.
%T

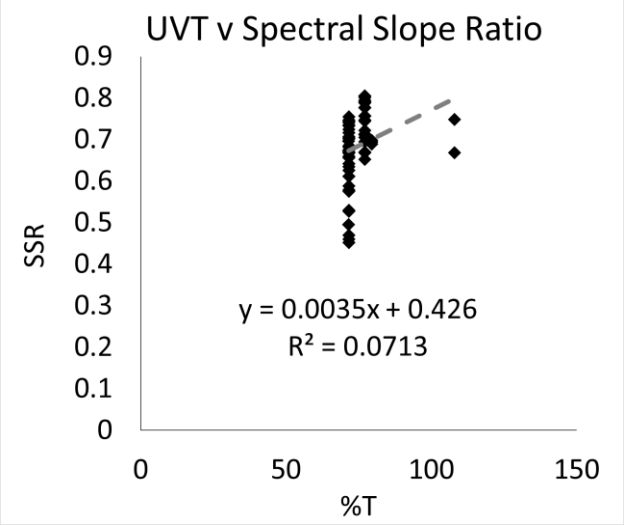

UVT v CDOM-EEM
y = -0.0096x + 1.7907
R² = 0.041
Intensity R.U.
%T


UVT v TrypEEM
y = -0.0052x + 1.5148
R² = 0.0121
Intensity R.U.
%T


UVT v CDOMO
y = -116.66x + 10499
R² = 0.1497
Intensity R.U.
%T

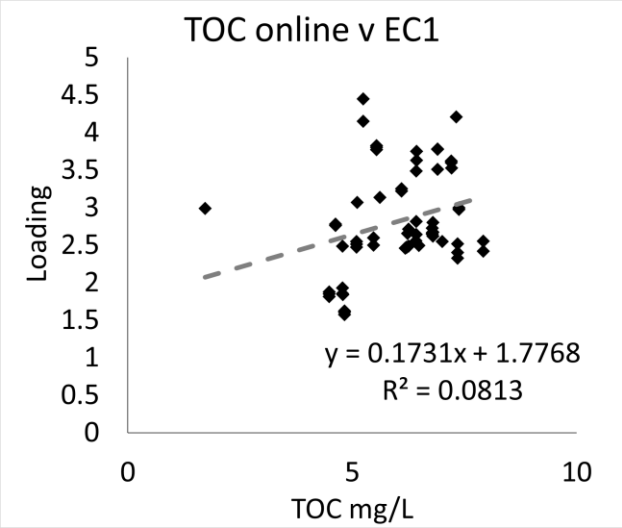


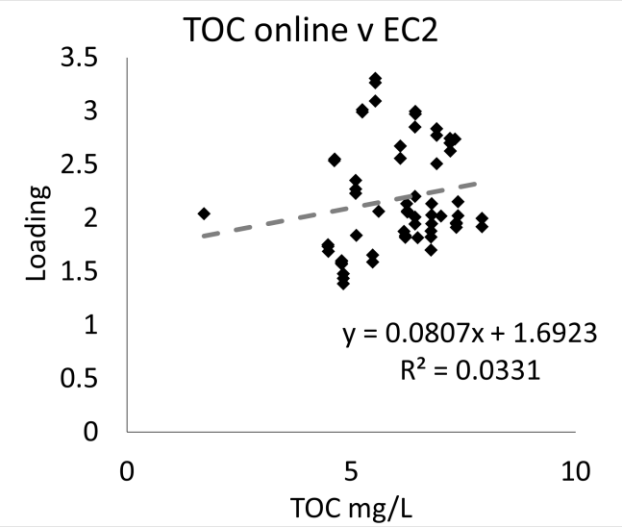


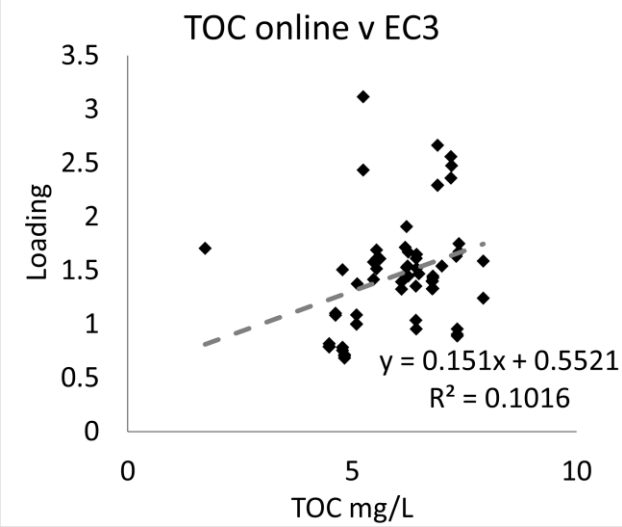


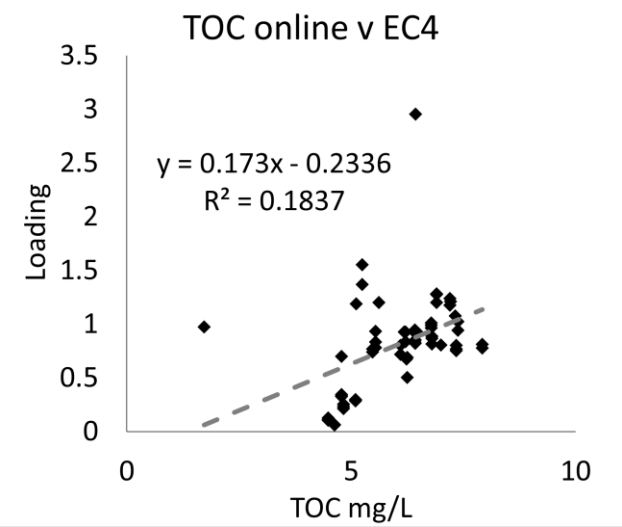
Total organic carbon – online

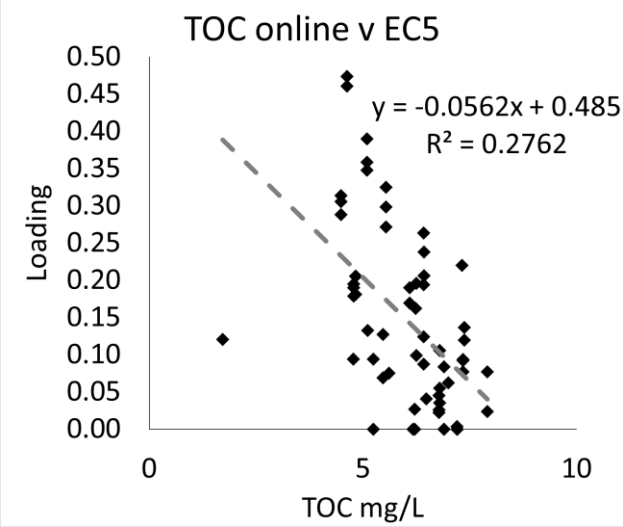
Effluent

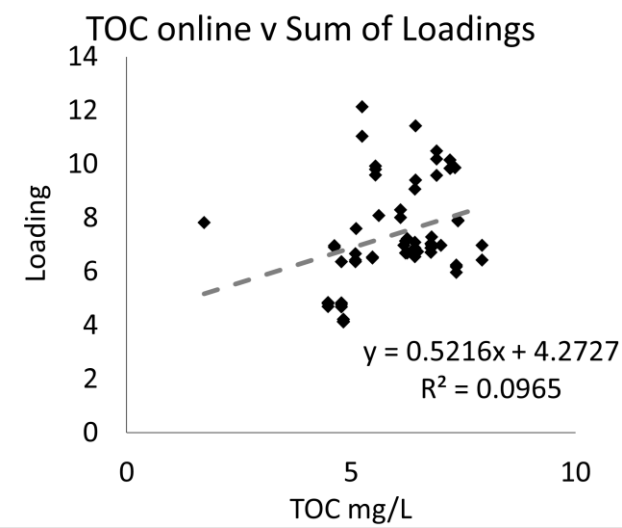

TOC online v EC1
Loading
TOC mg/L
y = 0.1731x + 1.7768
R² = 0.0813

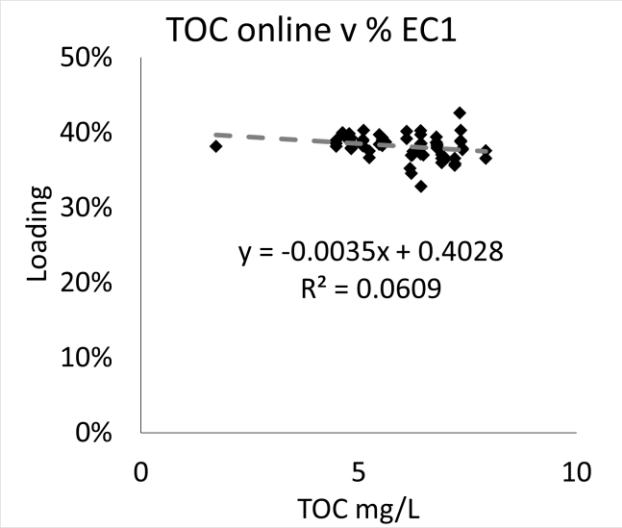

TOC online v EC2
Loading
TOC mg/L
y = 0.0807x + 1.6923
R² = 0.0331

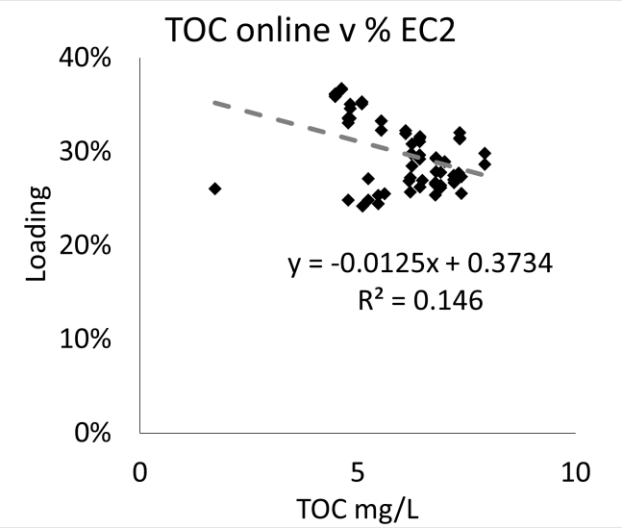

TOC online v EC3
Loading
TOC mg/L
y = 0.151x + 0.5521
R² = 0.1016

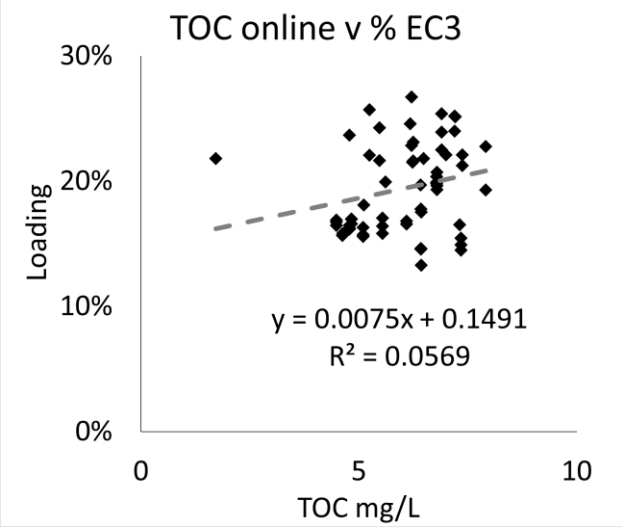

TOC online v EC4
Loading
TOC mg/L
y = 0.173x - 0.2336
R² = 0.1837

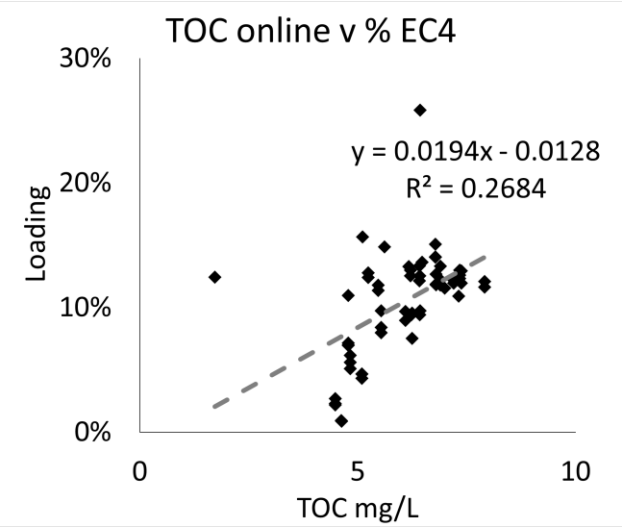

TOC online v EC5
Loading
TOC mg/L
y = -0.0562x + 0.485
R² = 0.2762

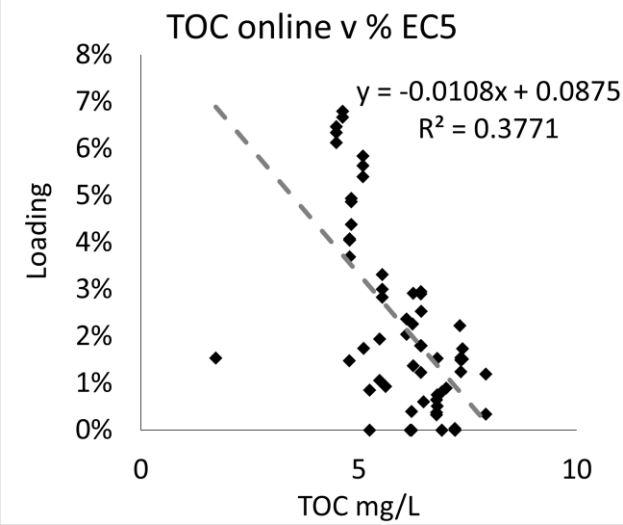

TOC online v Sum of Loadings
Loading
TOC mg/L
y = 0.5216x + 4.2727
R² = 0.0965

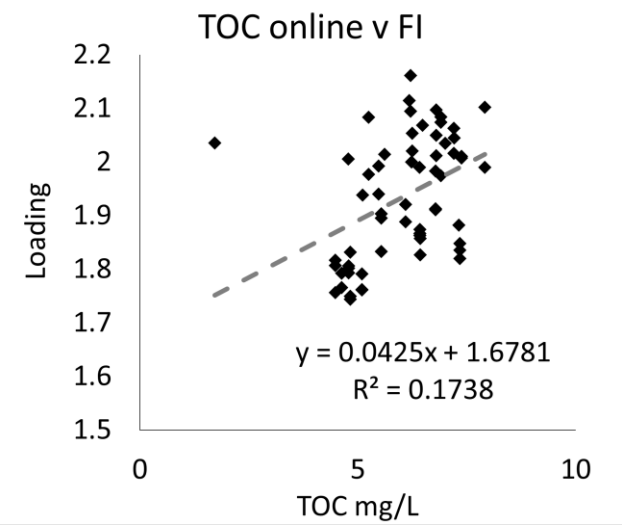

TOC online v % EC1
50%
40%
30%
20%
10%
0%
Loading
y = -0.0035x + 0.4028
R² = 0.0609
0
5
10
TOC mg/L

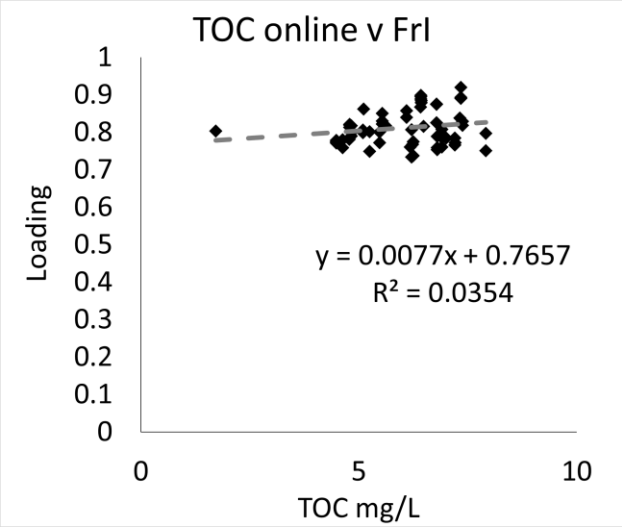

TOC online v % EC2
40%
30%
20%
10%
0%
Loading
y = -0.0125x + 0.3734
R² = 0.146
0
5
10
TOC mg/L

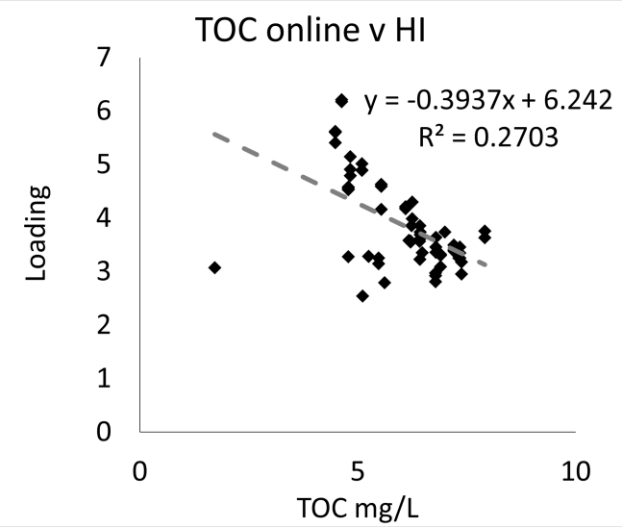

TOC online v % EC3
30%
20%
10%
0%
Loading
y = 0.0075x + 0.1491
R² = 0.0569
0
5
10
TOC mg/L

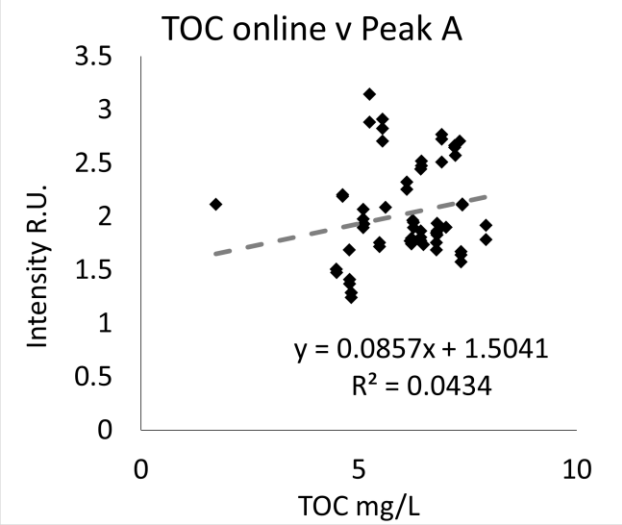

TOC online v % EC4
30%
20%
10%
0%
Loading
y = 0.0194x - 0.0128
R² = 0.2684
0
5
10
TOC mg/L

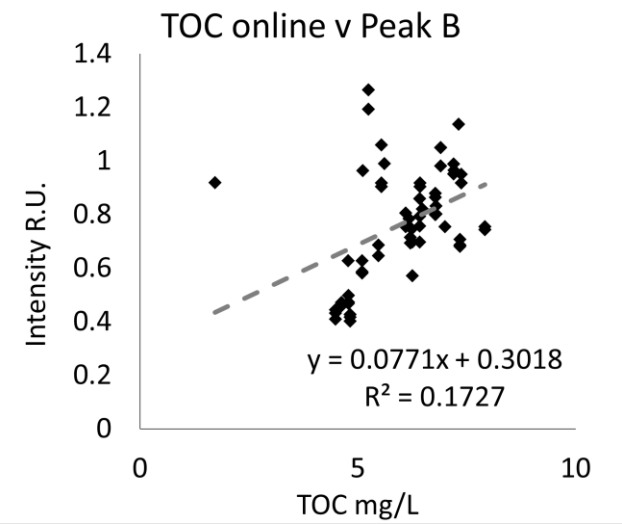

TOC online v % EC5
8%
7%
6%
5%
4%
3%
2%
1%
0%
Loading
y = -0.0108x + 0.0875
R² = 0.3771
0
5
10
TOC mg/L

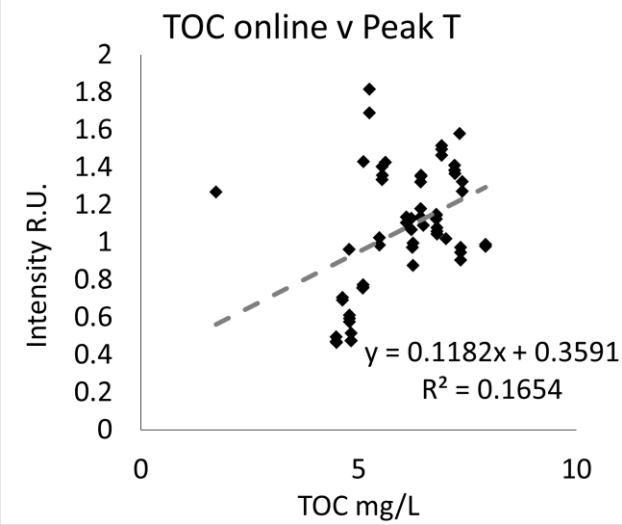

TOC online v FI
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
Loading
y = 0.0425x + 1.6781
R² = 0.1738
0
5
10
TOC mg/L

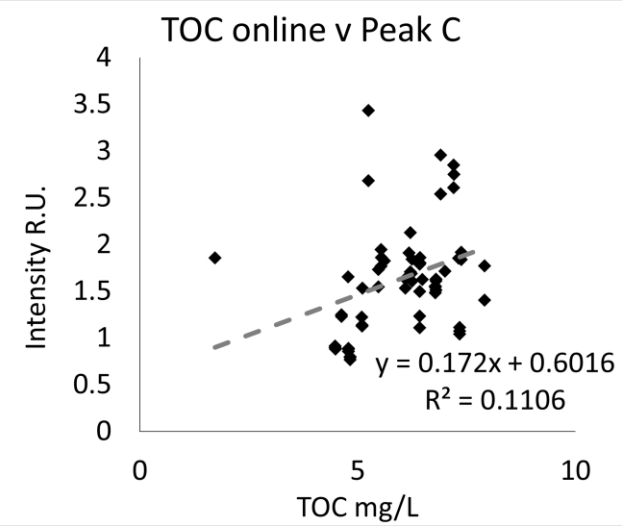

TOC online v FrI
Loading
TOC mg/L
y = 0.0077x + 0.7657
R² = 0.0354

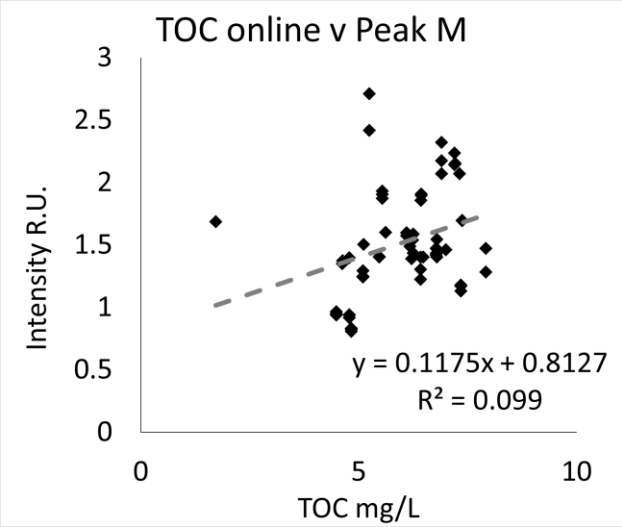

TOC online v HI
Loading
TOC mg/L
y = -0.3937x + 6.242
R² = 0.2703

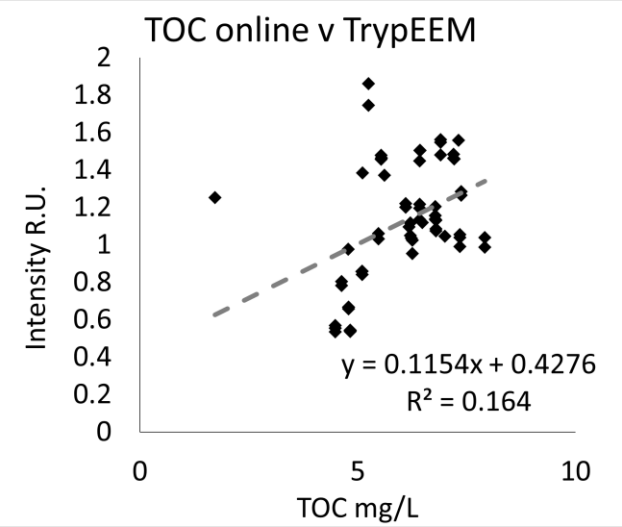

TOC online v Peak A
Intensity R.U.
TOC mg/L
y = 0.0857x + 1.5041
R² = 0.0434

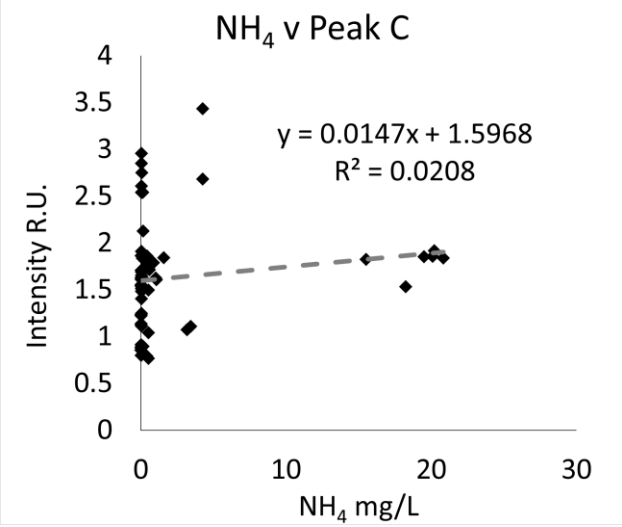

TOC online v Peak B
Intensity R.U.
TOC mg/L
y = 0.0771x + 0.3018
R² = 0.1727

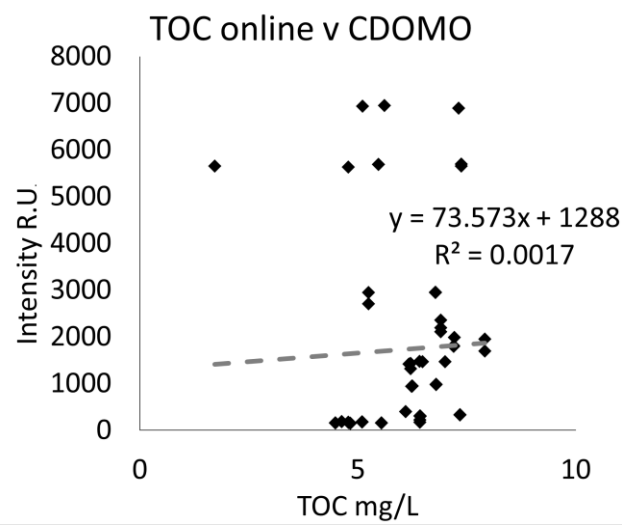

TOC online v Peak T
Intensity R.U.
TOC mg/L
y = 0.1182x + 0.3591
R² = 0.1654

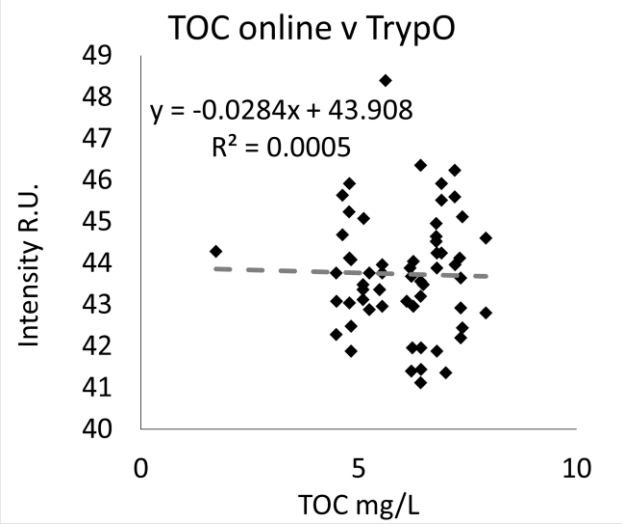

TOC online v Peak C
Intensity R.U.
TOC mg/L
y = 0.172x + 0.6016
R² = 0.1106

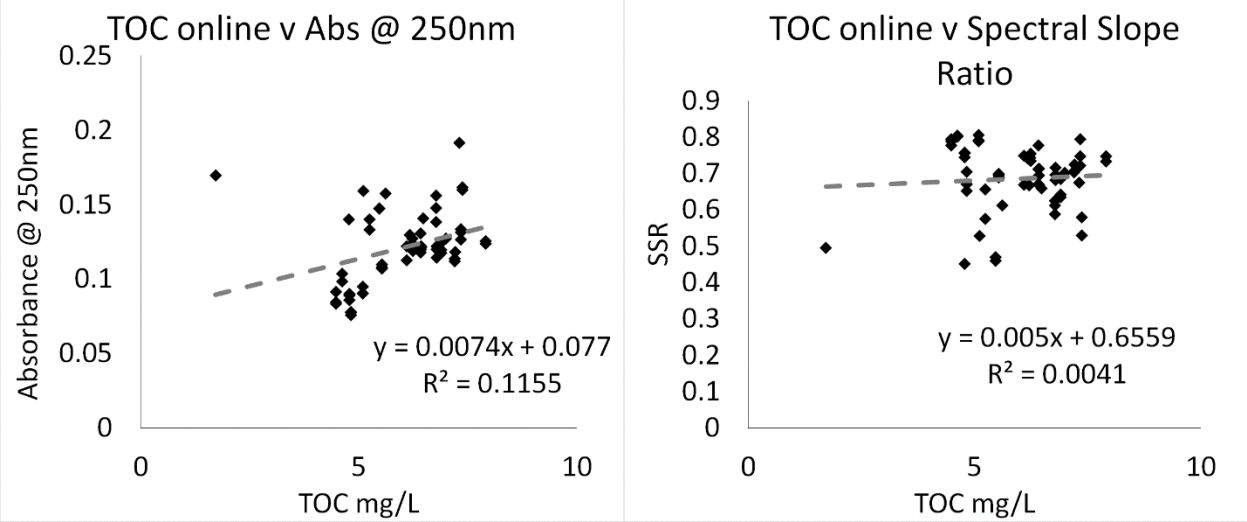

TOC online v Peak M
Intensity R.U.
TOC mg/L
y = 0.1175x + 0.8127
R² = 0.099


TOC online v TrypEEM
Intensity R.U.
TOC mg/L
y = 0.1154x + 0.4276
R² = 0.164


NH4 v Peak C
Intensity R.U.
NH4 mg/L
y = 0.0147x + 1.5968
R² = 0.0208

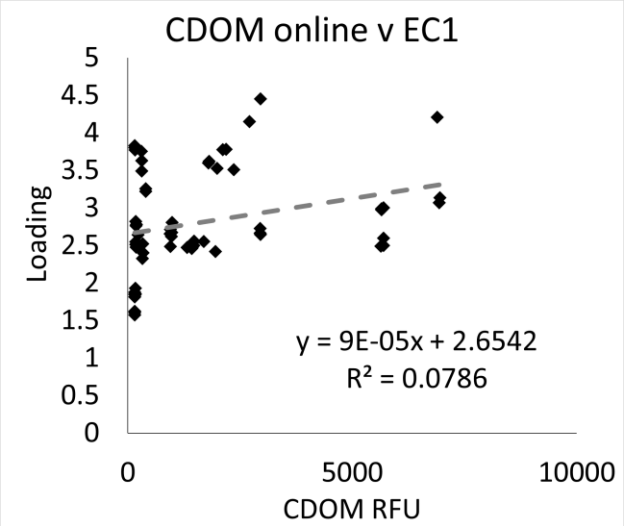

TOC online v CDOMO
Intensity R.U
TOC mg/L
y = 73.573x + 1288
R² = 0.0017

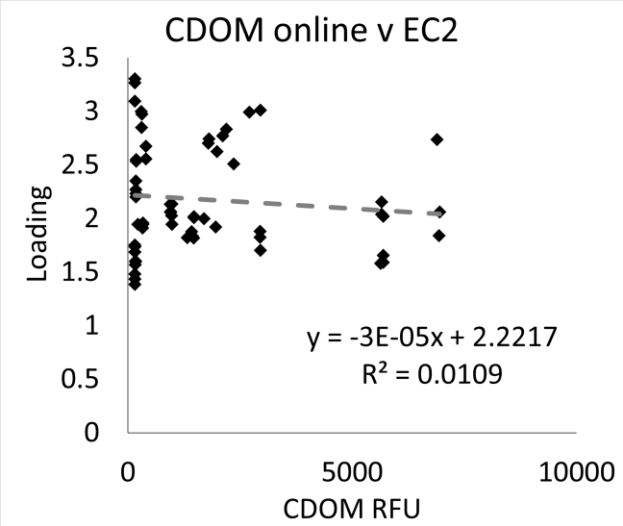

TOC online v TrypO
Intensity R.U.
TOC mg/L
y = -0.0284x + 43.908
R² = 0.0005

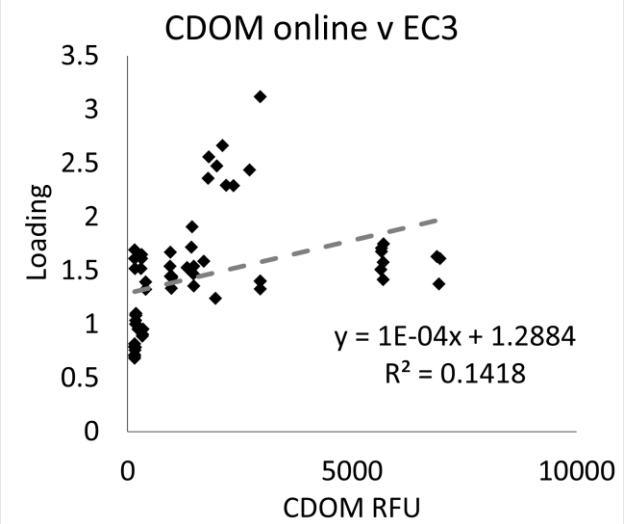


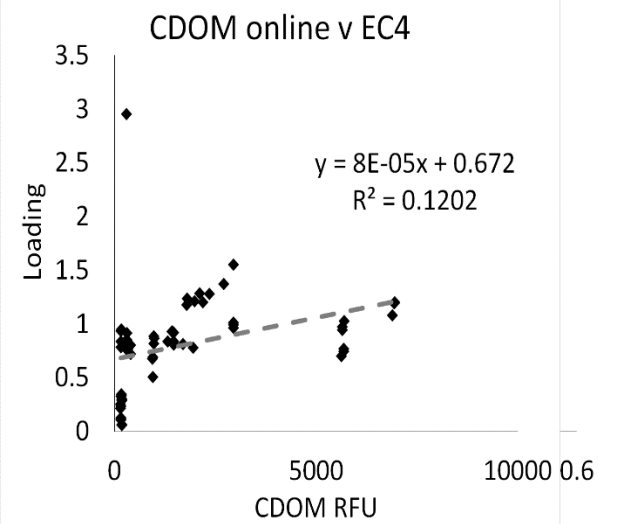
Chromophoric dissolved organic matter fluorescence- online

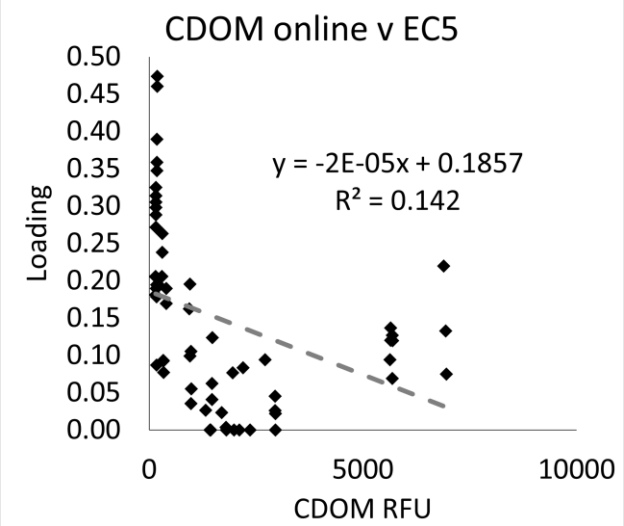
Effluent

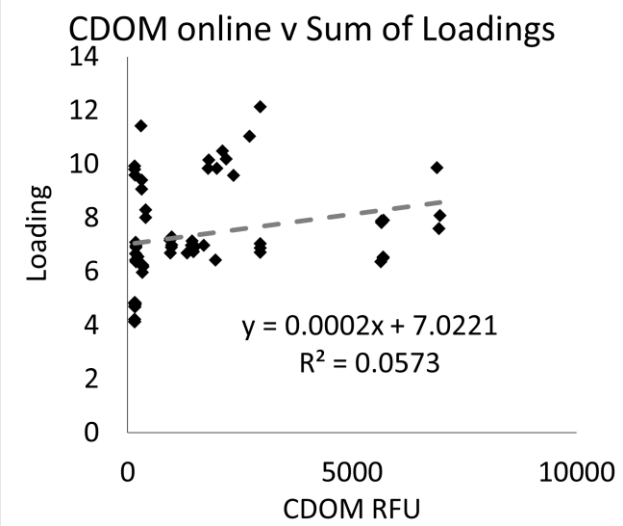

CDOM online v EC1
Loading
CDOM RFU
y = 9E-05x + 2.6542
R² = 0.0786
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
0
5000
10000

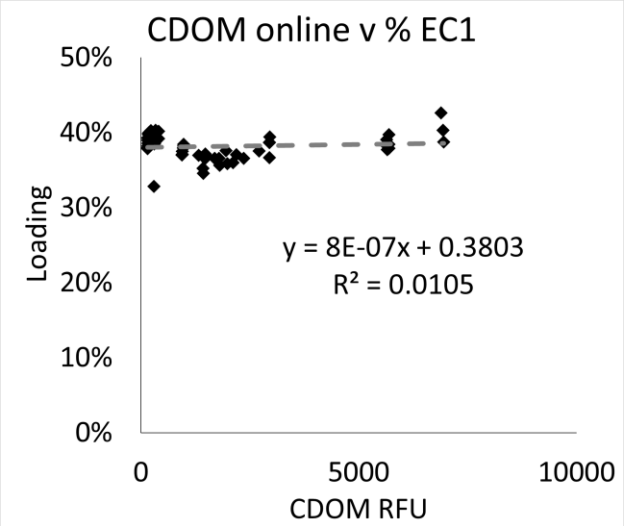

CDOM online v EC2
Loading
CDOM RFU
y = -3E-05x + 2.2217
R² = 0.0109
0
0.5
1
1.5
2
2.5
3
3.5
0
5000
10000

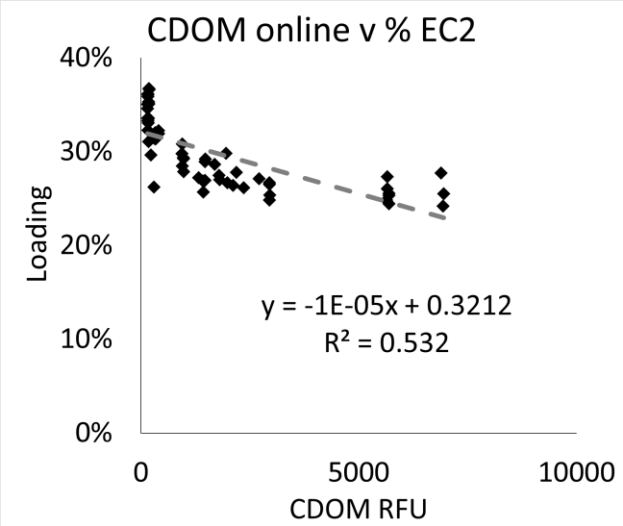

CDOM online v EC3
Loading
CDOM RFU
y = 1E-04x + 1.2884
R² = 0.1418
0
0.5
1
1.5
2
2.5
3
3.5
0
5000
10000

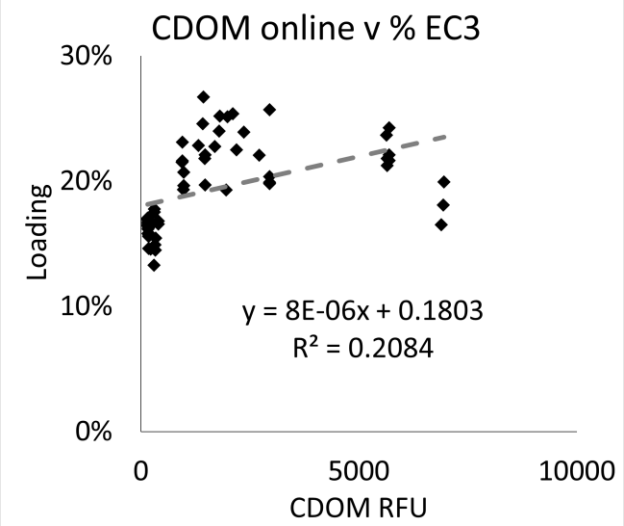

CDOM online v EC4
Loading
CDOM RFU
y = 8E-05x + 0.672
R² = 0.1202
0
0.5
1
1.5
2
2.5
3
3.5
0
5000
10000
0.6

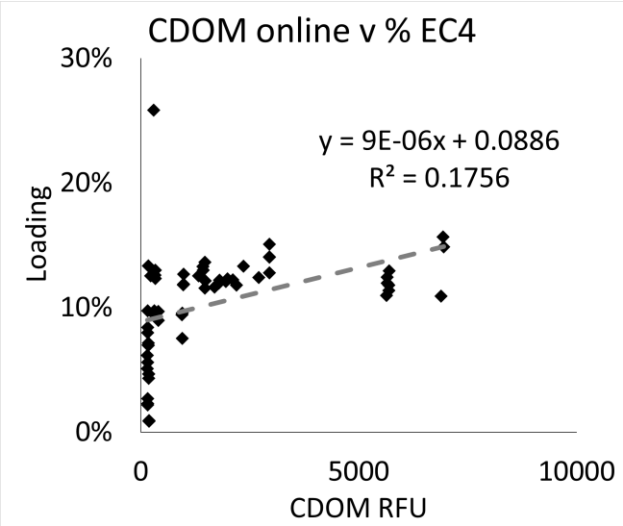

CDOM online v EC5
Loading
CDOM RFU
y = -2E-05x + 0.1857
R² = 0.142
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0.45
0.50
0
5000
10000

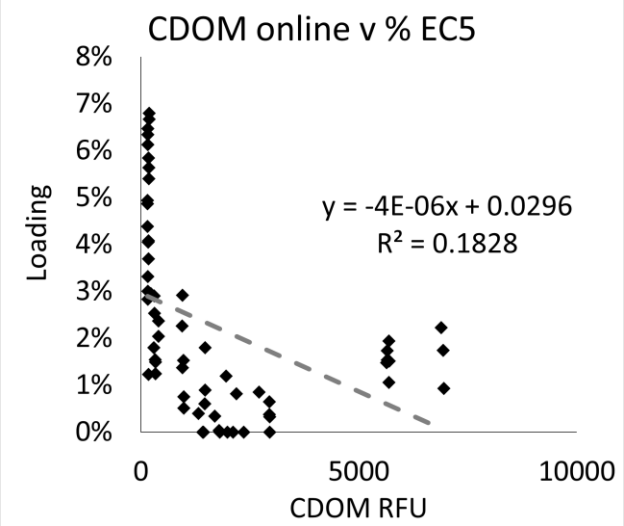

CDOM online v Sum of Loadings
Loading
CDOM RFU
y = 0.0002x + 7.0221
R² = 0.0573
0
2
4
6
8
10
12
14
0
5000
10000

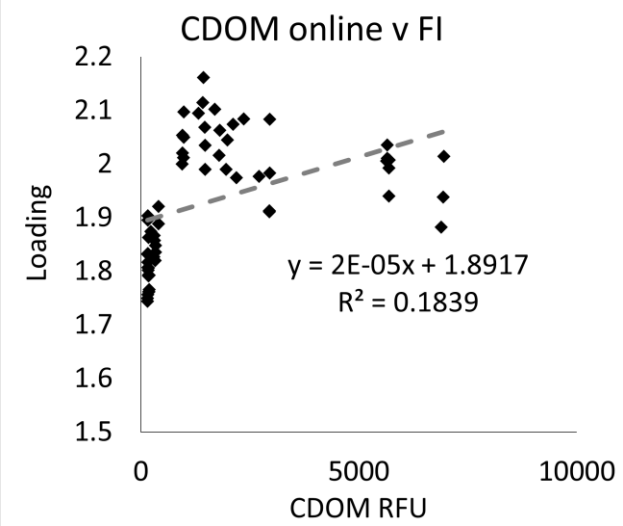

CDOM online v % EC1
Loading
50%
40%
30%
20%
10%
0%
y = 8E-07x + 0.3803
R² = 0.0105
0
5000
10000
CDOM RFU

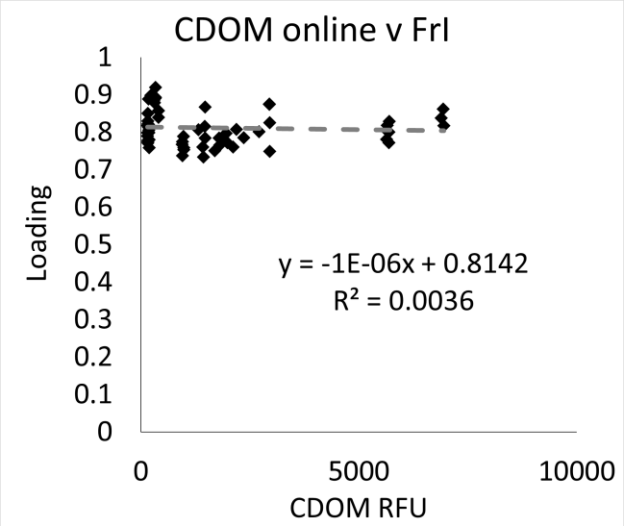

CDOM online v % EC2
Loading
40%
30%
20%
10%
0%
y = -1E-05x + 0.3212
R² = 0.532
0
5000
10000
CDOM RFU

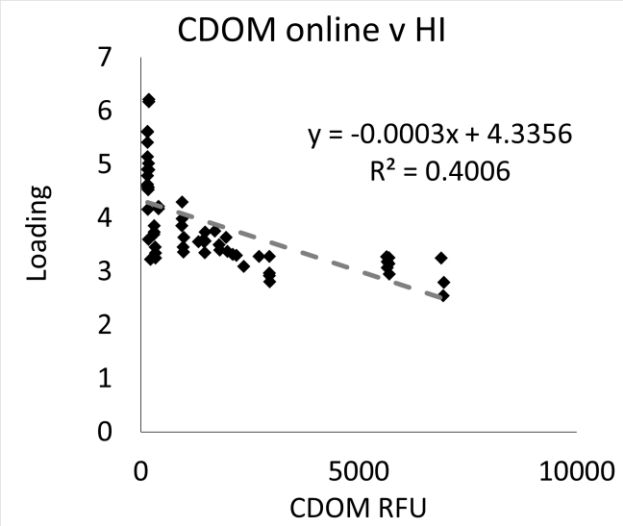

CDOM online v % EC3
Loading
30%
20%
10%
0%
y = 8E-06x + 0.1803
R² = 0.2084
0
5000
10000
CDOM RFU

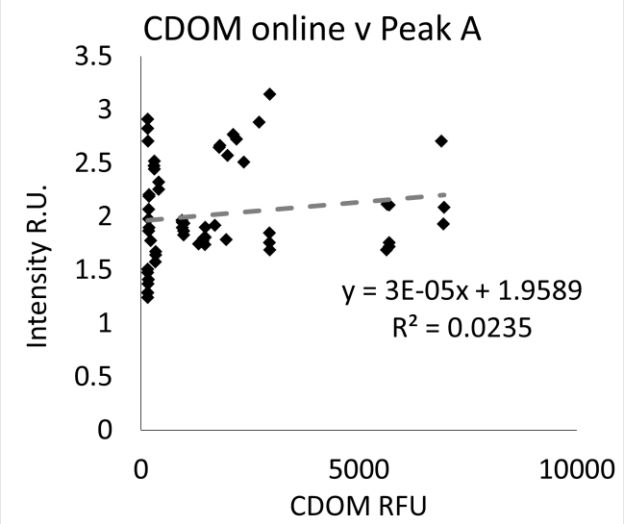

CDOM online v % EC4
Loading
30%
20%
10%
0%
y = 9E-06x + 0.0886
R² = 0.1756
0
5000
10000
CDOM RFU

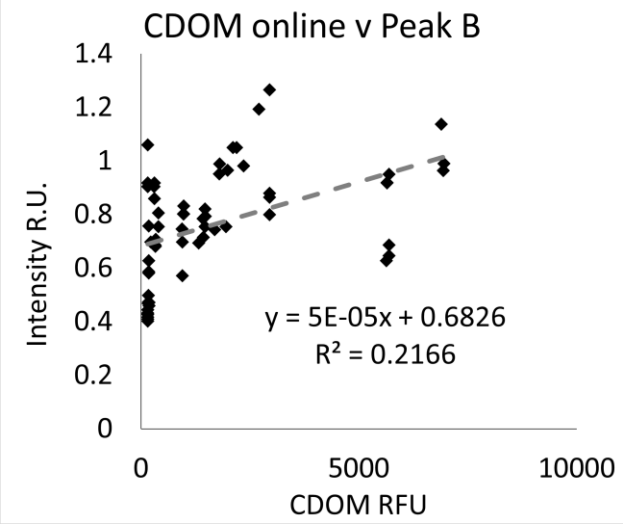

CDOM online v % EC5
Loading
8%
7%
6%
5%
4%
3%
2%
1%
0%
y = -4E-06x + 0.0296
R² = 0.1828
0
5000
10000
CDOM RFU

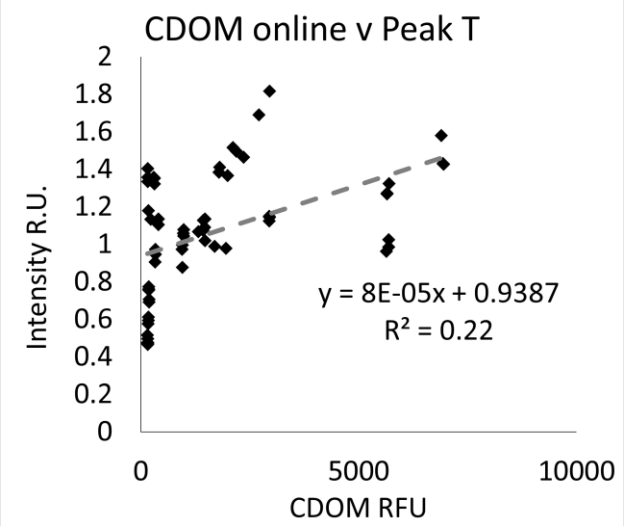

CDOM online v FI
Loading
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
y = 2E-05x + 1.8917
R² = 0.1839
0
5000
10000
CDOM RFU

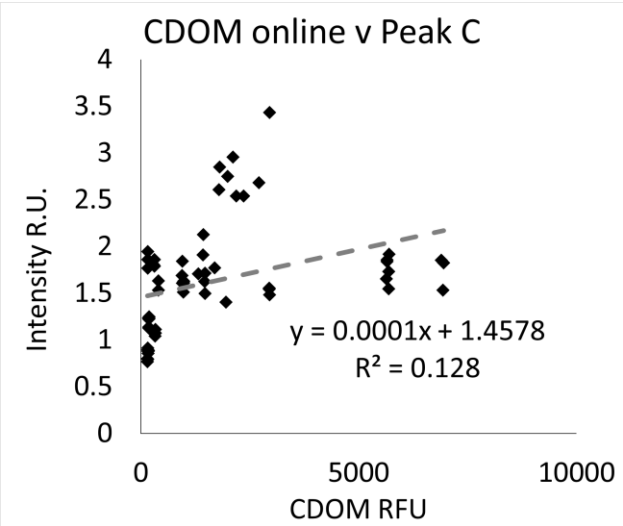

CDOM online v FrI
Loading
CDOM RFU
y = -1E-06x + 0.8142
R² = 0.0036
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
5000
10000

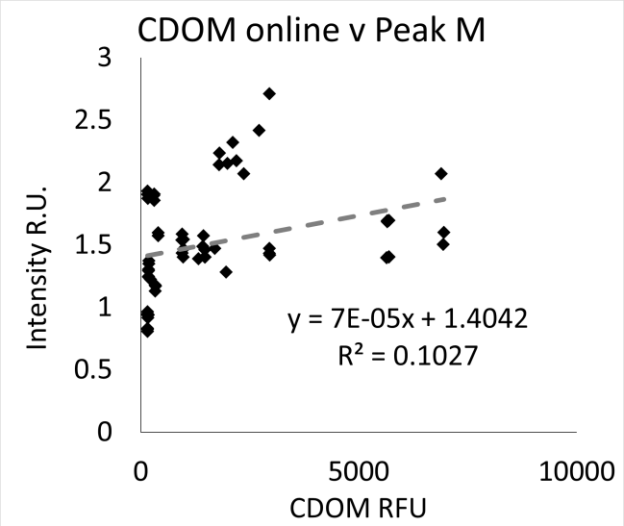

CDOM online v HI
Loading
CDOM RFU
y = -0.0003x + 4.3356
R² = 0.4006
0
1
2
3
4
5
6
7
0
5000
10000

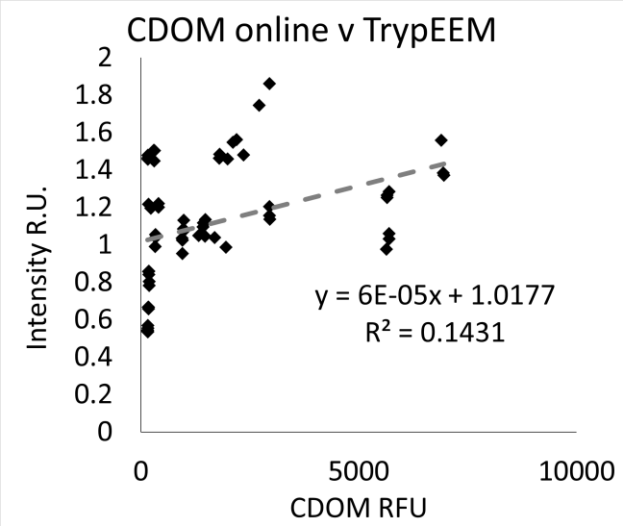

CDOM online v Peak A
Intensity R.U.
CDOM RFU
y = 3E-05x + 1.9589
R² = 0.0235
0
0.5
1
1.5
2
2.5
3
3.5
0
5000
10000

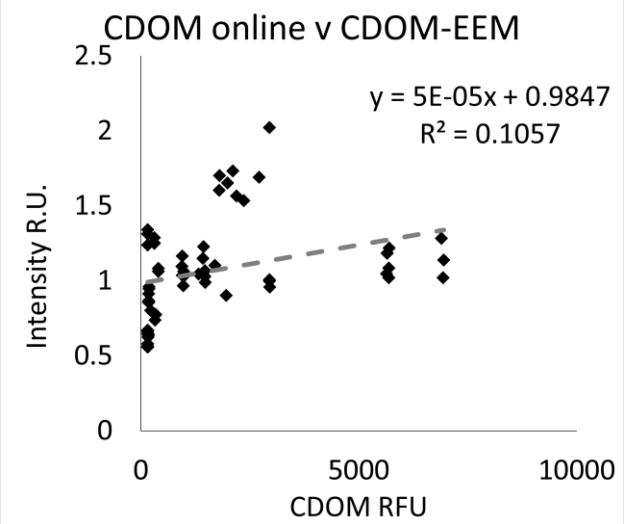

CDOM online v Peak B
Intensity R.U.
CDOM RFU
y = 5E-05x + 0.6826
R² = 0.2166
0
0.2
0.4
0.6
0.8
1
1.2
1.4
0
5000
10000

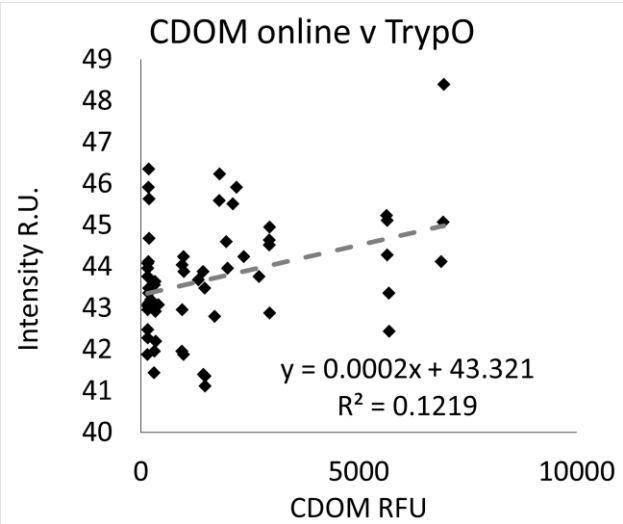

CDOM online v Peak T
Intensity R.U.
CDOM RFU
y = 8E-05x + 0.9387
R² = 0.22
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0
5000
10000

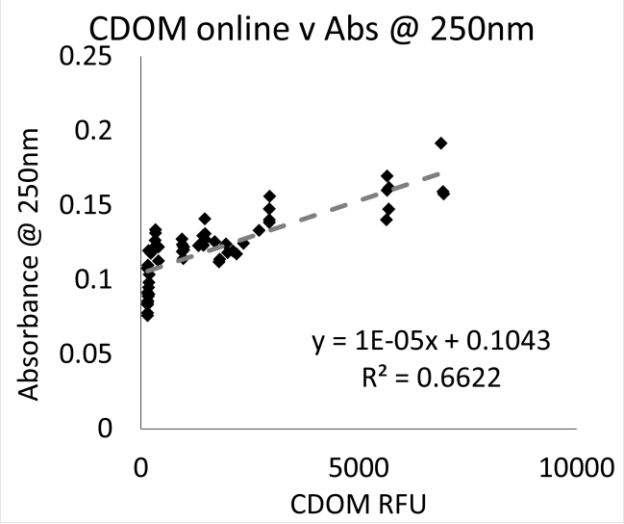

CDOM online v Peak C
Intensity R.U.
CDOM RFU
y = 0.0001x + 1.4578
R² = 0.128
0
0.5
1
1.5
2
2.5
3
3.5
4
0
5000
10000

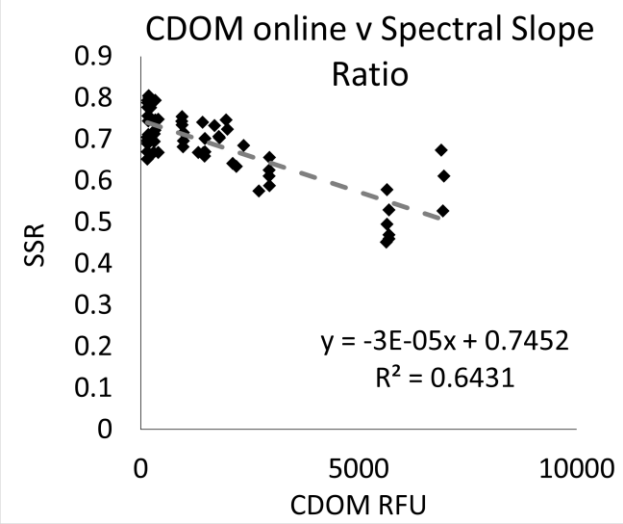

CDOM online v Peak M
Intensity R.U.
CDOM RFU
y = 7E-05x + 1.4042
R² = 0.1027
0
0.5
1
1.5
2
2.5
3
0
5000
10000


CDOM online v TrypEEM
Intensity R.U.
CDOM RFU
y = 6E-05x + 1.0177
R² = 0.1431
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0
5000
10000


CDOM online v CDOM-EEM
Intensity R.U.
CDOM RFU
y = 5E-05x + 0.9847
R² = 0.1057
0
0.5
1
1.5
2
2.5
0
5000
10000

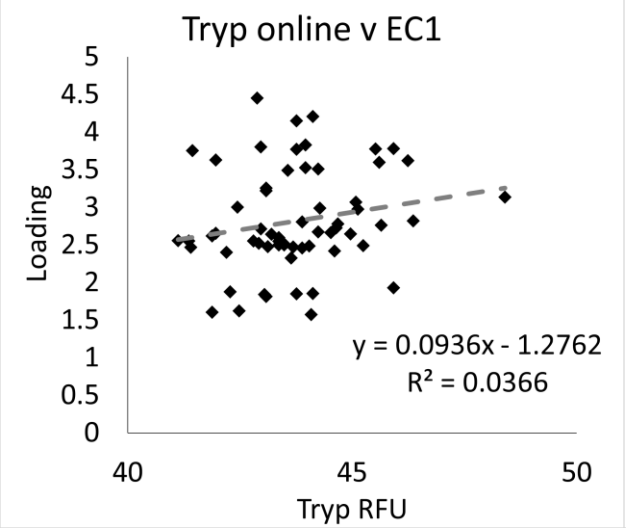

CDOM online v TrypO
Intensity R.U.
CDOM RFU
y = 0.0002x + 43.321
R² = 0.1219
40
41
42
43
44
45
46
47
48
49
0
5000
10000

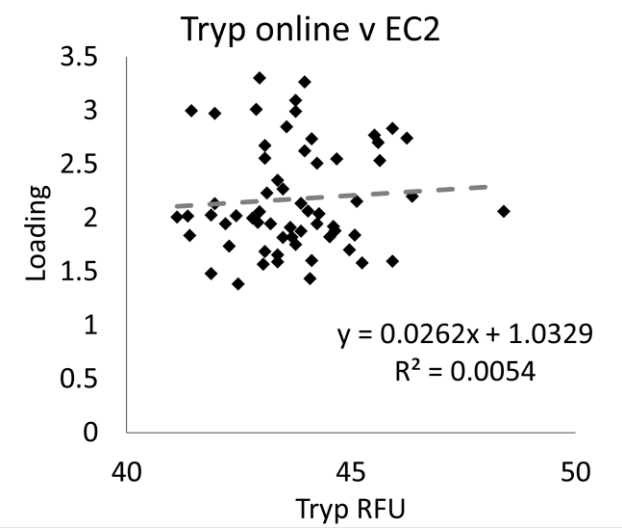

CDOM online v Abs @ 250nm
Absorbance @ 250nm
CDOM RFU
y = 1E-05x + 0.1043
R² = 0.6622
0
0.05
0.1
0.15
0.2
0.25
0
5000
10000

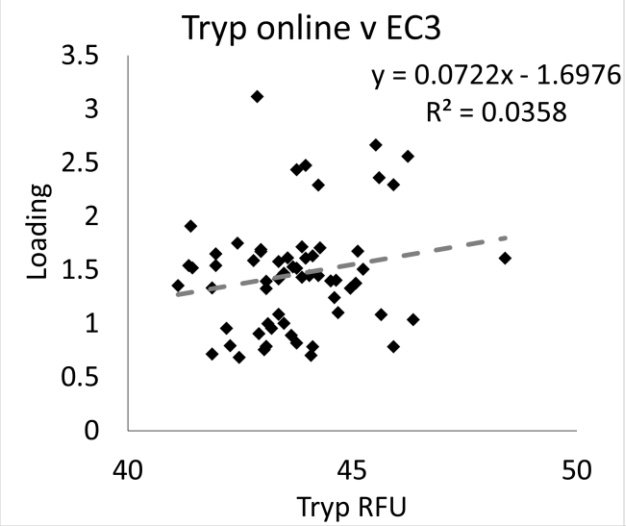

CDOM online v Spectral Slope Ratio
SSR
CDOM RFU
y = -3E-05x + 0.7452
R² = 0.6431
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0
5000
10000

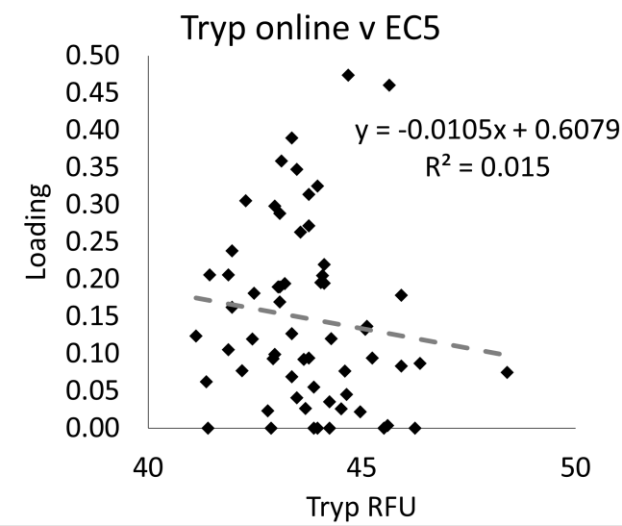
Tryptophan fluorescence – online

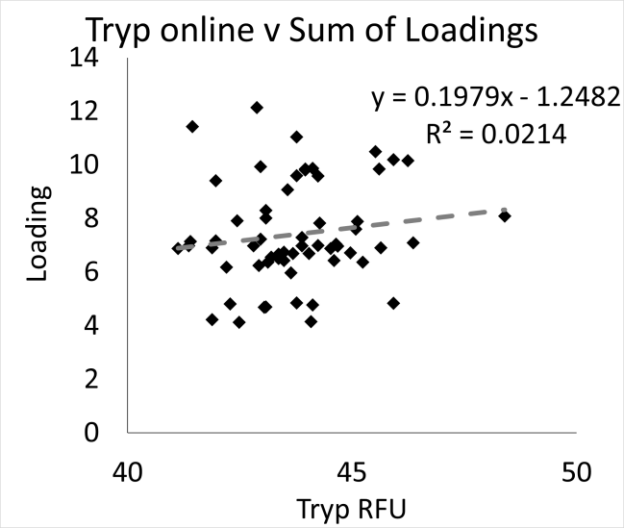
Effluent

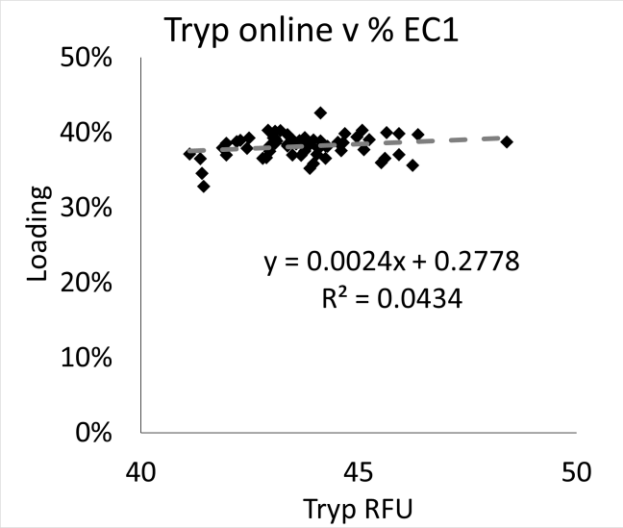


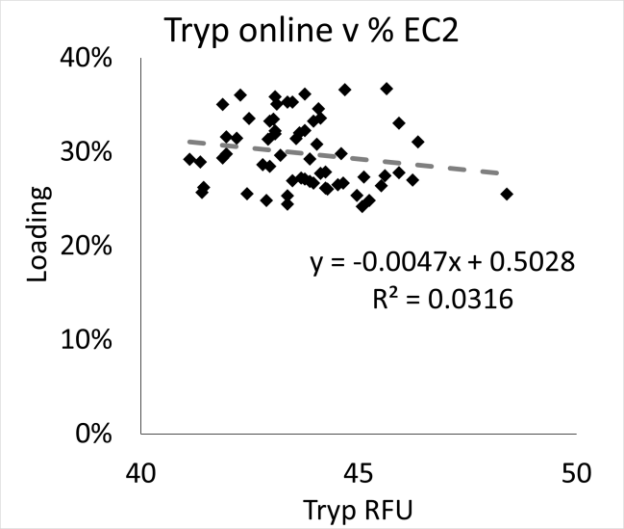


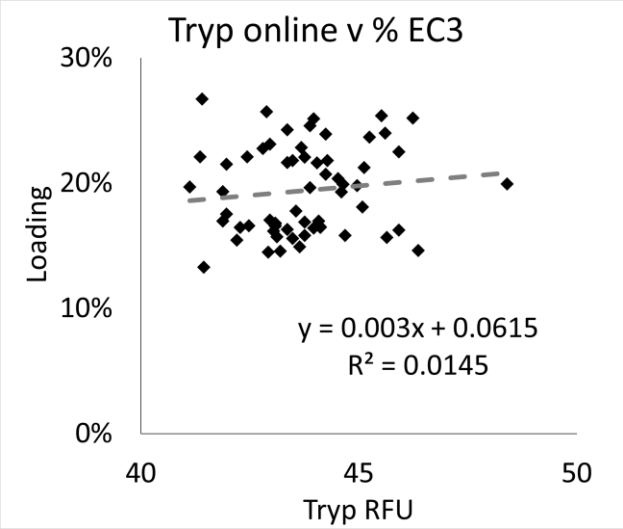


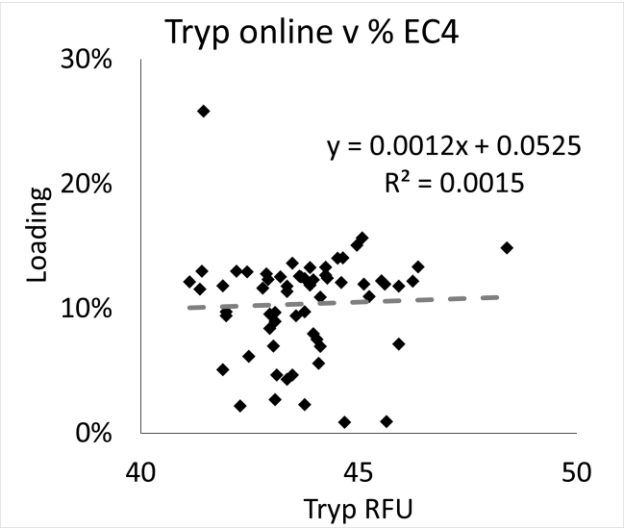


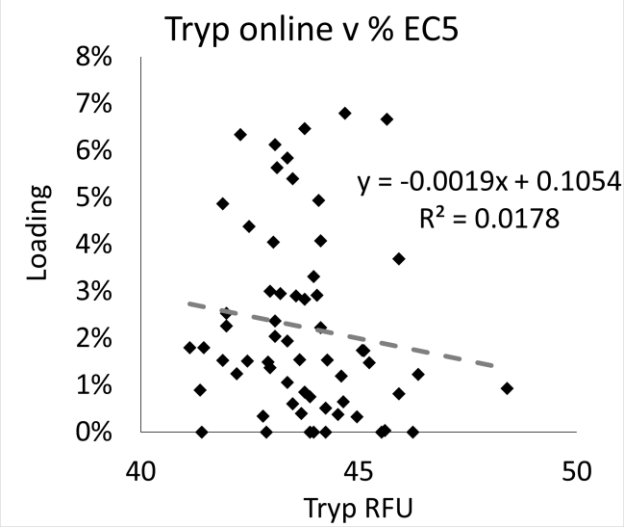

Tryp online v Sum of Loadings
y = 0.1979x - 1.2482
R² = 0.0214
Loading
Tryp RFU
0
2
4
6
8
10
12
14
40
45
50

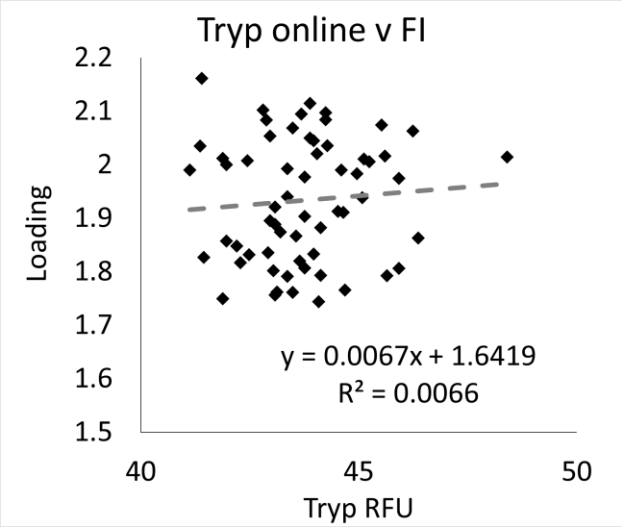

Tryp online v % EC1
y = 0.0024x + 0.2778
R² = 0.0434
Loading
Tryp RFU
0%
10%
20%
30%
40%
50%
40
45
50

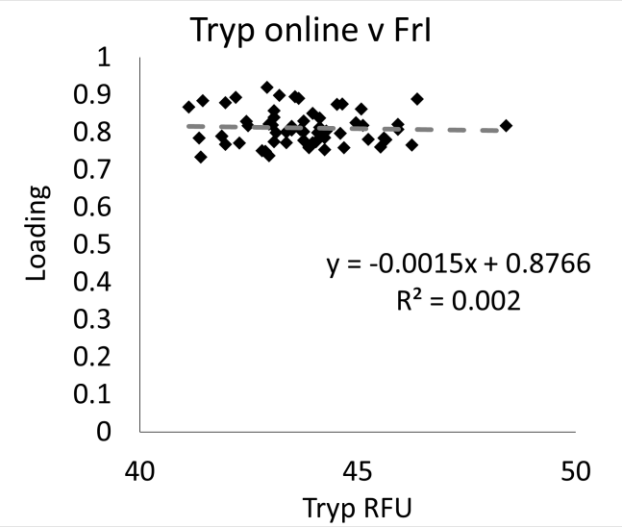

Tryp online v % EC2
y = -0.0047x + 0.5028
R² = 0.0316
Loading
Tryp RFU
0%
10%
20%
30%
40%
40
45
50

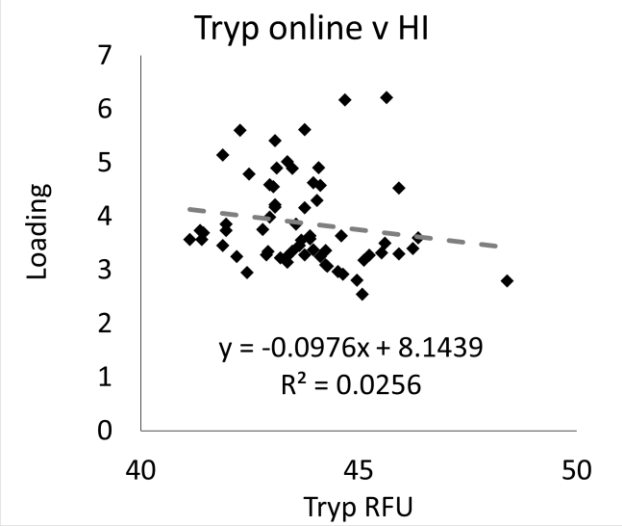

Tryp online v % EC3
y = 0.003x + 0.0615
R² = 0.0145
Loading
Tryp RFU
0%
10%
20%
30%
40
45
50

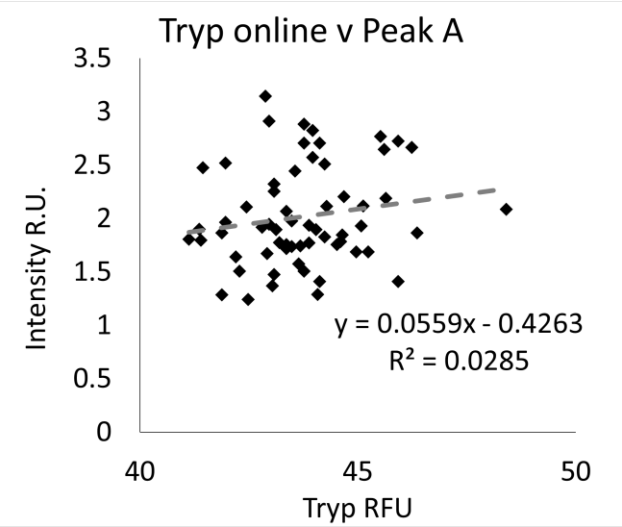

Tryp online v % EC4
y = 0.0012x + 0.0525
R² = 0.0015
Loading
Tryp RFU
0%
10%
20%
30%
40
45
50

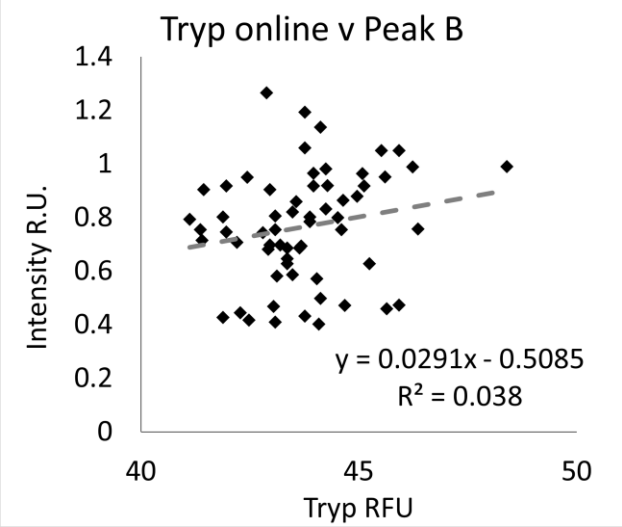

Tryp online v % EC5
y = -0.0019x + 0.1054
R² = 0.0178
Loading
Tryp RFU
0%
1%
2%
3%
4%
5%
6%
7%
8%
40
45
50

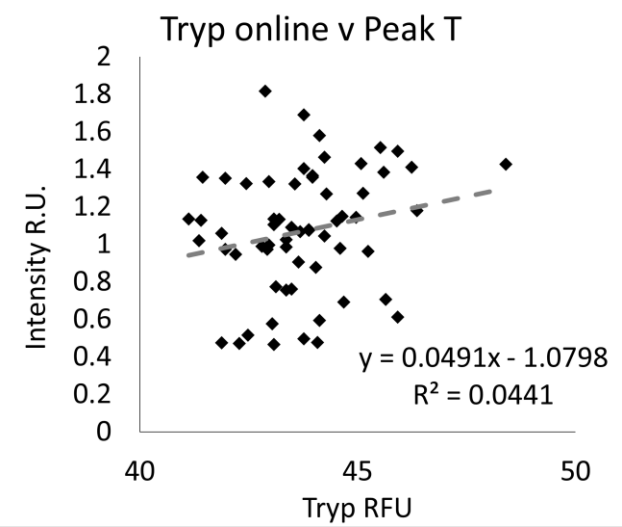

Tryp online v FI
Loading
Tryp RFU
y = 0.0067x + 1.6419
R² = 0.0066
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
40
45
50

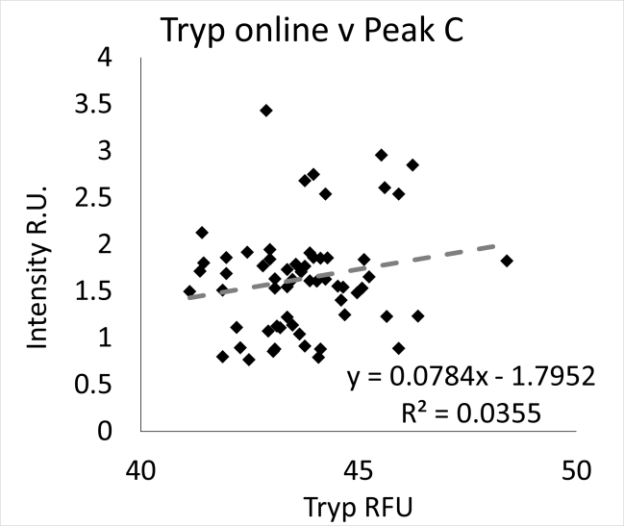

Tryp online v FrI
Loading
Tryp RFU
y = -0.0015x + 0.8766
R² = 0.002
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
40
45
50

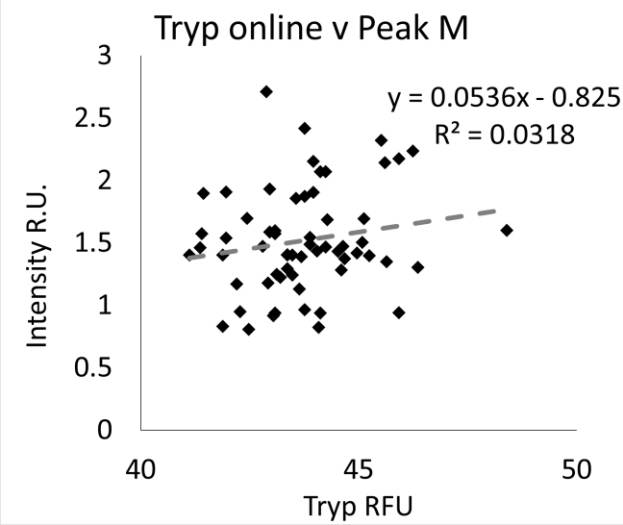

Tryp online v HI
Loading
Tryp RFU
y = -0.0976x + 8.1439
R² = 0.0256
7
6
5
4
3
2
1
0
40
45
50

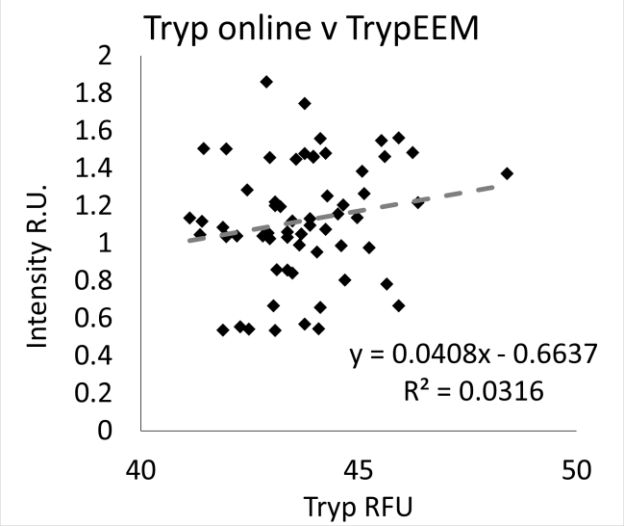

Tryp online v Peak A
Intensity R.U.
Tryp RFU
y = 0.0559x - 0.4263
R² = 0.0285
3.5
3
2.5
2
1.5
1
0.5
0
40
45
50

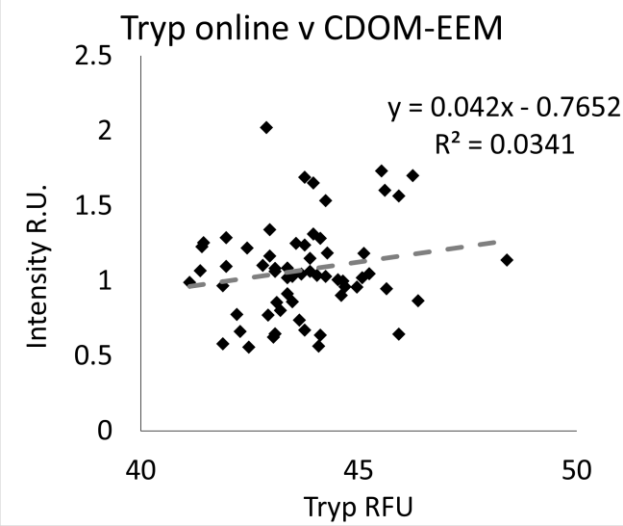

Tryp online v Peak B
Intensity R.U.
Tryp RFU
y = 0.0291x - 0.5085
R² = 0.038
1.4
1.2
1
0.8
0.6
0.4
0.2
0
40
45
50

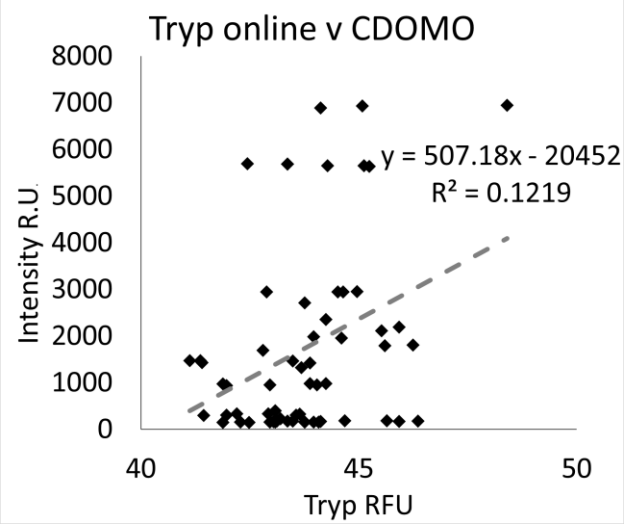

Tryp online v Peak T
Intensity R.U.
Tryp RFU
y = 0.0491x - 1.0798
R² = 0.0441
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
40
45
50

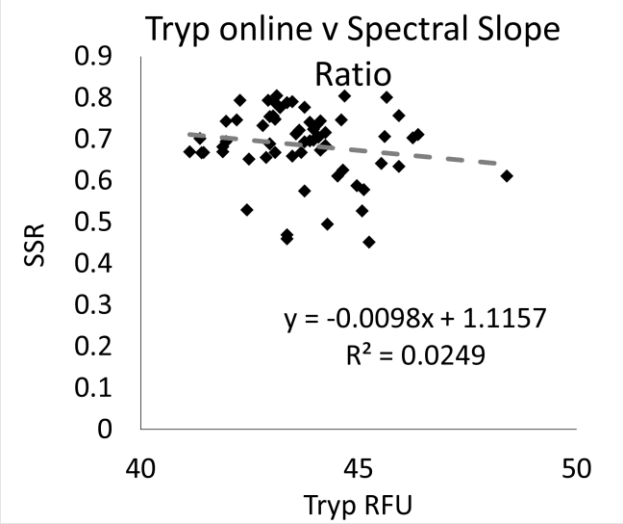

Tryp online v Peak C
Intensity R.U.
Tryp RFU
y = 0.0784x - 1.7952
R² = 0.0355


Tryp online v Peak M
Intensity R.U.
Tryp RFU
y = 0.0536x - 0.825
R² = 0.0318


Tryp online v TrypEEM
Intensity R.U.
Tryp RFU
y = 0.0408x - 0.6637
R² = 0.0316

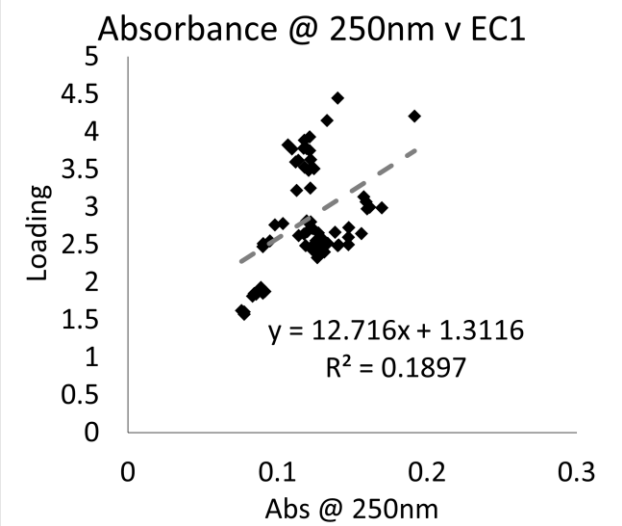

Tryp online v CDOM-EEM
Intensity R.U.
Tryp RFU
y = 0.042x - 0.7652
R² = 0.0341

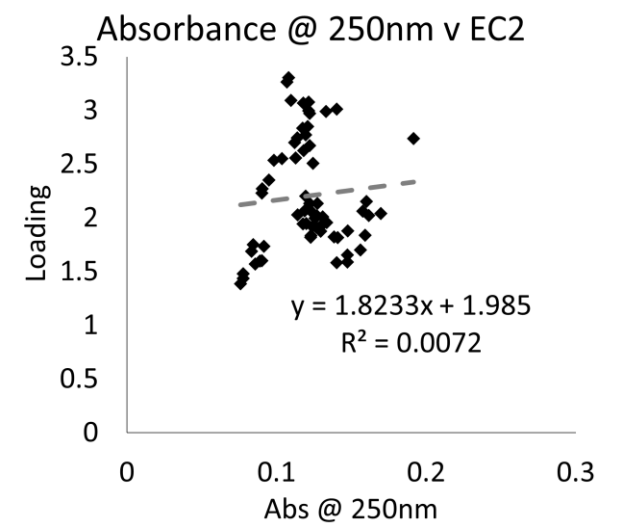

Tryp online v CDOMO
Intensity R.U.
Tryp RFU
y = 507.18x - 20452
R² = 0.1219

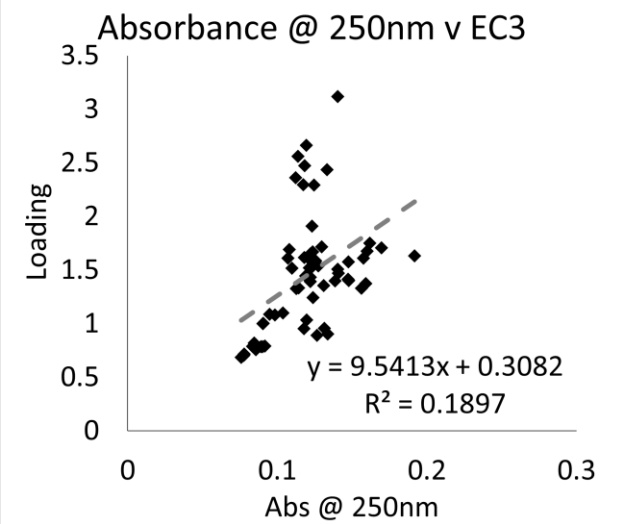

Tryp online v Spectral Slope Ratio
SSR
Tryp RFU
y = -0.0098x + 1.1157
R² = 0.0249

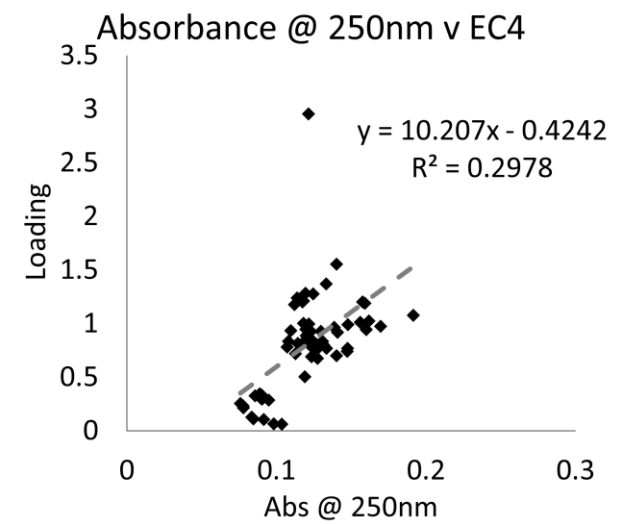
Absorbance @ 250nm

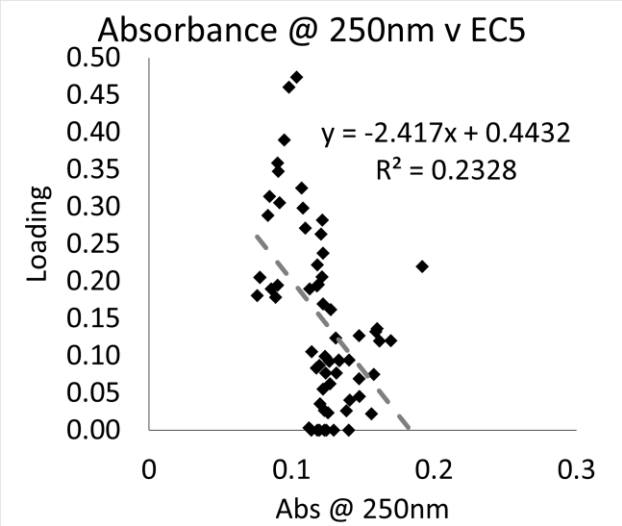
Effluent

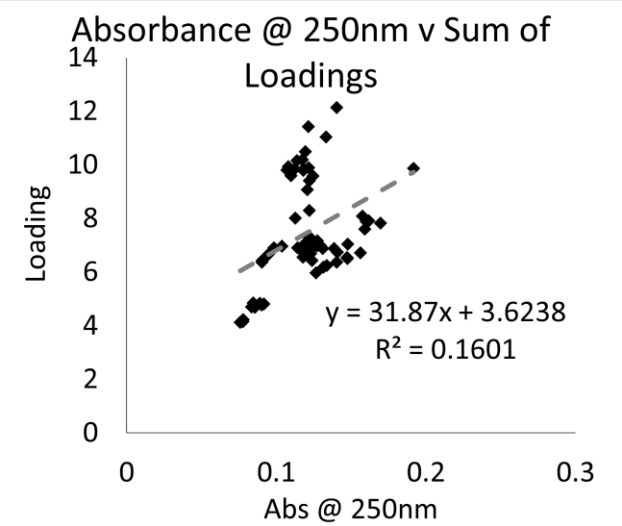


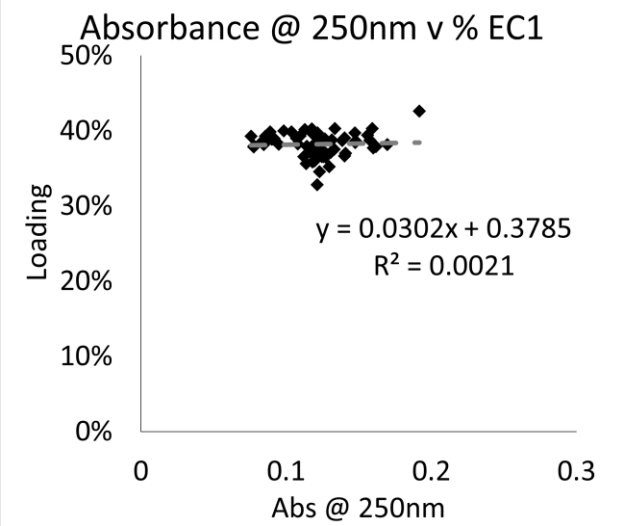


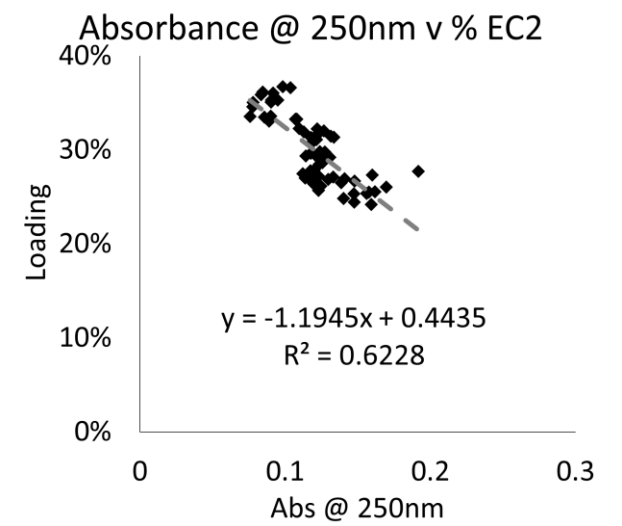


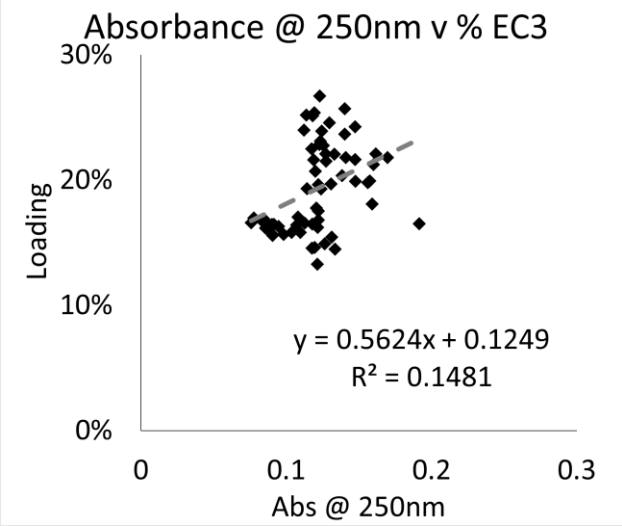


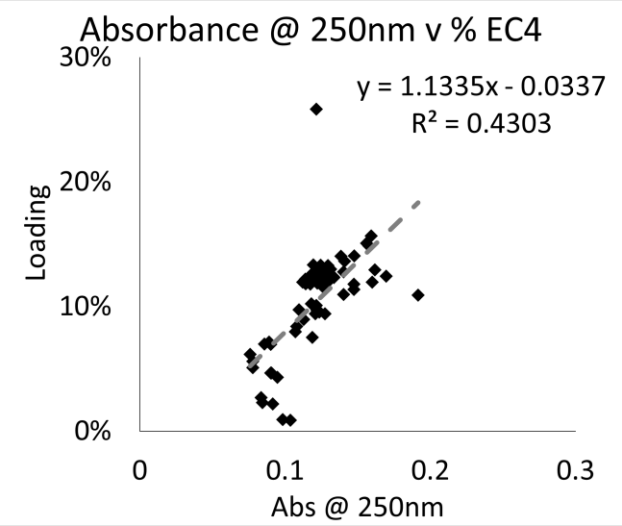

Absorbance @ 250nm v EC5
y = -2.417x + 0.4432
R² = 0.2328
Loading
Abs @ 250nm
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
0.1
0.2
0.3

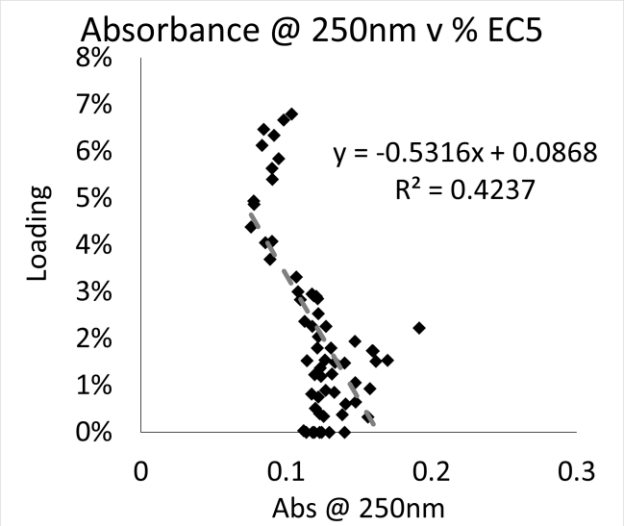

Absorbance @ 250nm v Sum of Loadings
y = 31.87x + 3.6238
R² = 0.1601
Loading
Abs @ 250nm
14
12
10
8
6
4
2
0
0
0.1
0.2
0.3

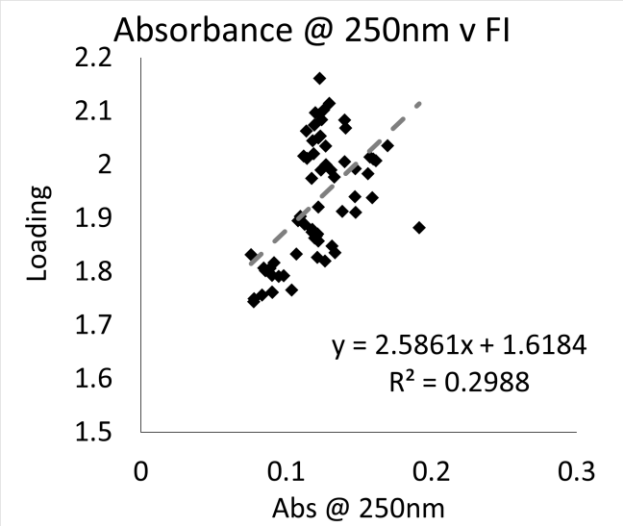

Absorbance @ 250nm v % EC1
y = 0.0302x + 0.3785
R² = 0.0021
Loading
Abs @ 250nm
50%
40%
30%
20%
10%
0%
0
0.1
0.2
0.3

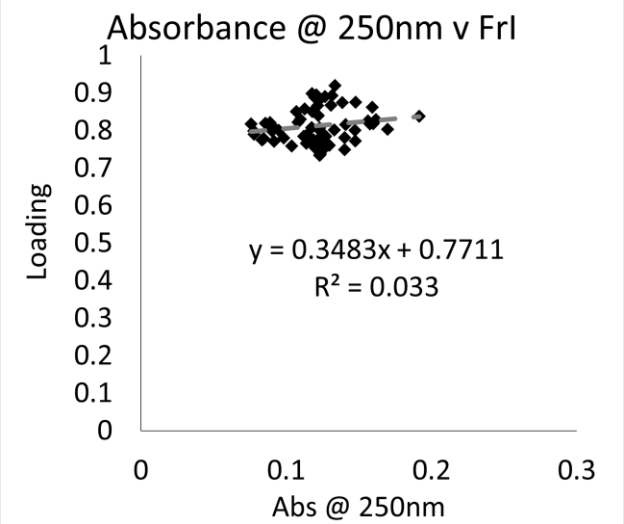

Absorbance @ 250nm v % EC2
y = -1.1945x + 0.4435
R² = 0.6228
Loading
Abs @ 250nm
40%
30%
20%
10%
0%
0
0.1
0.2
0.3

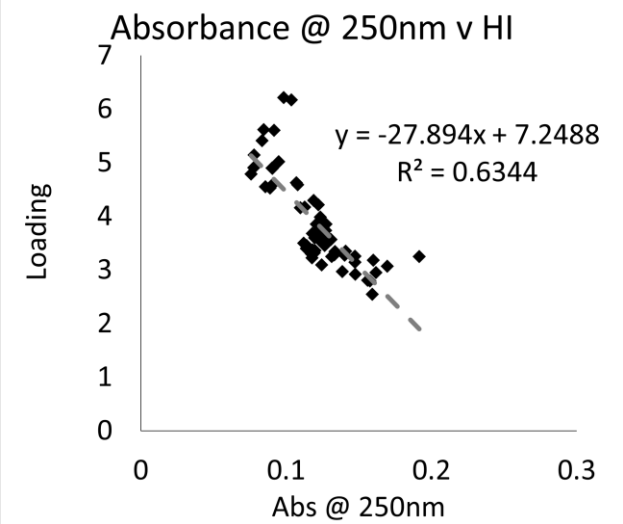

Absorbance @ 250nm v % EC3
y = 0.5624x + 0.1249
R² = 0.1481
Loading
Abs @ 250nm
30%
20%
10%
0%
0
0.1
0.2
0.3

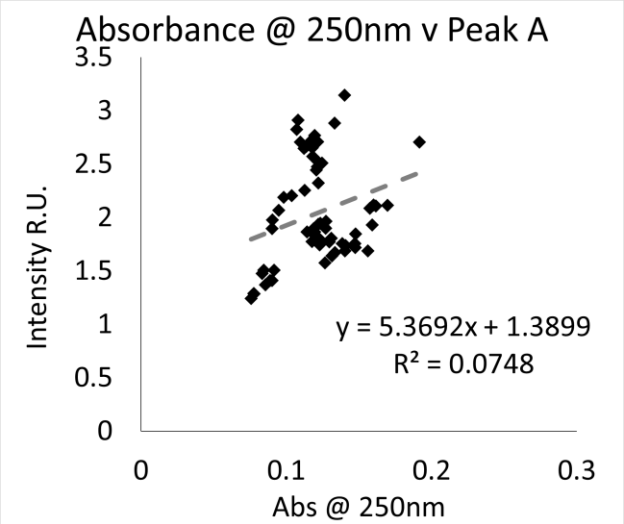

Absorbance @ 250nm v % EC4
y = 1.1335x - 0.0337
R² = 0.4303
Loading
Abs @ 250nm
30%
20%
10%
0%
0
0.1
0.2
0.3

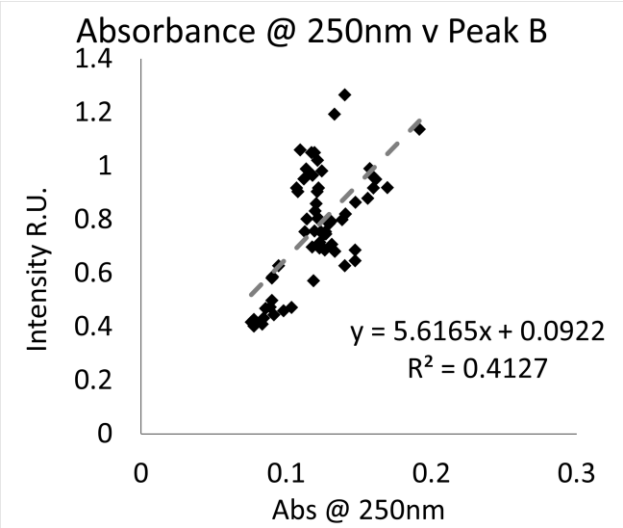

Absorbance @ 250nm v % EC5
Loading
Abs @ 250nm
y = -0.5316x + 0.0868
R² = 0.4237
8%
7%
6%
5%
4%
3%
2%
1%
0%
0
0.1
0.2
0.3

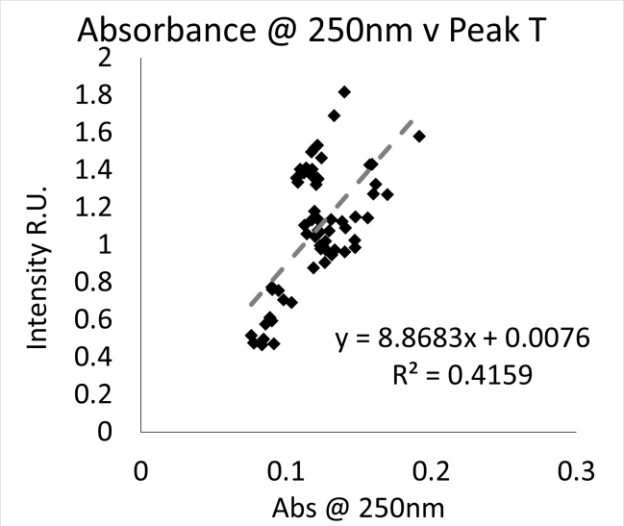

Absorbance @ 250nm v FI
Loading
Abs @ 250nm
y = 2.5861x + 1.6184
R² = 0.2988
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
0
0.1
0.2
0.3

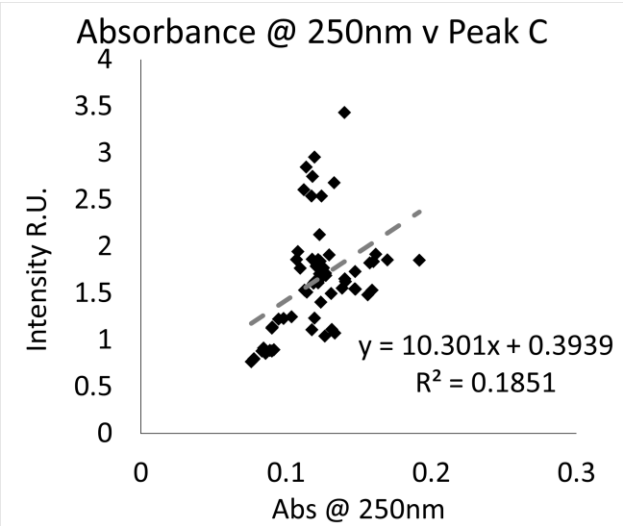

Absorbance @ 250nm v FrI
Loading
Abs @ 250nm
y = 0.3483x + 0.7711
R² = 0.033
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.1
0.2
0.3

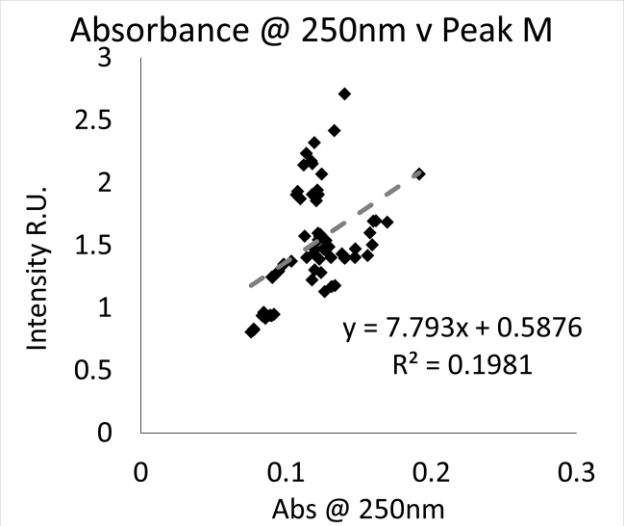

Absorbance @ 250nm v HI
Loading
Abs @ 250nm
y = -27.894x + 7.2488
R² = 0.6344
7
6
5
4
3
2
1
0
0
0.1
0.2
0.3

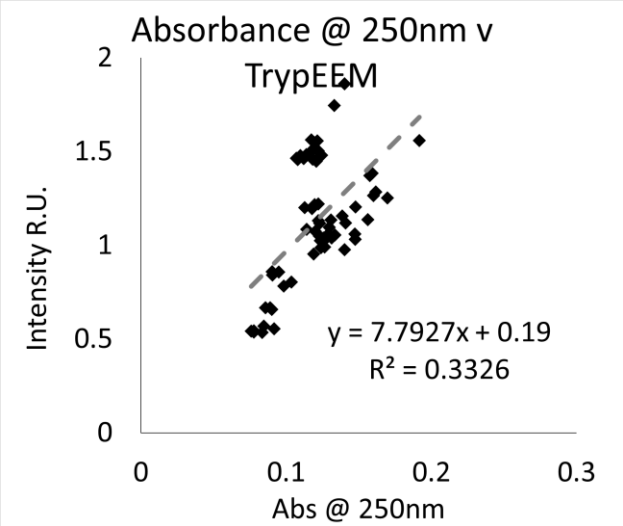

Absorbance @ 250nm v Peak A
Intensity R.U.
Abs @ 250nm
y = 5.3692x + 1.3899
R² = 0.0748
3.5
3
2.5
2
1.5
1
0.5
0
0
0.1
0.2
0.3

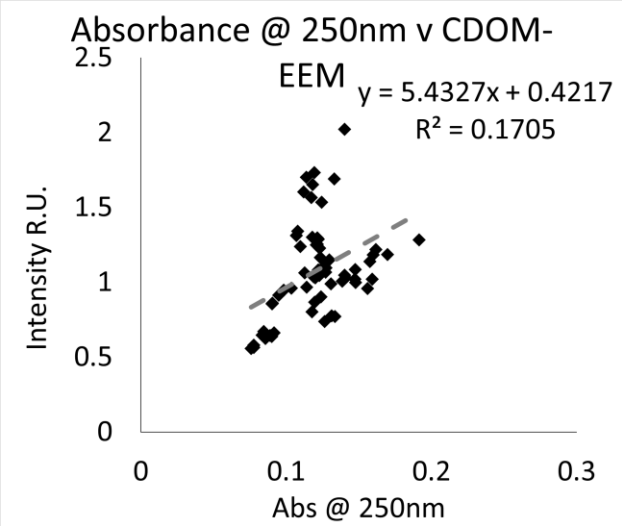

Absorbance @ 250nm v Peak B
Intensity R.U.
Abs @ 250nm
y = 5.6165x + 0.0922
R² = 0.4127
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0
0.1
0.2
0.3

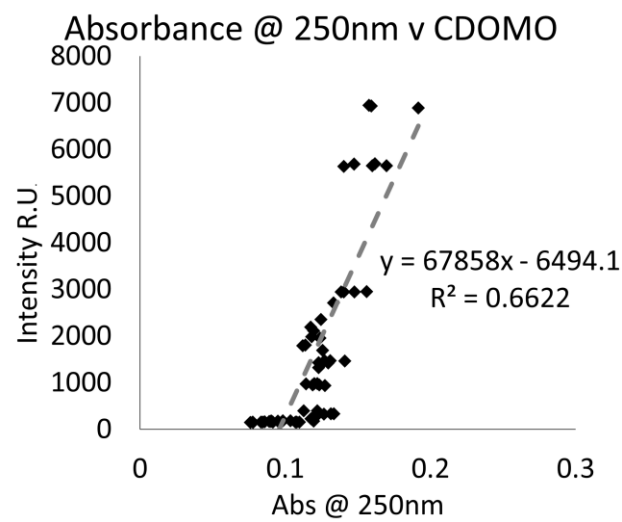

Absorbance @ 250nm v Peak T
Intensity R.U.
Abs @ 250nm
y = 8.8683x + 0.0076
R² = 0.4159
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
0
0.1
0.2
0.3

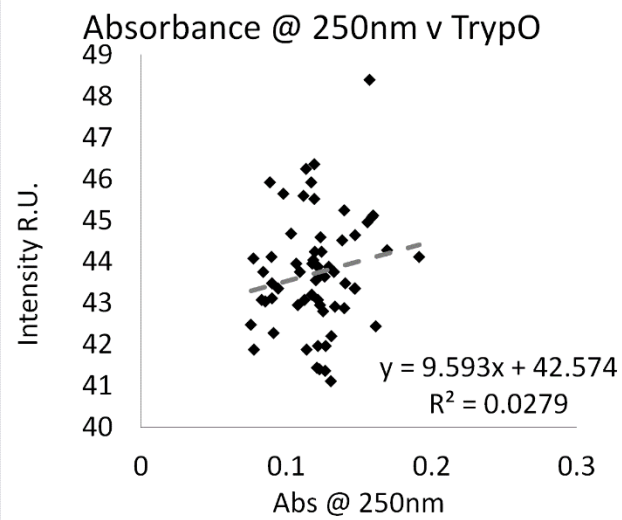

Absorbance @ 250nm v Peak C
Intensity R.U.
Abs @ 250nm
y = 10.301x + 0.3939
R² = 0.1851
0
0.5
1
1.5
2
2.5
3
3.5
4
0
0.1
0.2
0.3

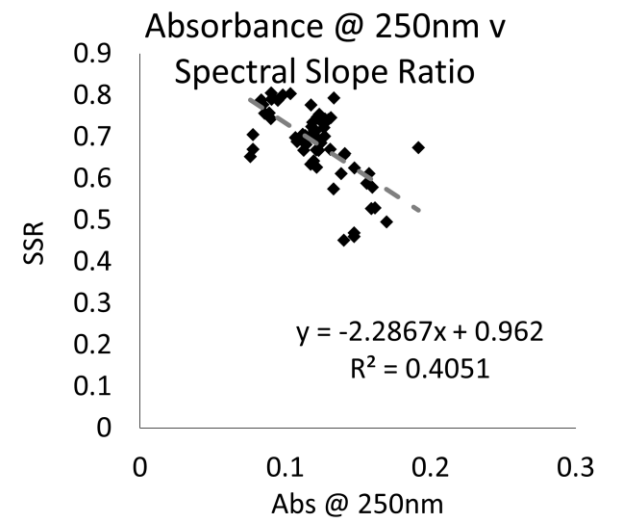

Absorbance @ 250nm v Peak M
Intensity R.U.
Abs @ 250nm
y = 7.793x + 0.5876
R² = 0.1981
0
0.5
1
1.5
2
2.5
3
0
0.1
0.2
0.3


Absorbance @ 250nm v TrypEEM
Intensity R.U.
Abs @ 250nm
y = 7.7927x + 0.19
R² = 0.3326
0
0.5
1
1.5
2
0
0.1
0.2
0.3

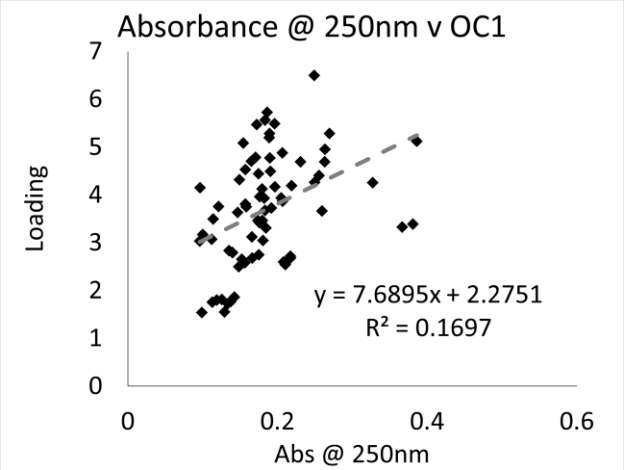

Absorbance @ 250nm v CDOM-EEM
y = 5.4327x + 0.4217
R² = 0.1705
Intensity R.U.
Abs @ 250nm

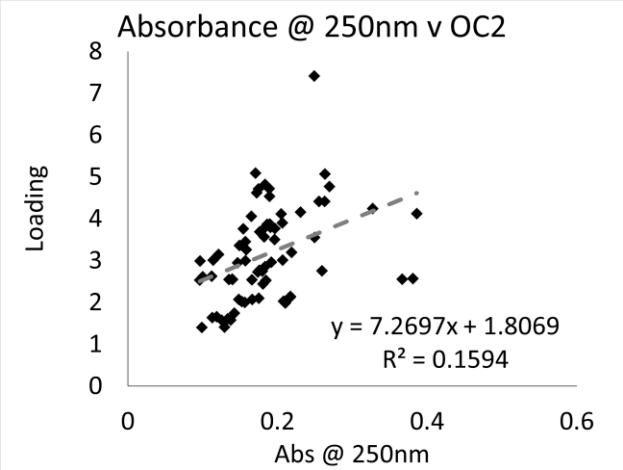

Absorbance @ 250nm v CDOMO
y = 67858x - 6494.1
R² = 0.6622
Intensity R.U
Abs @ 250nm

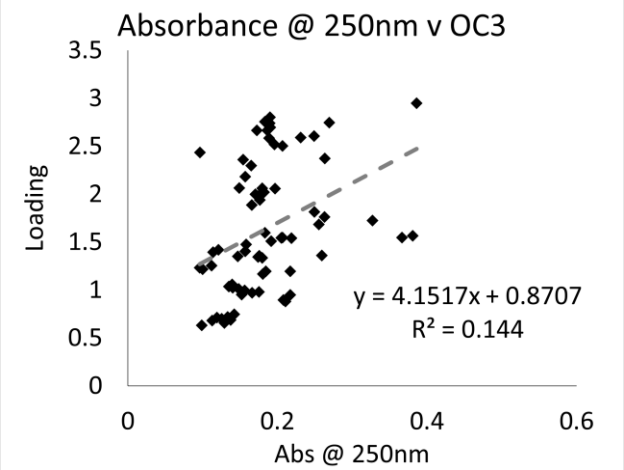

Absorbance @ 250nm v TrypO
y = 9.593x + 42.574
R² = 0.0279
Intensity R.U.
Abs @ 250nm

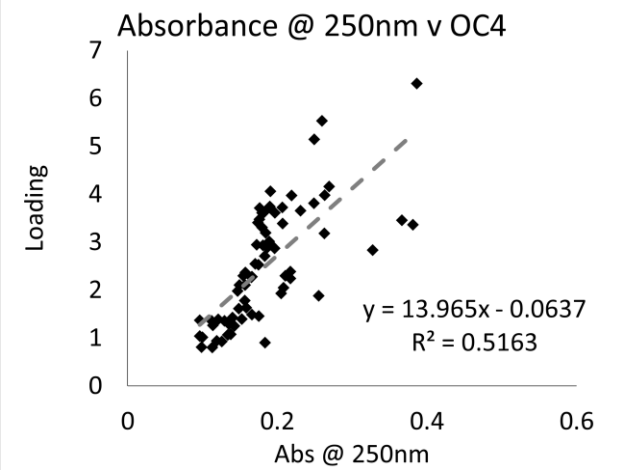

Absorbance @ 250nm v Spectral Slope Ratio
y = -2.2867x + 0.962
R² = 0.4051
SSR
Abs @ 250nm

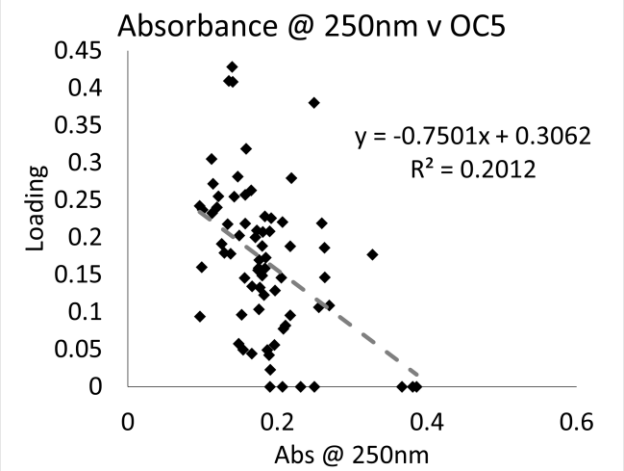
Oxic Tank

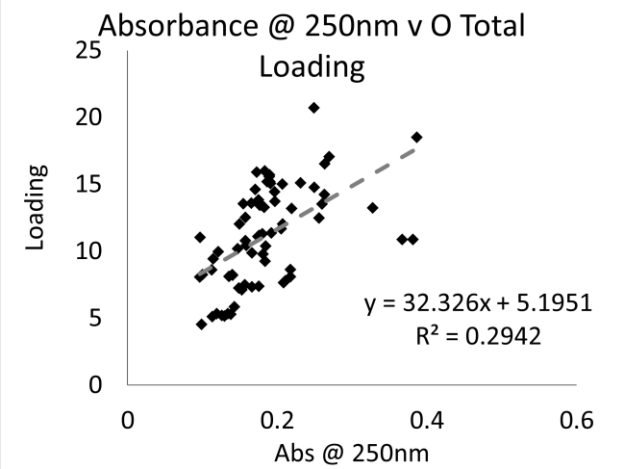

Absorbance @ 250nm v OC1
Loading
Abs @ 250nm
y = 7.6895x + 2.2751
R² = 0.1697

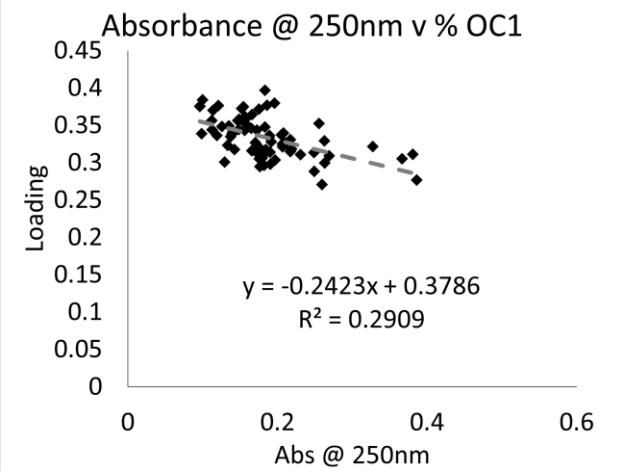

Absorbance @ 250nm v OC2
Loading
Abs @ 250nm
y = 7.2697x + 1.8069
R² = 0.1594

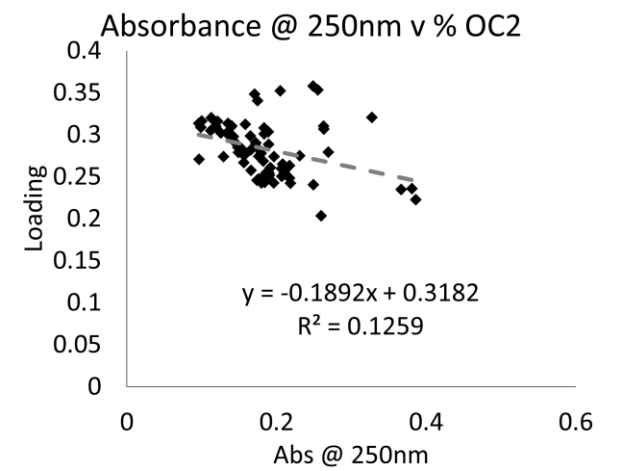

Absorbance @ 250nm v OC3
Loading
Abs @ 250nm
y = 4.1517x + 0.8707
R² = 0.144

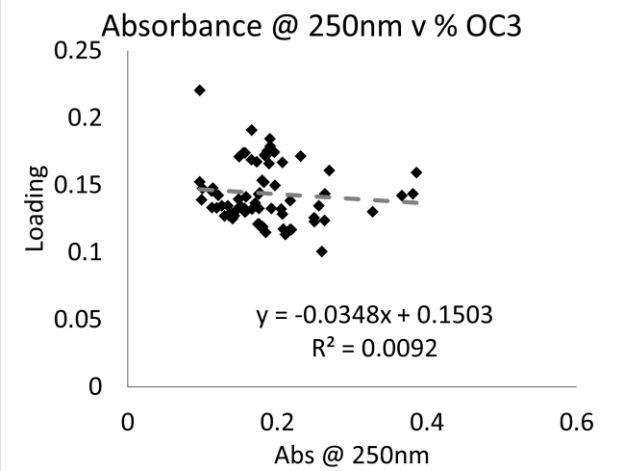

Absorbance @ 250nm v OC4
Loading
Abs @ 250nm
y = 13.965x - 0.0637
R² = 0.5163

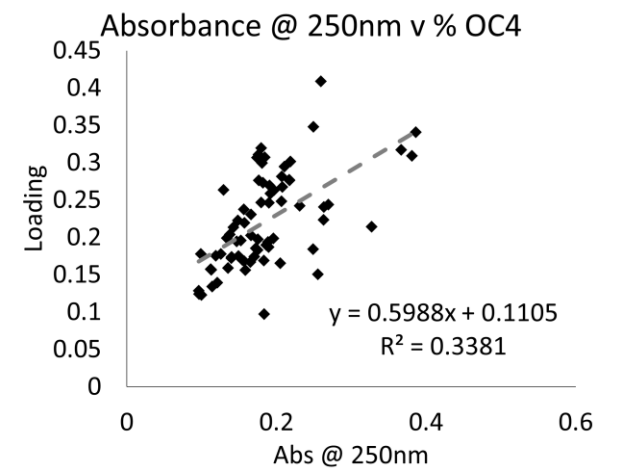

Absorbance @ 250nm v OC5
Loading
Abs @ 250nm
y = -0.7501x + 0.3062
R² = 0.2012

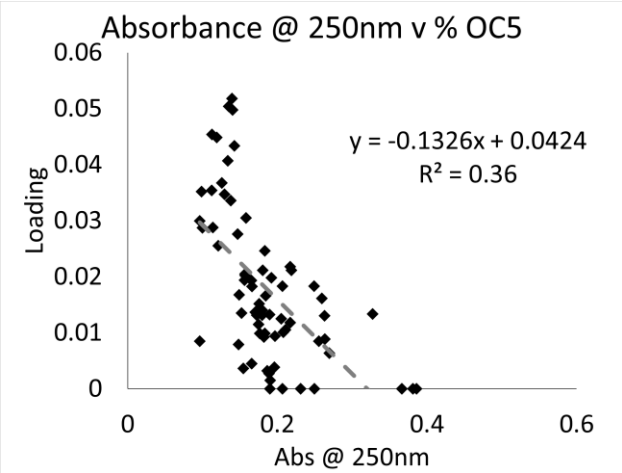

Absorbance @ 250nm v O Total Loading
Loading
Abs @ 250nm
y = 32.326x + 5.1951
R² = 0.2942

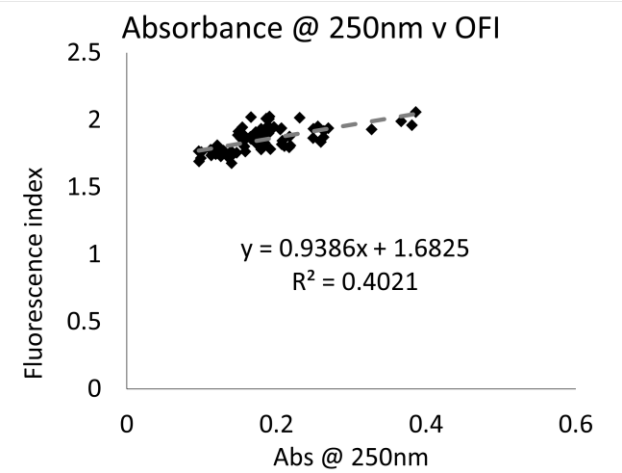

Absorbance @ 250nm v % OC1
Loading
Abs @ 250nm
y = -0.2423x + 0.3786
R² = 0.2909
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
0.2
0.4
0.6

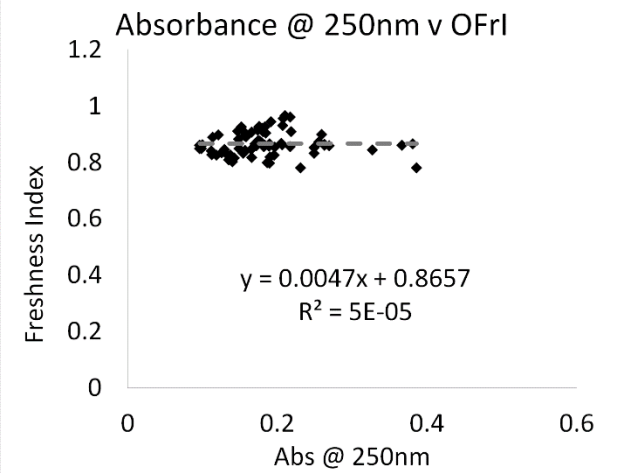

Absorbance @ 250nm v % OC2
Loading
Abs @ 250nm
y = -0.1892x + 0.3182
R² = 0.1259
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
0.2
0.4
0.6

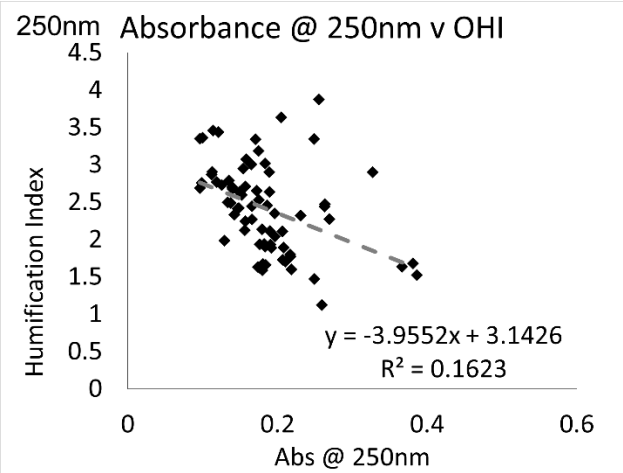

Absorbance @ 250nm v % OC3
Loading
Abs @ 250nm
y = -0.0348x + 0.1503
R² = 0.0092
0.25
0.2
0.15
0.1
0.05
0
0
0.2
0.4
0.6

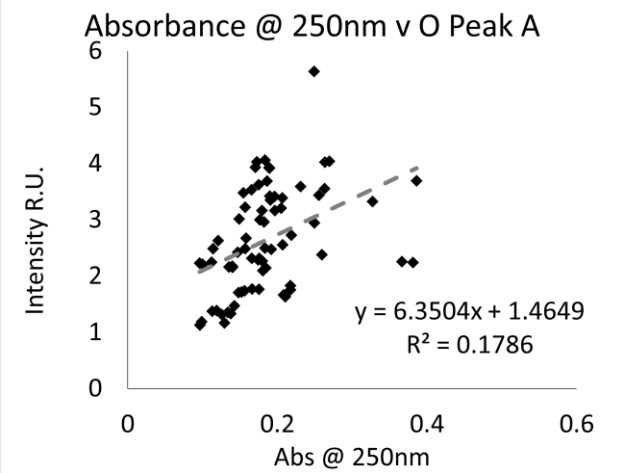

Absorbance @ 250nm v % OC4
Loading
Abs @ 250nm
y = 0.5988x + 0.1105
R² = 0.3381
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
0.2
0.4
0.6

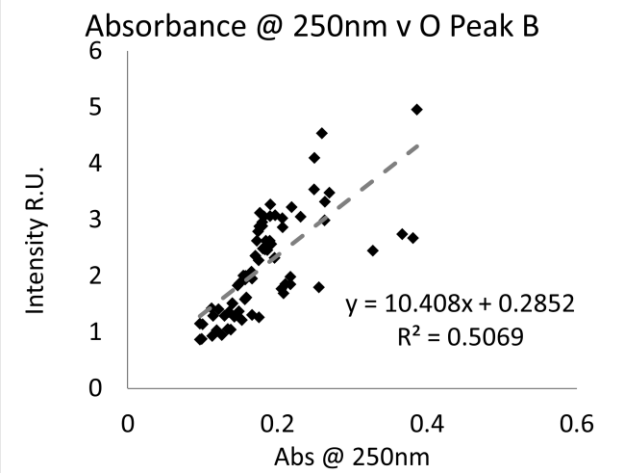

Absorbance @ 250nm v % OC5
Loading
Abs @ 250nm
y = -0.1326x + 0.0424
R² = 0.36
0.06
0.05
0.04
0.03
0.02
0.01
0
0
0.2
0.4
0.6

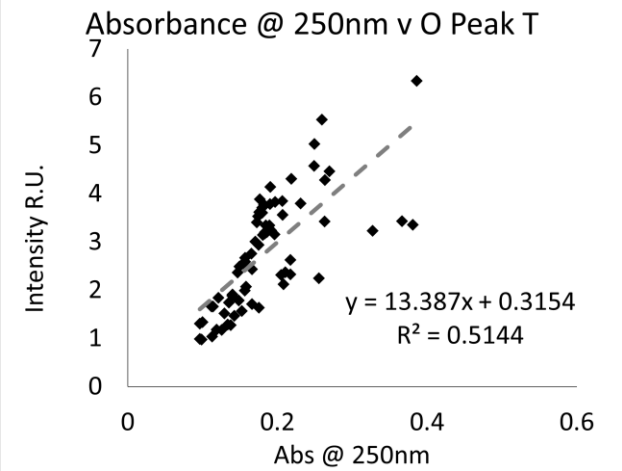

Absorbance @ 250nm v OFI
Fluorescence index
Abs @ 250nm
y = 0.9386x + 1.6825
R² = 0.4021
2.5
2
1.5
1
0.5
0
0
0.2
0.4
0.6

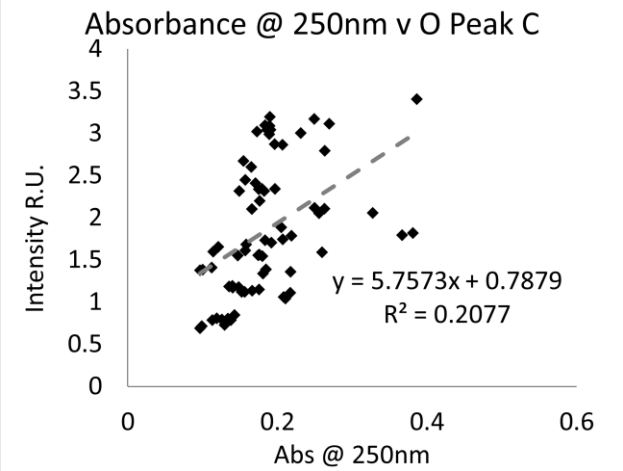

Absorbance @ 250nm v OFrI
Freshness Index
1.2
1
0.8
0.6
0.4
0.2
0
y = 0.0047x + 0.8657
R² = 5E-05
0
0.2
0.4
0.6
Abs @ 250nm

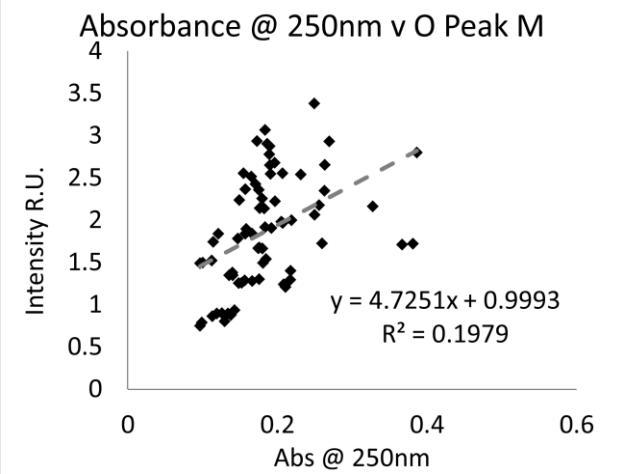

250nm
Absorbance @ 250nm v OHI
Humification Index
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
y = -3.9552x + 3.1426
R² = 0.1623
0
0.2
0.4
0.6
Abs @ 250nm

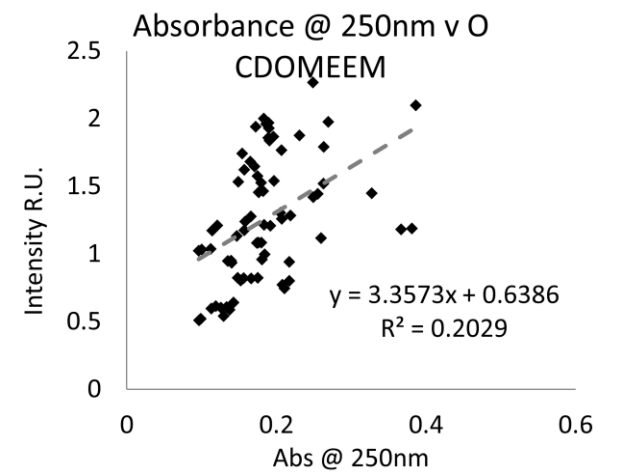

Absorbance @ 250nm v O Peak A
Intensity R.U.
6
5
4
3
2
1
0
y = 6.3504x + 1.4649
R² = 0.1786
0
0.2
0.4
0.6
Abs @ 250nm

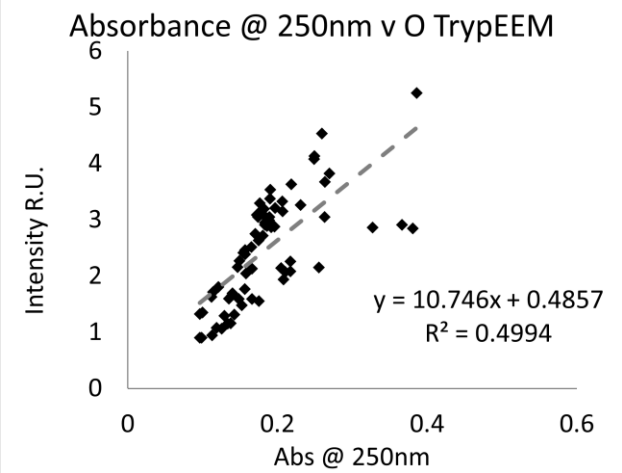

Absorbance @ 250nm v O Peak B
Intensity R.U.
6
5
4
3
2
1
0
y = 10.408x + 0.2852
R² = 0.5069
0
0.2
0.4
0.6
Abs @ 250nm


Absorbance @ 250nm v O Peak T
Intensity R.U.
7
6
5
4
3
2
1
0
y = 13.387x + 0.3154
R² = 0.5144
0
0.2
0.4
0.6
Abs @ 250nm

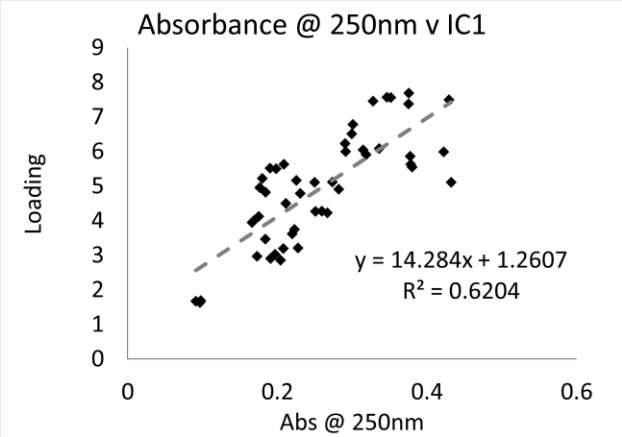

Absorbance @ 250nm v O Peak C
Intensity R.U.
4
3.5
3
2.5
2
1.5
1
0.5
0
y = 5.7573x + 0.7879
R² = 0.2077
0
0.2
0.4
0.6
Abs @ 250nm

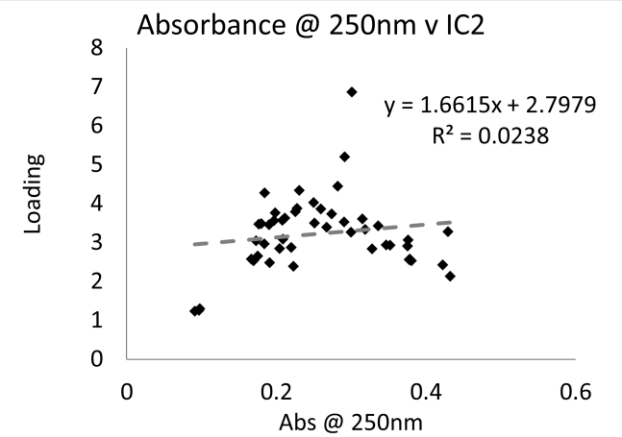

Absorbance @ 250nm v O Peak M
Intensity R.U.
Abs @ 250nm
y = 4.7251x + 0.9993
R² = 0.1979
0
0.5
1
1.5
2
2.5
3
3.5
4
0
0.2
0.4
0.6

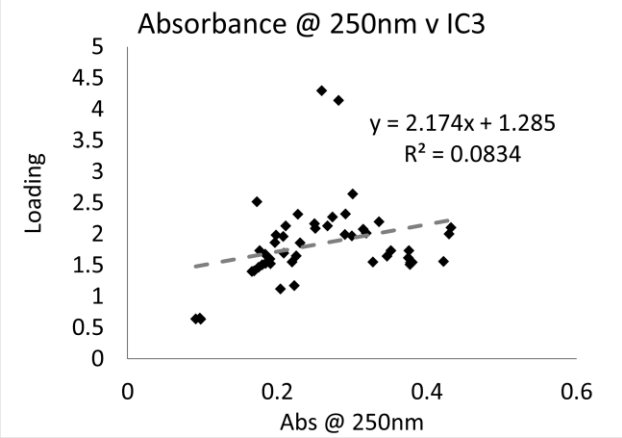

Absorbance @ 250nm v O CDOMEEM
Intensity R.U.
Abs @ 250nm
y = 3.3573x + 0.6386
R² = 0.2029
0
0.5
1
1.5
2
2.5
0
0.2
0.4
0.6

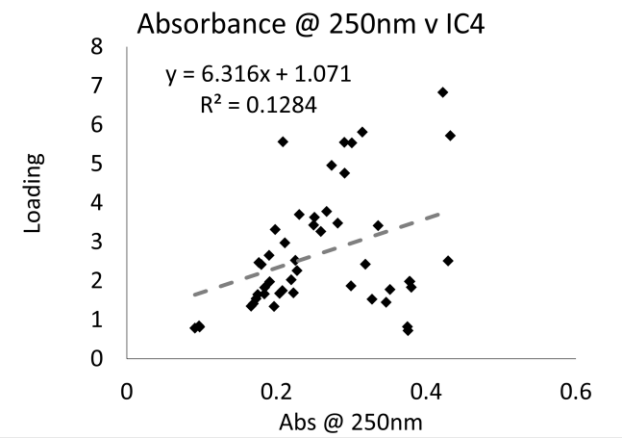

Absorbance @ 250nm v O TrypEEM
Intensity R.U.
Abs @ 250nm
y = 10.746x + 0.4857
R² = 0.4994
0
1
2
3
4
5
6
0
0.2
0.4
0.6

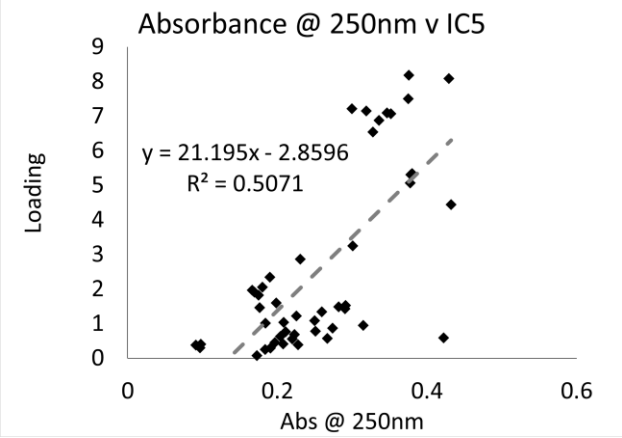
Influent

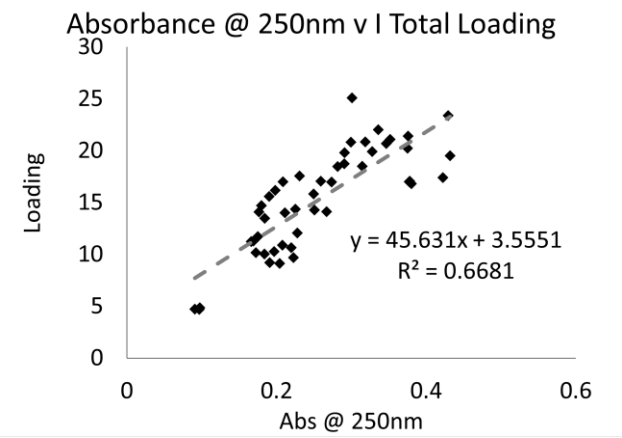

Absorbance @ 250nm v IC1
Loading
Abs @ 250nm
y = 14.284x + 1.2607
R² = 0.6204

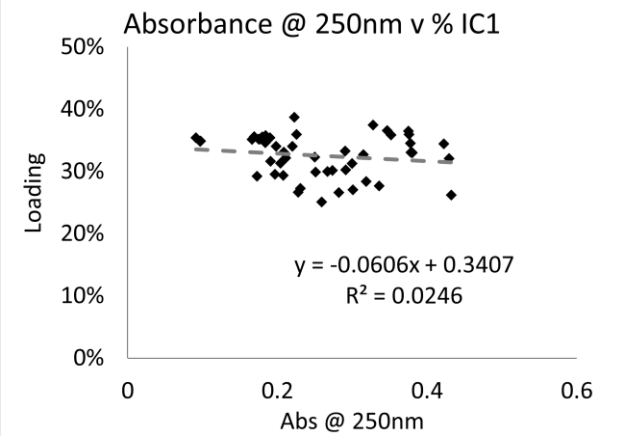

Absorbance @ 250nm v IC2
Loading
Abs @ 250nm
y = 1.6615x + 2.7979
R² = 0.0238

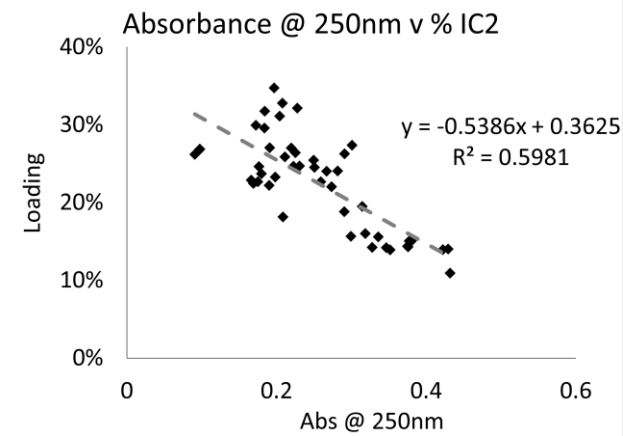

Absorbance @ 250nm v IC3
Loading
Abs @ 250nm
y = 2.174x + 1.285
R² = 0.0834

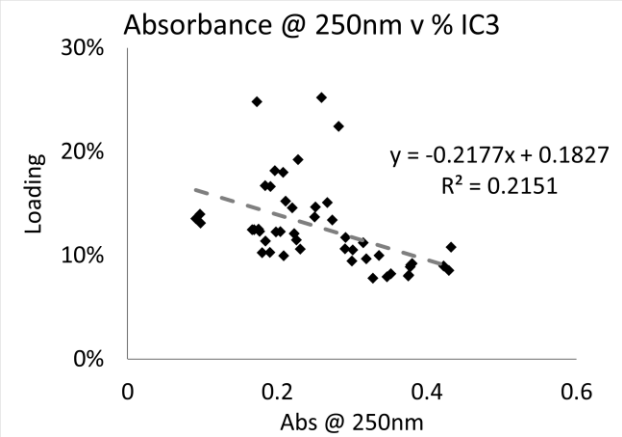

Absorbance @ 250nm v IC4
Loading
Abs @ 250nm
y = 6.316x + 1.071
R² = 0.1284

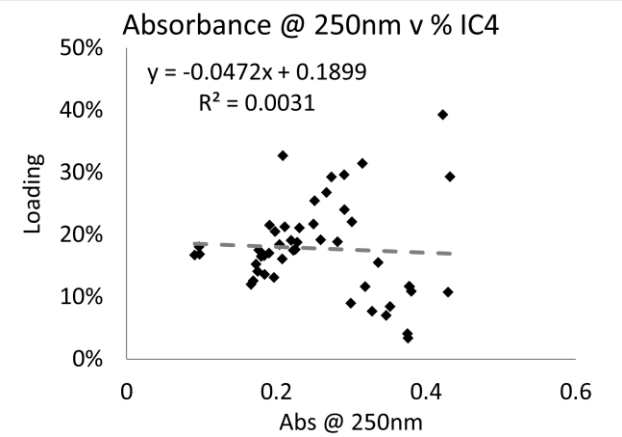

Absorbance @ 250nm v IC5
Loading
Abs @ 250nm
y = 21.195x - 2.8596
R² = 0.5071

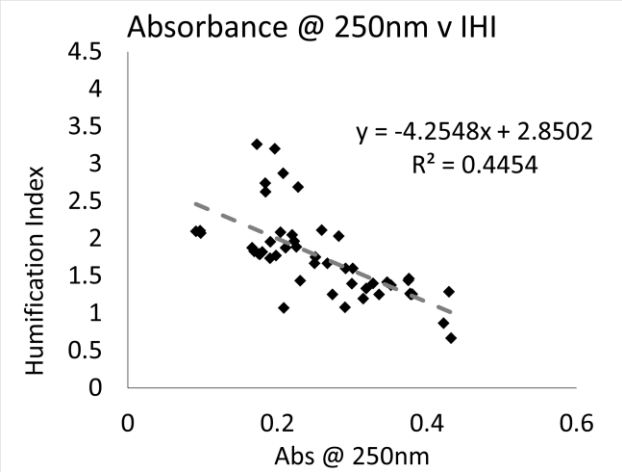

Absorbance @ 250nm v I Total Loading
Loading
Abs @ 250nm
y = 45.631x + 3.5551
R² = 0.6681

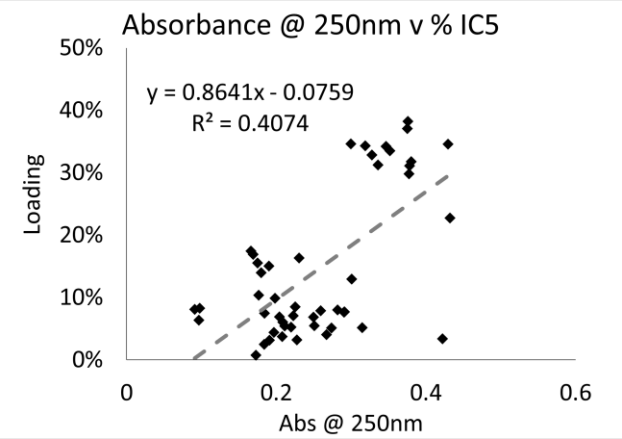

Absorbance @ 250nm v % IC1
Loading
50%
40%
30%
20%
10%
0%
y = -0.0606x + 0.3407
R² = 0.0246
0
0.2
0.4
0.6
Abs @ 250nm

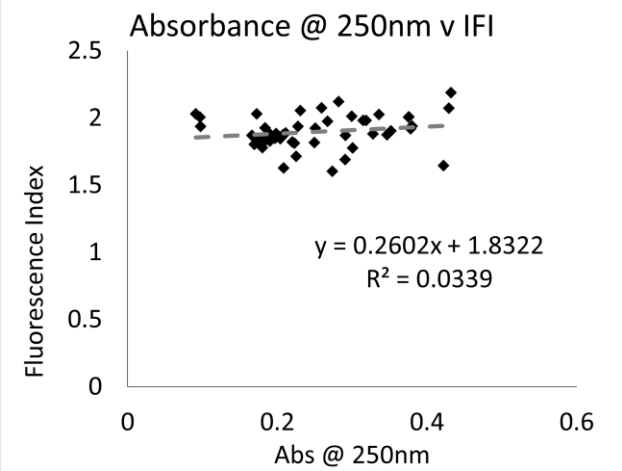

Absorbance @ 250nm v % IC2
Loading
40%
30%
20%
10%
0%
y = -0.5386x + 0.3625
R² = 0.5981
0
0.2
0.4
0.6
Abs @ 250nm

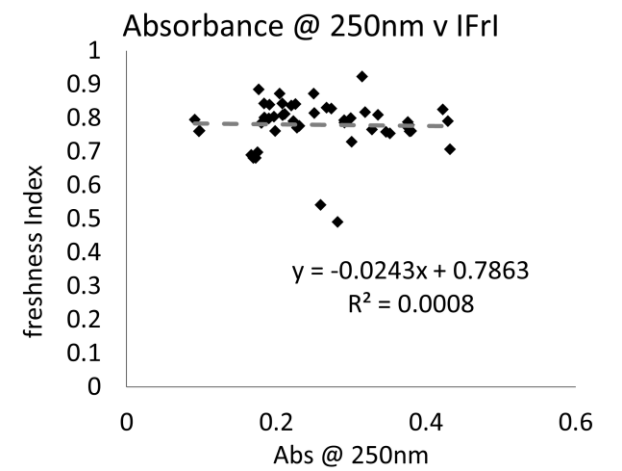

Absorbance @ 250nm v % IC3
Loading
30%
20%
10%
0%
y = -0.2177x + 0.1827
R² = 0.2151
0
0.2
0.4
0.6
Abs @ 250nm

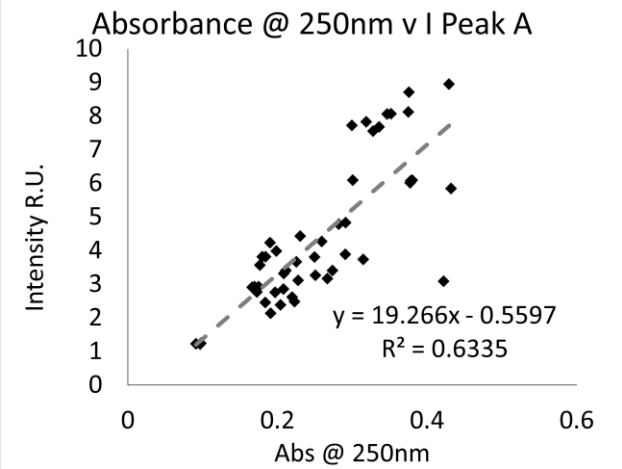

Absorbance @ 250nm v % IC4
Loading
50%
40%
30%
20%
10%
0%
y = -0.0472x + 0.1899
R² = 0.0031
0
0.2
0.4
0.6
Abs @ 250nm

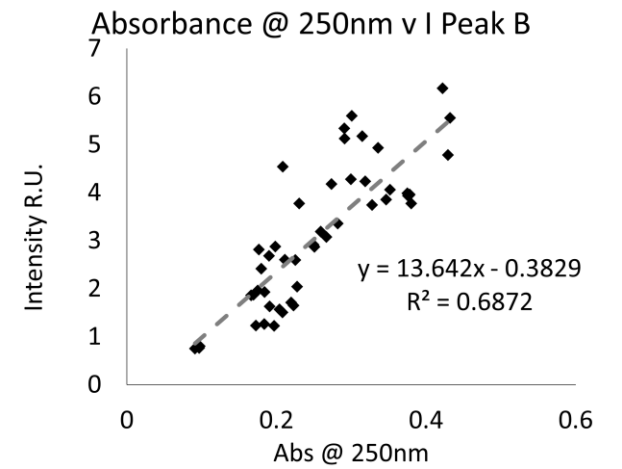

Absorbance @ 250nm v IHI
Humification Index
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
y = -4.2548x + 2.8502
R² = 0.4454
0
0.2
0.4
0.6
Abs @ 250nm

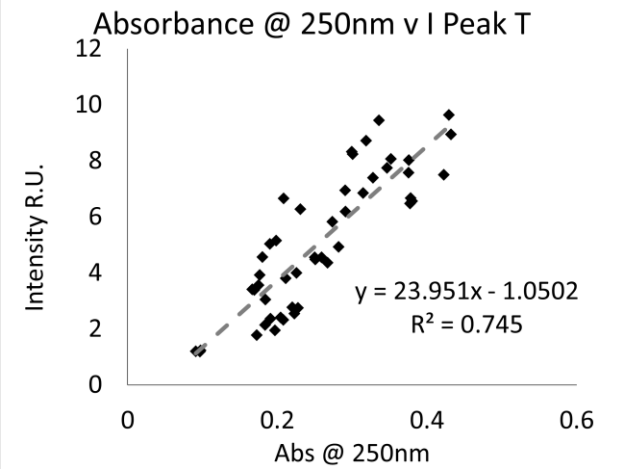

Absorbance @ 250nm v % IC5
Loading
50%
40%
30%
20%
10%
0%
y = 0.8641x - 0.0759
R² = 0.4074
0
0.2
0.4
0.6
Abs @ 250nm

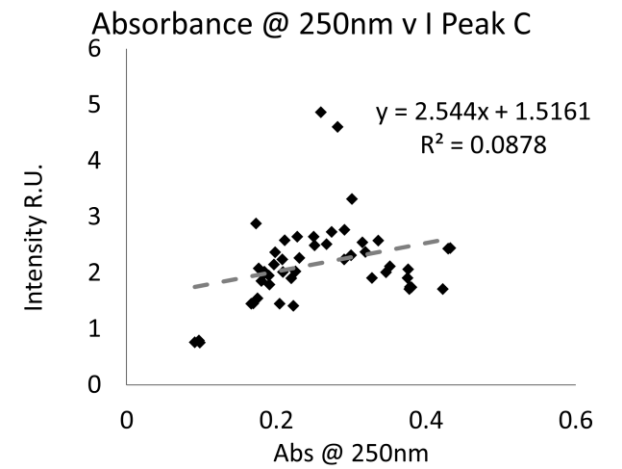

Absorbance @ 250nm v IFI
Fluorescence Index
Abs @ 250nm
y = 0.2602x + 1.8322
R² = 0.0339

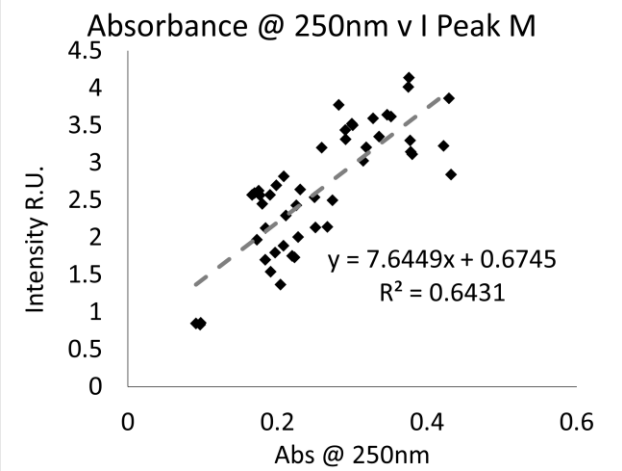

Absorbance @ 250nm v IFrI
freshness Index
Abs @ 250nm
y = -0.0243x + 0.7863
R² = 0.0008

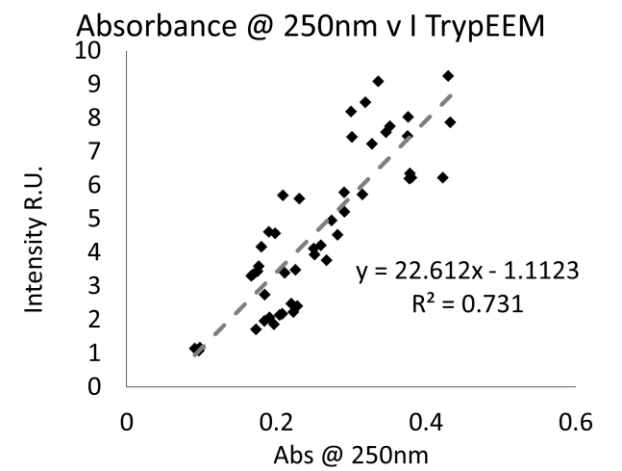

Absorbance @ 250nm v I Peak A
Intensity R.U.
Abs @ 250nm
y = 19.266x - 0.5597
R² = 0.6335

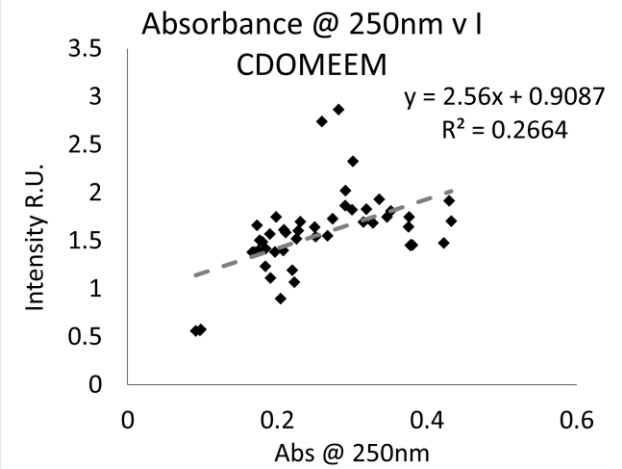

Absorbance @ 250nm v I Peak B
Intensity R.U.
Abs @ 250nm
y = 13.642x - 0.3829
R² = 0.6872

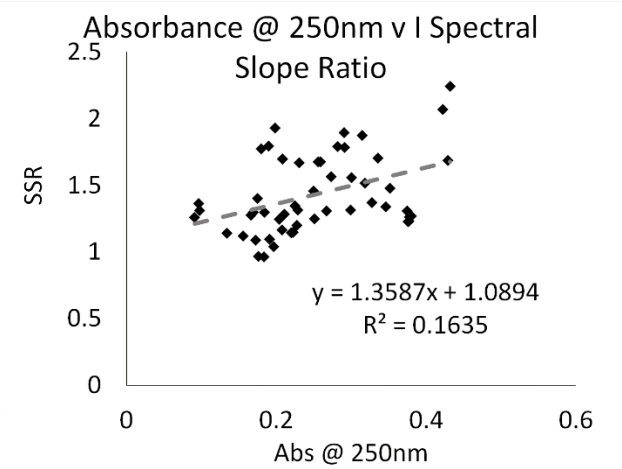

Absorbance @ 250nm v I Peak T
Intensity R.U.
Abs @ 250nm
y = 23.951x - 1.0502
R² = 0.745


Absorbance @ 250nm v I Peak C
Intensity R.U.
Abs @ 250nm
y = 2.544x + 1.5161
R² = 0.0878



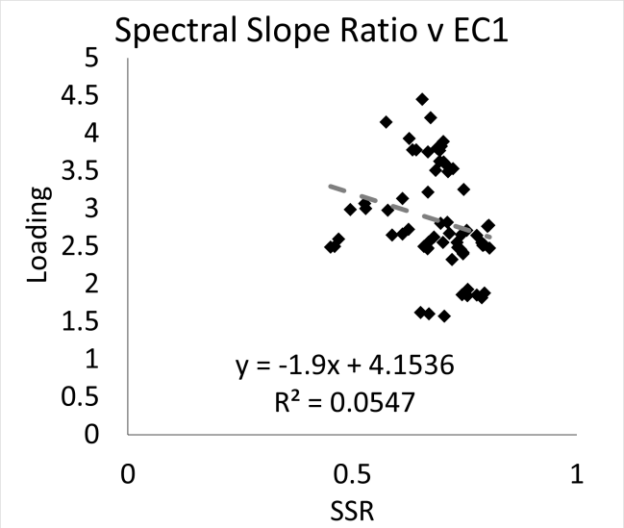


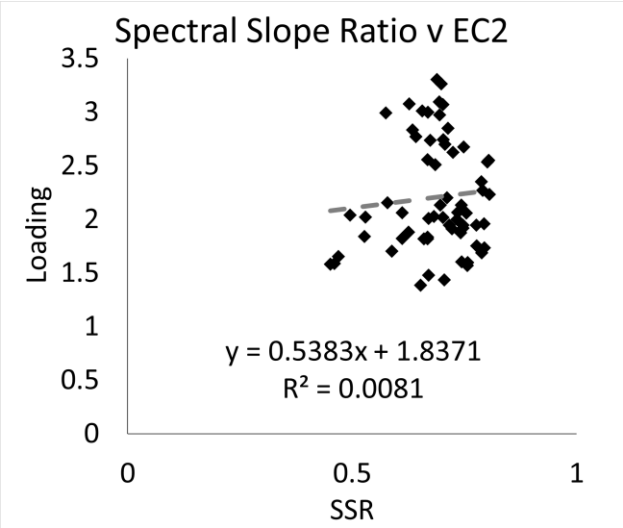


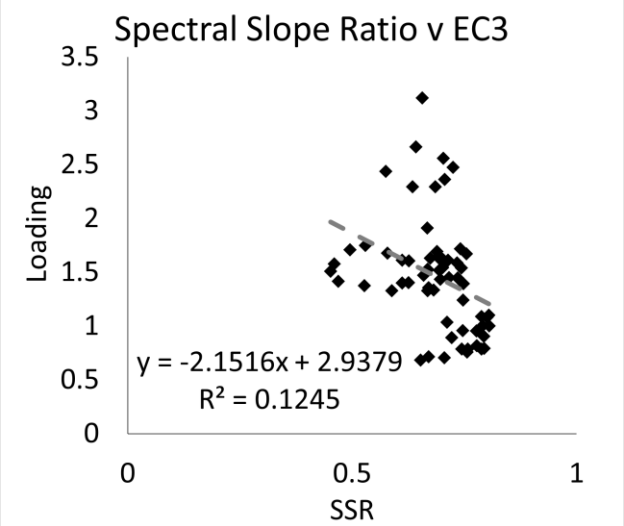


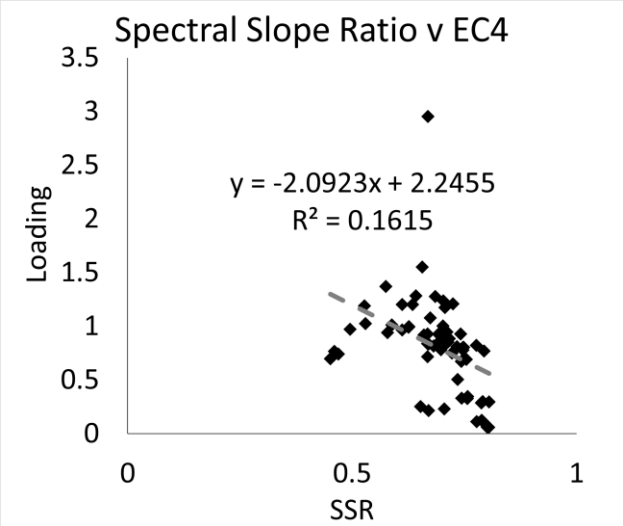
Spectral slope ratio

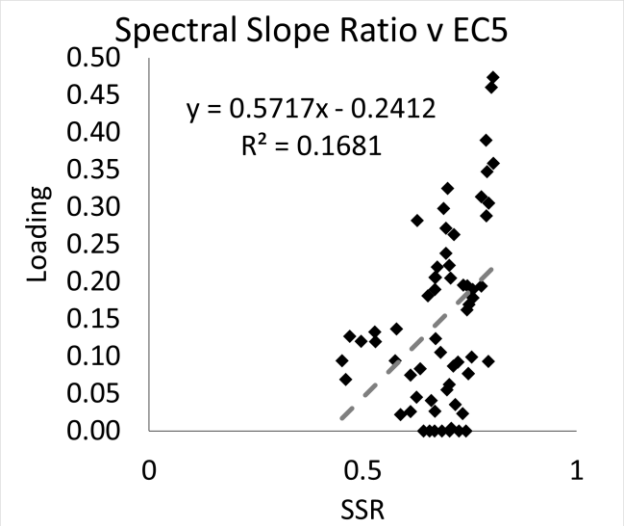
Effluent

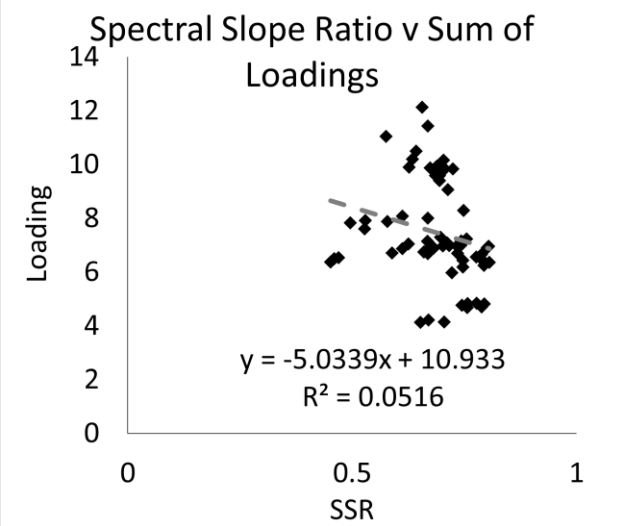

Spectral Slope Ratio v EC1
Loading
SSR
y = -1.9x + 4.1536
R² = 0.0547

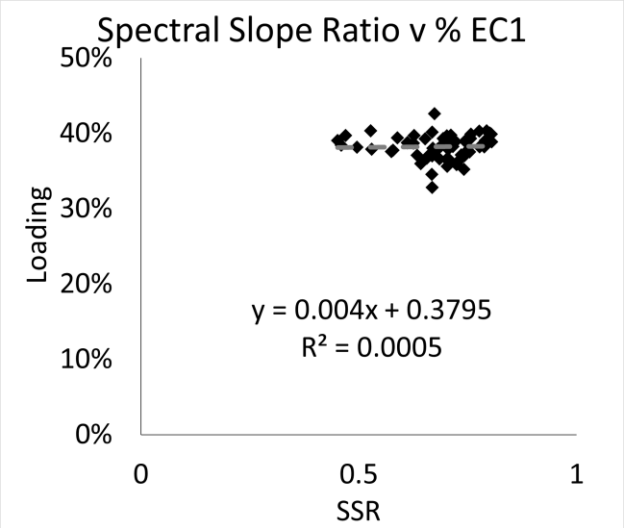

Spectral Slope Ratio v EC2
Loading
SSR
y = 0.5383x + 1.8371
R² = 0.0081

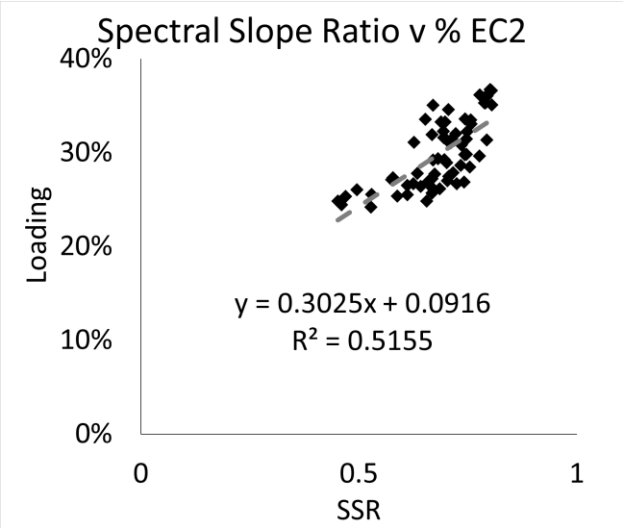

Spectral Slope Ratio v EC3
Loading
SSR
y = -2.1516x + 2.9379
R² = 0.1245

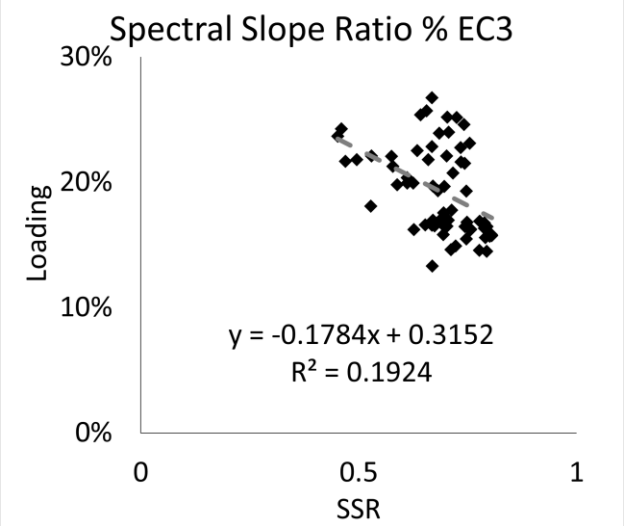

Spectral Slope Ratio v EC4
Loading
SSR
y = -2.0923x + 2.2455
R² = 0.1615

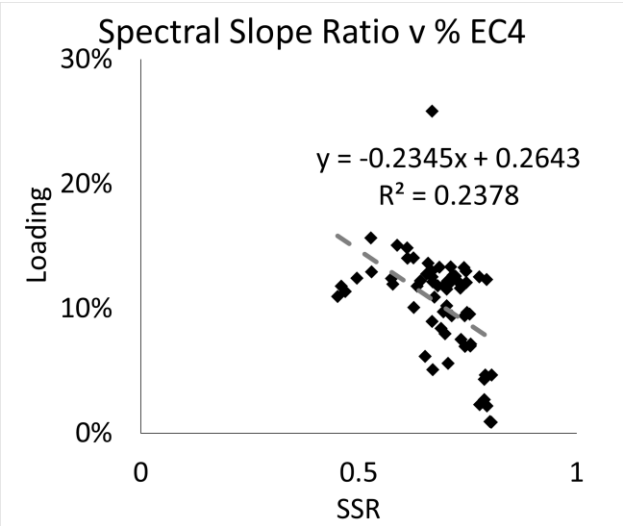

Spectral Slope Ratio v EC5
Loading
SSR
y = 0.5717x - 0.2412
R² = 0.1681

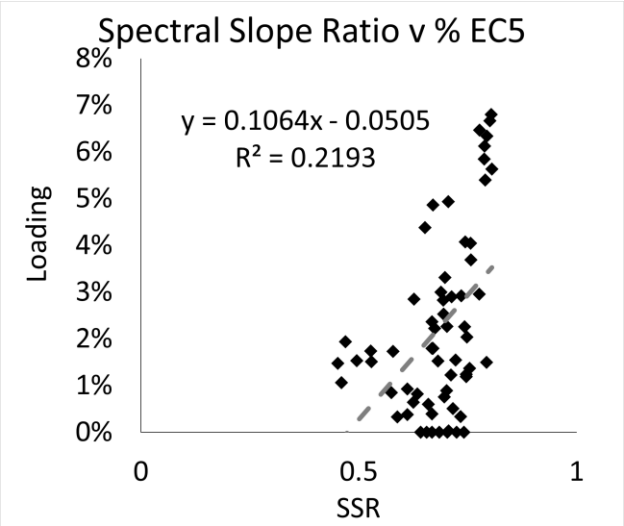

Spectral Slope Ratio v Sum of Loadings
Loading
SSR
y = -5.0339x + 10.933
R² = 0.0516

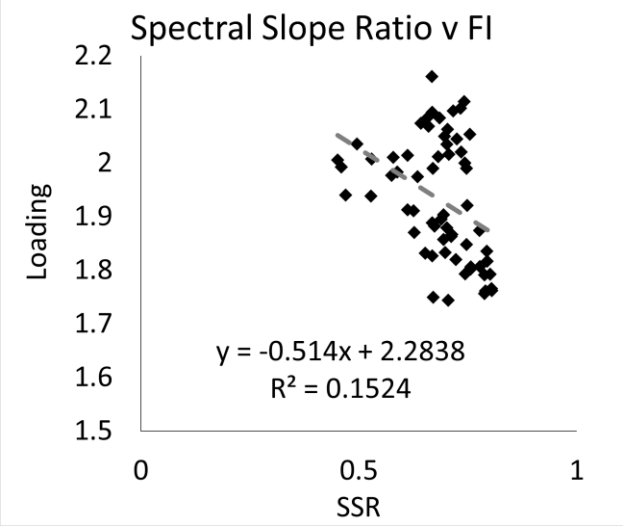

Spectral Slope Ratio v % EC1
50%
40%
30%
20%
10%
0%
Loading
y = 0.004x + 0.3795
R² = 0.0005
0
0.5
1
SSR

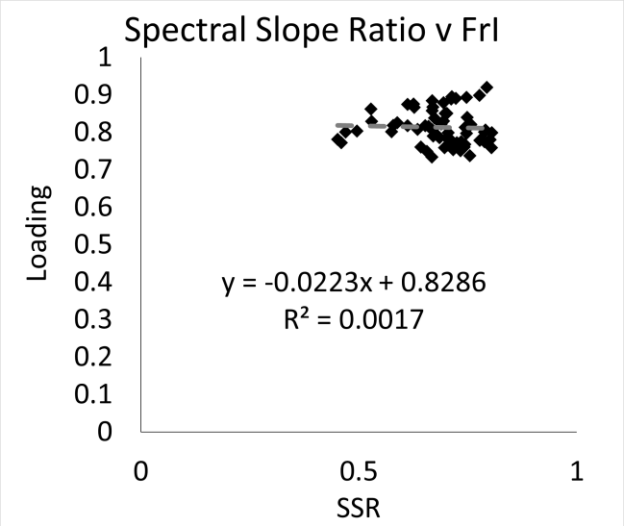

Spectral Slope Ratio v % EC2
40%
30%
20%
10%
0%
Loading
y = 0.3025x + 0.0916
R² = 0.5155
0
0.5
1
SSR

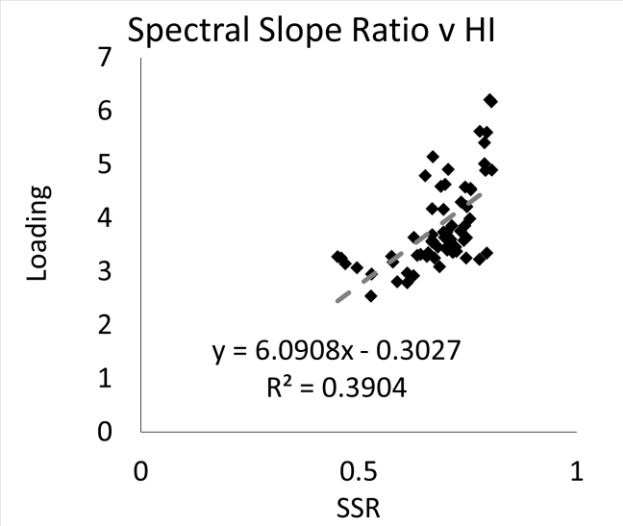

Spectral Slope Ratio % EC3
30%
20%
10%
0%
Loading
y = -0.1784x + 0.3152
R² = 0.1924
0
0.5
1
SSR

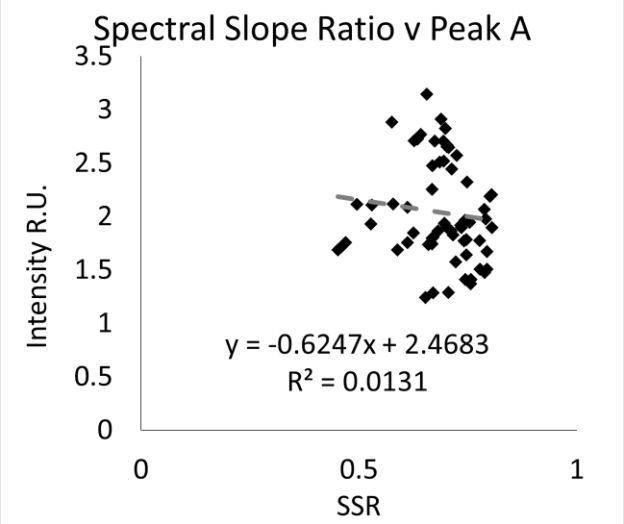

Spectral Slope Ratio v % EC4
30%
20%
10%
0%
Loading
y = -0.2345x + 0.2643
R² = 0.2378
0
0.5
1
SSR

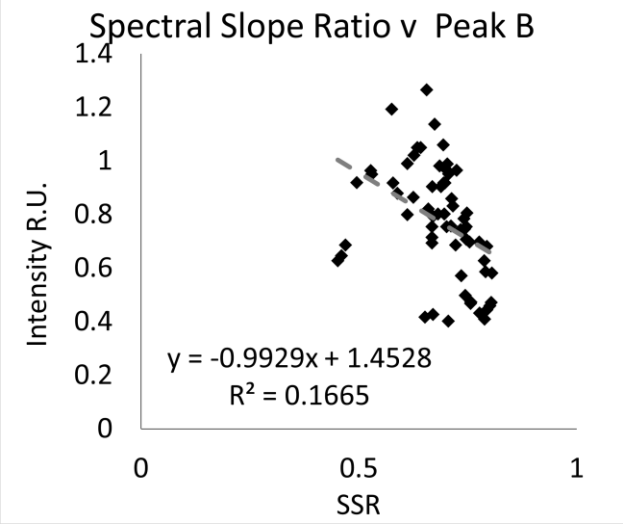

Spectral Slope Ratio v % EC5
8%
7%
6%
5%
4%
3%
2%
1%
0%
Loading
y = 0.1064x - 0.0505
R² = 0.2193
0
0.5
1
SSR

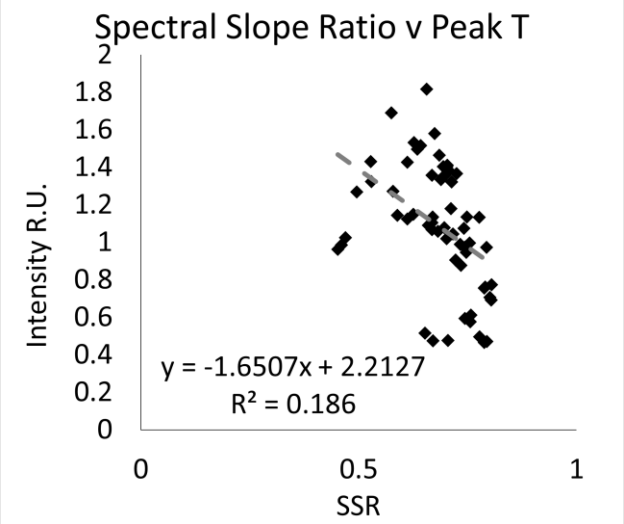

Spectral Slope Ratio v FI
2.2
2.1
2
1.9
1.8
1.7
1.6
1.5
Loading
y = -0.514x + 2.2838
R² = 0.1524
0
0.5
1
SSR

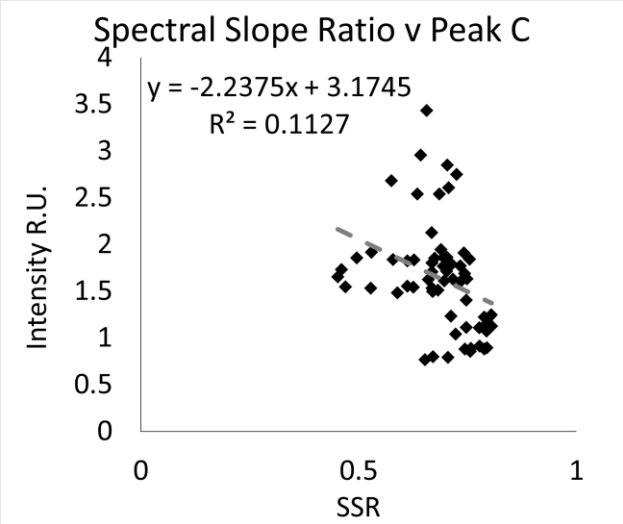

Spectral Slope Ratio v FrI
Loading
SSR
y = -0.0223x + 0.8286
R² = 0.0017

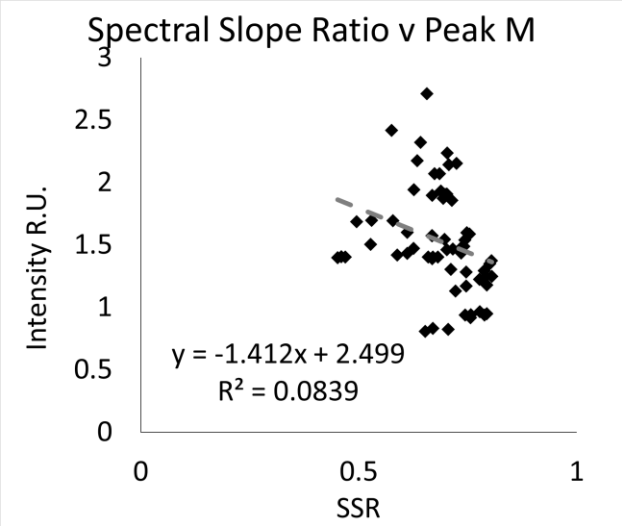

Spectral Slope Ratio v HI
Loading
SSR
y = 6.0908x - 0.3027
R² = 0.3904

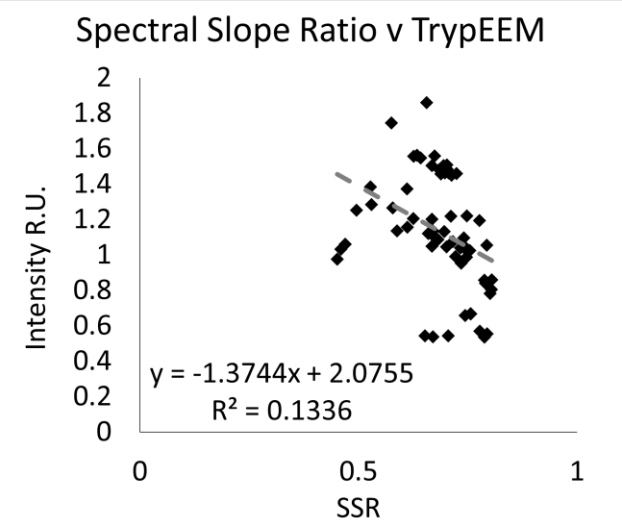

Spectral Slope Ratio v Peak A
Intensity R.U.
SSR
y = -0.6247x + 2.4683
R² = 0.0131

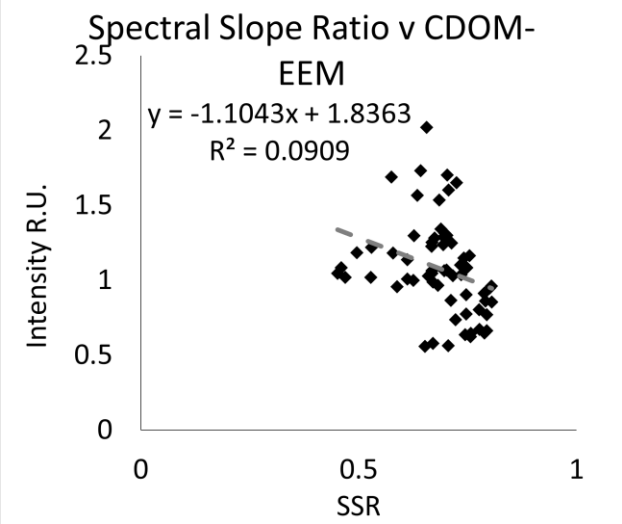

Spectral Slope Ratio v Peak B
Intensity R.U.
SSR
y = -0.9929x + 1.4528
R² = 0.1665

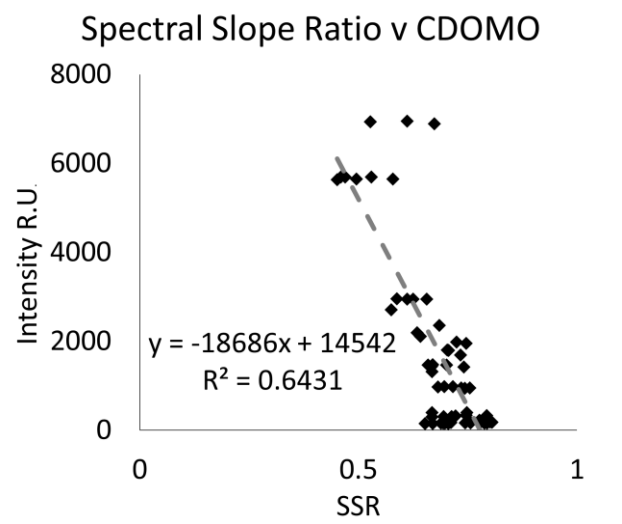

Spectral Slope Ratio v Peak T
Intensity R.U.
SSR
y = -1.6507x + 2.2127
R² = 0.186

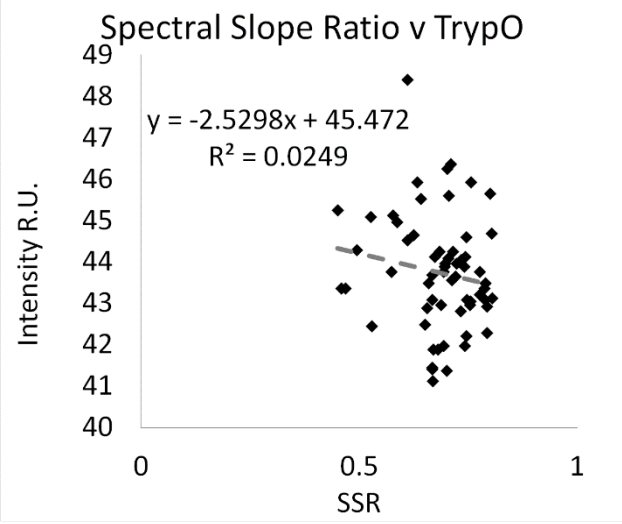

Spectral Slope Ratio v Peak C
Intensity R.U.
SSR
y = -2.2375x + 3.1745
R² = 0.1127

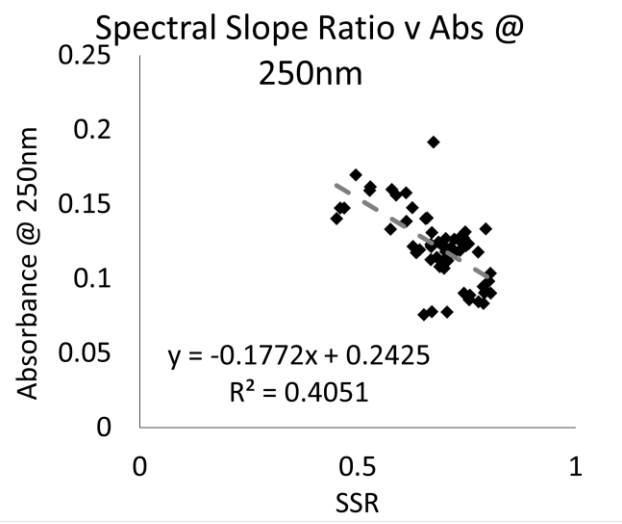

Spectral Slope Ratio v Peak M
Intensity R.U.
SSR
y = -1.412x + 2.499
R² = 0.0839


Spectral Slope Ratio v TrypEEM
Intensity R.U.
SSR
y = -1.3744x + 2.0755
R² = 0.1336

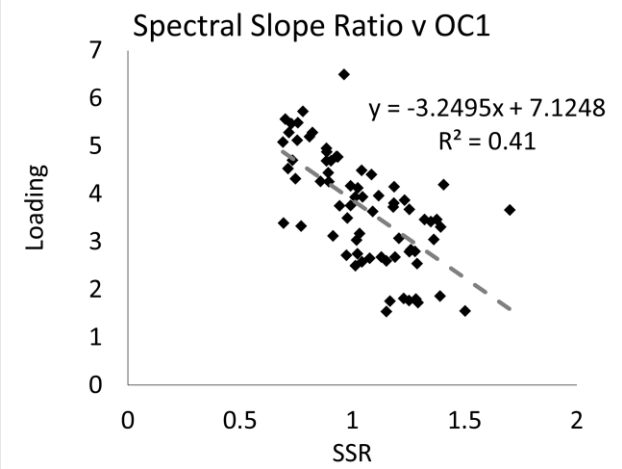

Spectral Slope Ratio v CDOM-EEM
Intensity R.U.
SSR
y = -1.1043x + 1.8363
R² = 0.0909

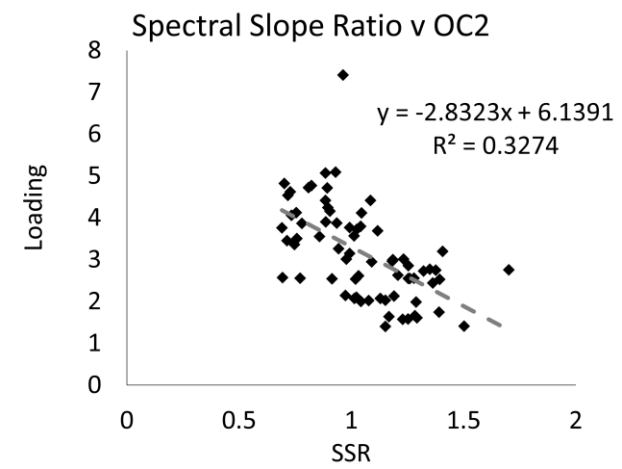

Spectral Slope Ratio v CDOMO
Intensity R.U
SSR
y = -18686x + 14542
R² = 0.6431

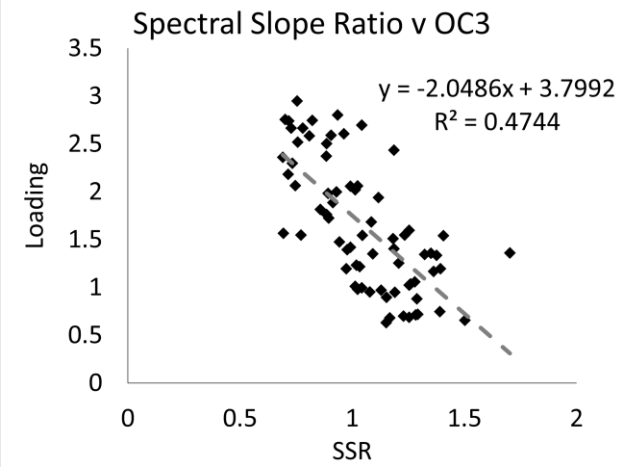

Spectral Slope Ratio v TrypO
Intensity R.U.
SSR
y = -2.5298x + 45.472
R² = 0.0249

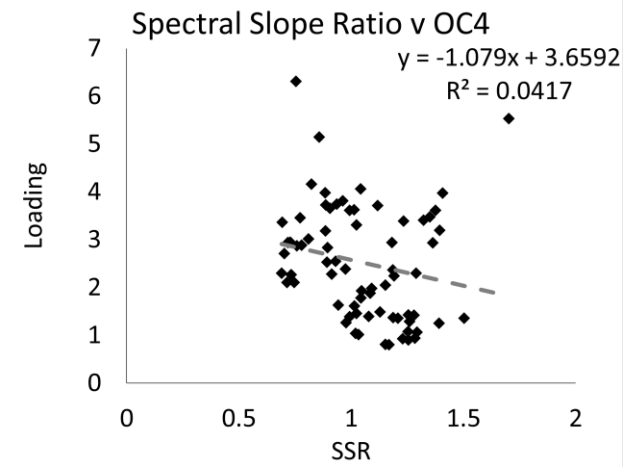

Spectral Slope Ratio v Abs @ 250nm
Absorbance @ 250nm
SSR
y = -0.1772x + 0.2425
R² = 0.4051

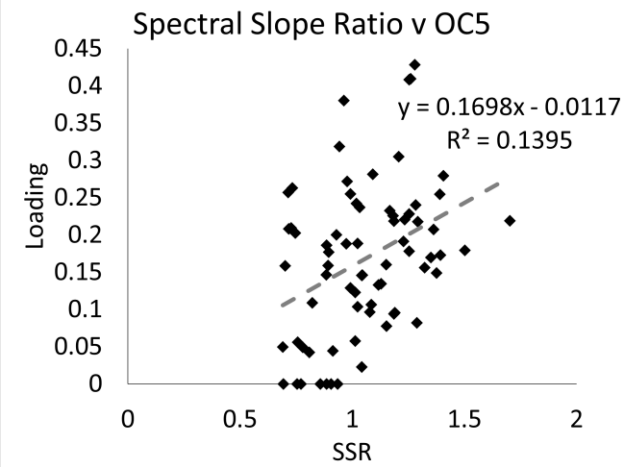
Oxic Tank

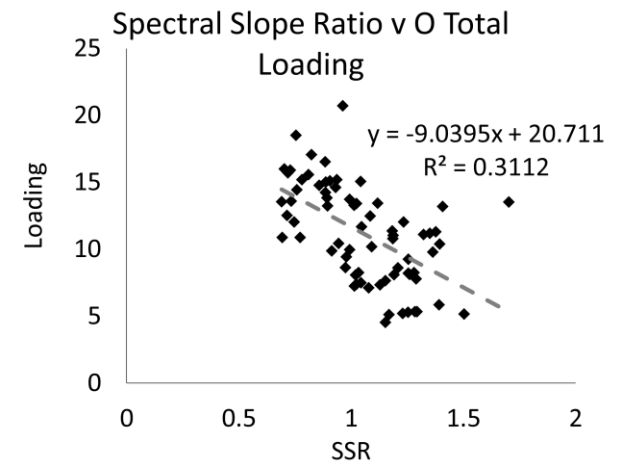

Spectral Slope Ratio v OC1
y = -3.2495x + 7.1248
R² = 0.41
Loading
SSR

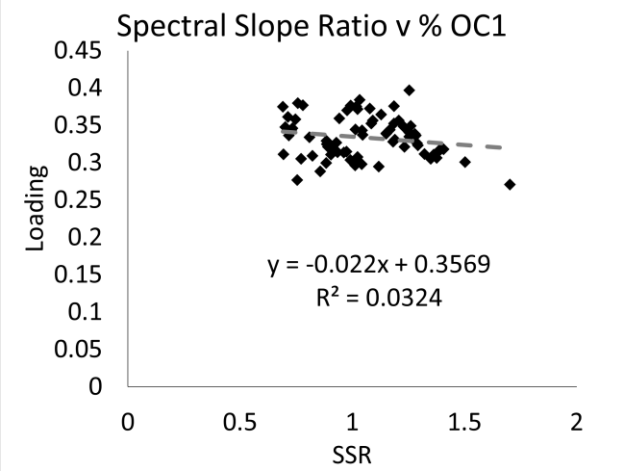

Spectral Slope Ratio v OC2
y = -2.8323x + 6.1391
R² = 0.3274
Loading
SSR

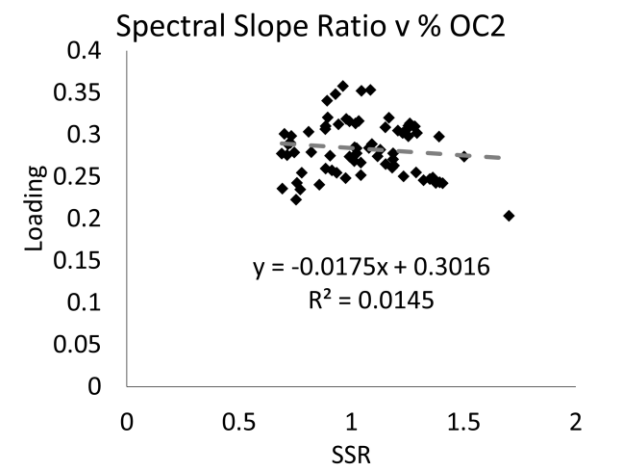

Spectral Slope Ratio v OC3
y = -2.0486x + 3.7992
R² = 0.4744
Loading
SSR

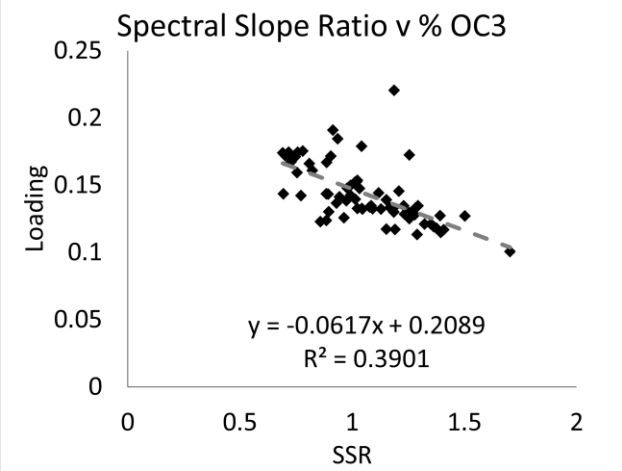

Spectral Slope Ratio v OC4
y = -1.079x + 3.6592
R² = 0.0417
Loading
SSR

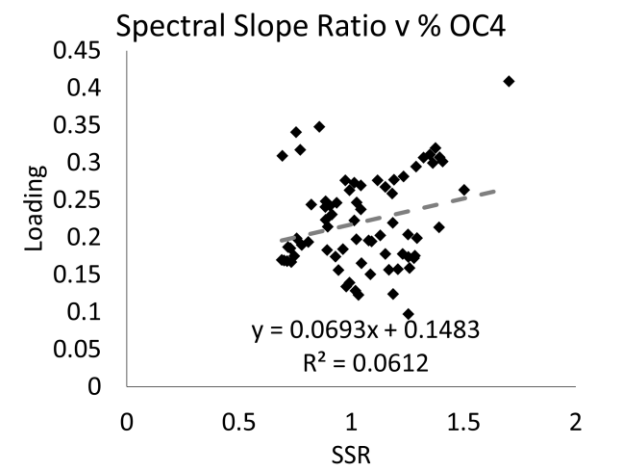

Spectral Slope Ratio v OC5
y = 0.1698x - 0.0117
R² = 0.1395
Loading
SSR

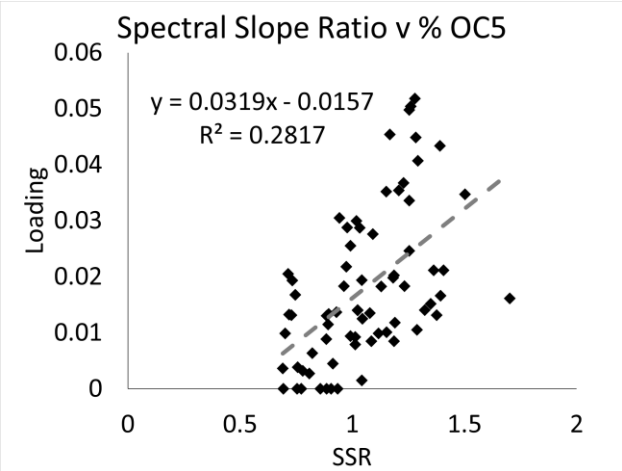

Spectral Slope Ratio v O Total Loading
y = -9.0395x + 20.711
R² = 0.3112
Loading
SSR

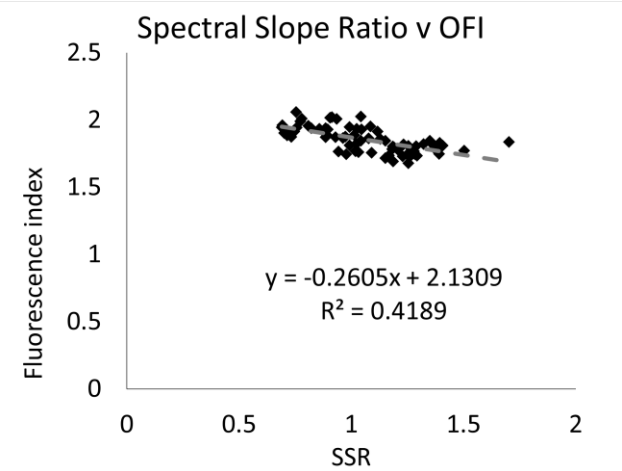

Spectral Slope Ratio v % OC1
Loading
SSR
y = -0.022x + 0.3569
R² = 0.0324
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
0.5
1
1.5
2

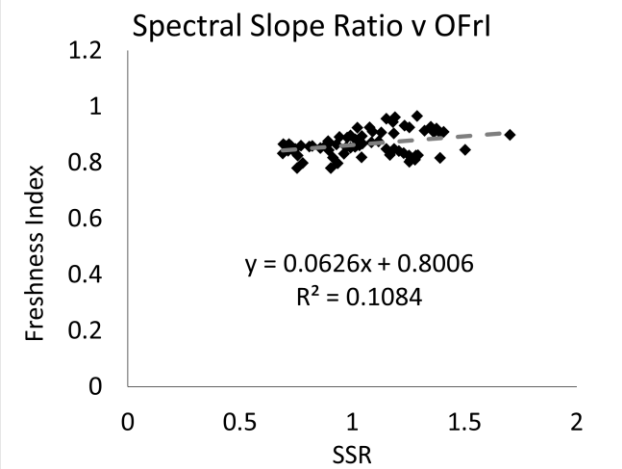

Spectral Slope Ratio v % OC2
Loading
SSR
y = -0.0175x + 0.3016
R² = 0.0145
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
0.5
1
1.5
2

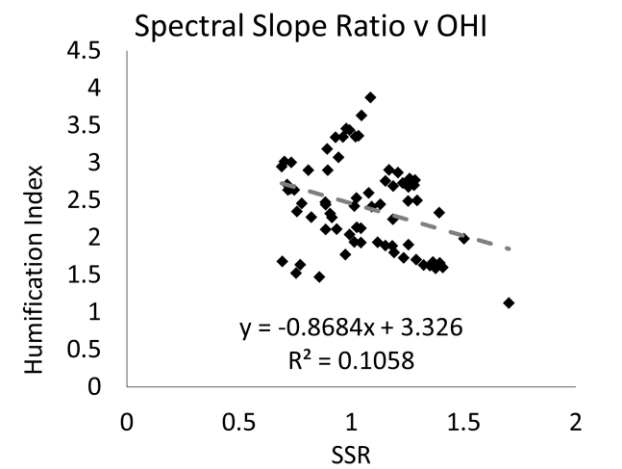

Spectral Slope Ratio v % OC3
Loading
SSR
y = -0.0617x + 0.2089
R² = 0.3901
0.25
0.2
0.15
0.1
0.05
0
0
0.5
1
1.5
2

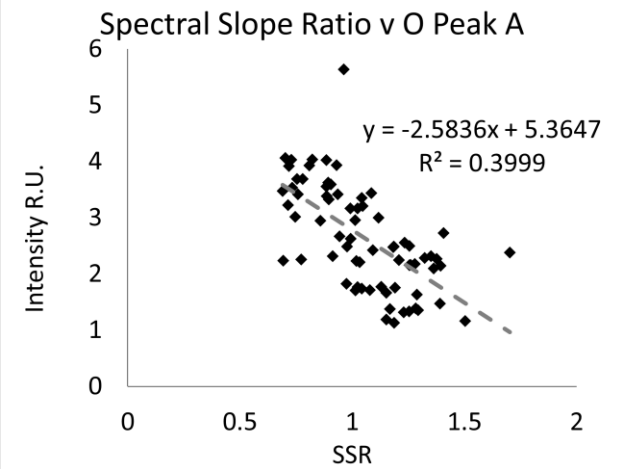

Spectral Slope Ratio v % OC4
Loading
SSR
y = 0.0693x + 0.1483
R² = 0.0612
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
0.5
1
1.5
2

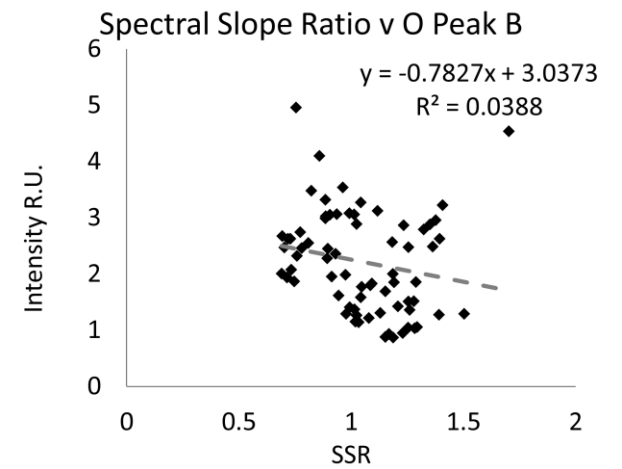

Spectral Slope Ratio v % OC5
Loading
SSR
y = 0.0319x - 0.0157
R² = 0.2817
0.06
0.05
0.04
0.03
0.02
0.01
0
0
0.5
1
1.5
2

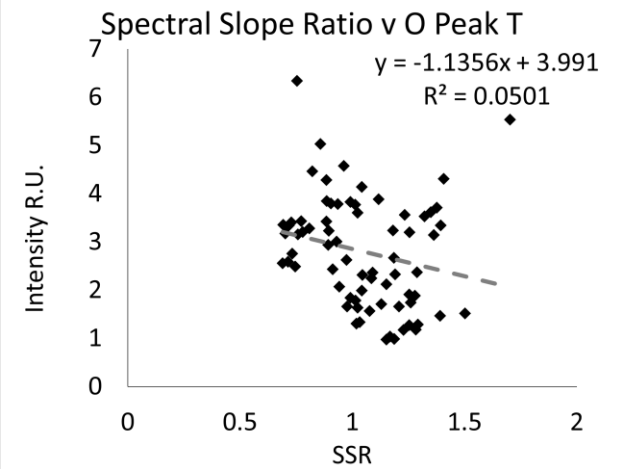

Spectral Slope Ratio v OFI
Fluorescence index
SSR
y = -0.2605x + 2.1309
R² = 0.4189
2.5
2
1.5
1
0.5
0
0
0.5
1
1.5
2

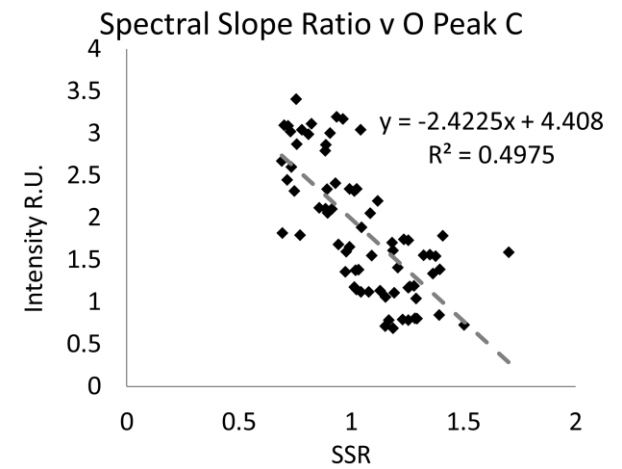

Spectral Slope Ratio v OFrI
Freshness Index
SSR
y = 0.0626x + 0.8006
R² = 0.1084

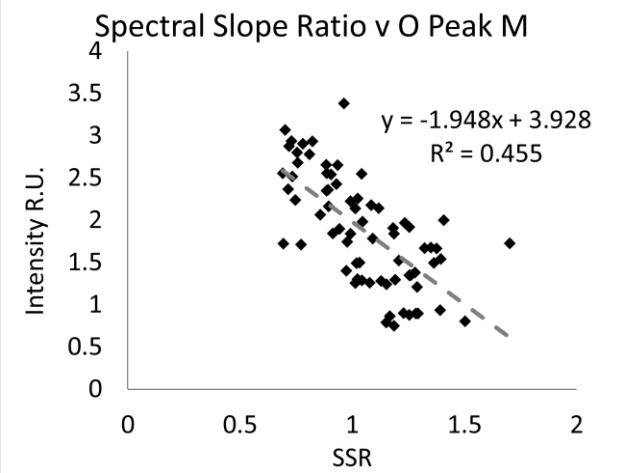

Spectral Slope Ratio v OHI
Humification Index
SSR
y = -0.8684x + 3.326
R² = 0.1058

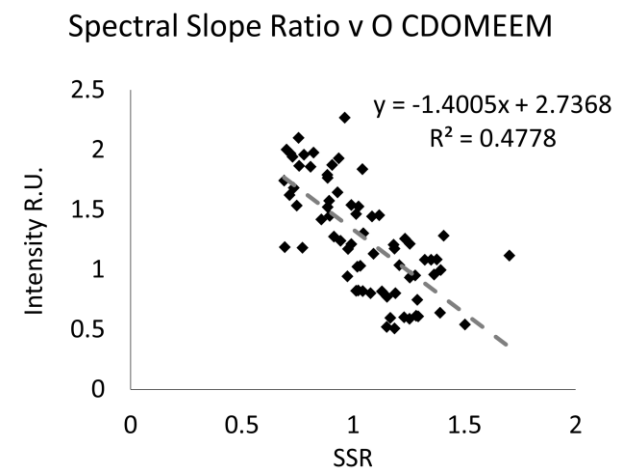

Spectral Slope Ratio v O Peak A
Intensity R.U.
SSR
y = -2.5836x + 5.3647
R² = 0.3999

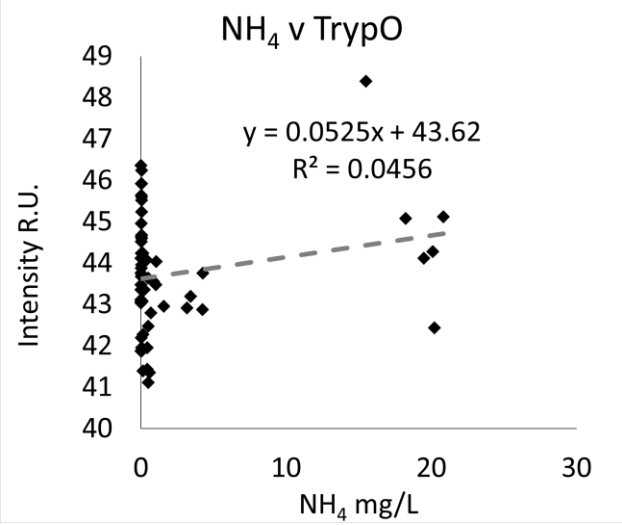

Spectral Slope Ratio v O Peak B
Intensity R.U.
SSR
y = -0.7827x + 3.0373
R² = 0.0388

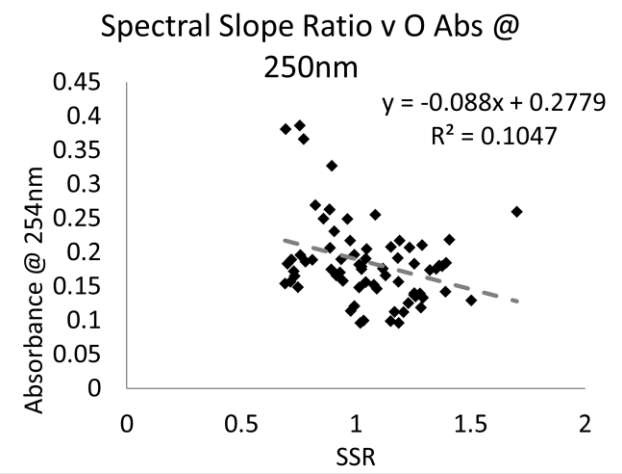

Spectral Slope Ratio v O Peak T
Intensity R.U.
SSR
y = -1.1356x + 3.991
R² = 0.0501


Spectral Slope Ratio v O Peak C
Intensity R.U.
SSR
y = -2.4225x + 4.408
R² = 0.4975

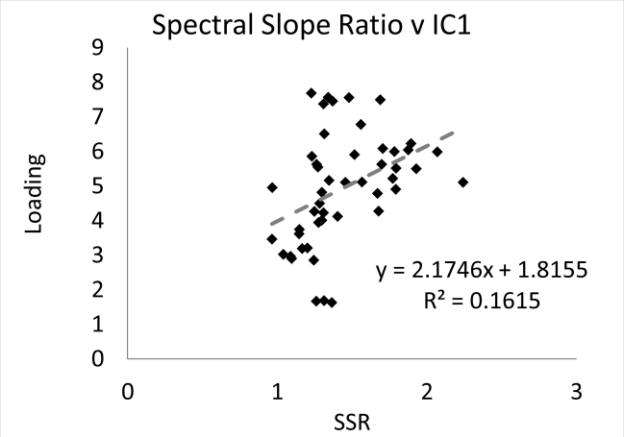

Spectral Slope Ratio v O Peak M
y = -1.948x + 3.928
R² = 0.455
Intensity R.U.
SSR

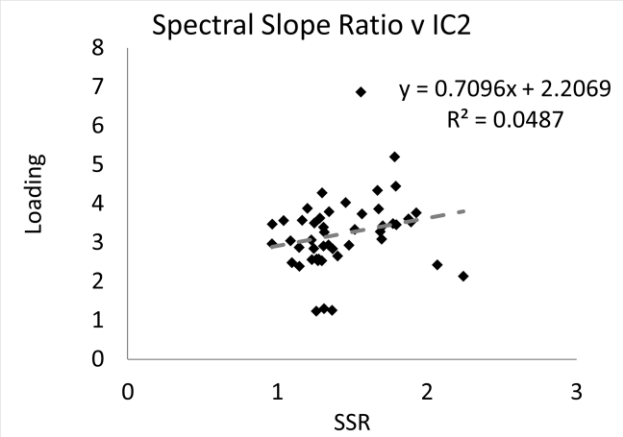

Spectral Slope Ratio v O CDOMEEM
y = -1.4005x + 2.7368
R² = 0.4778
Intensity R.U.
SSR

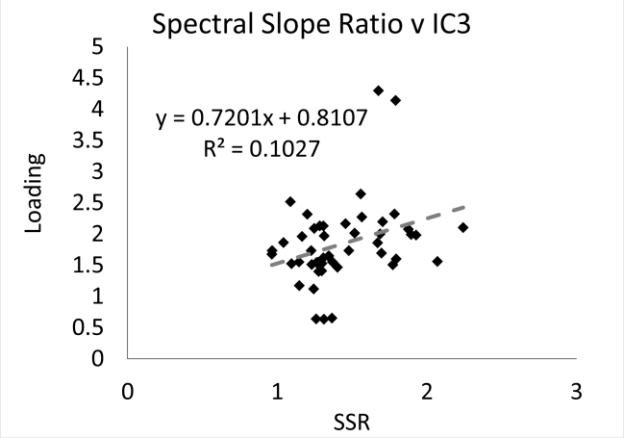

NH4 v TrypO
y = 0.0525x + 43.62
R² = 0.0456
Intensity R.U.
NH4 mg/L

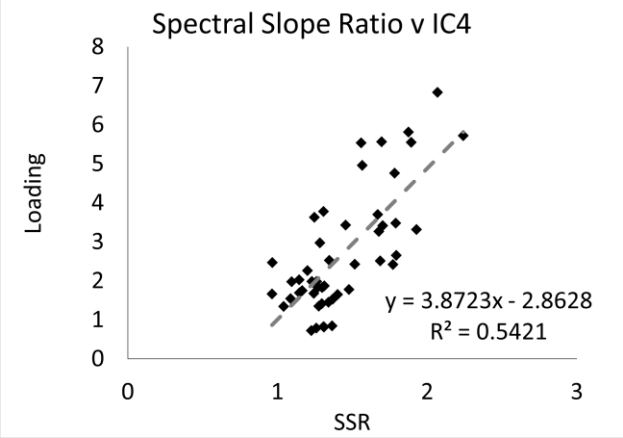

Spectral Slope Ratio v O Abs @ 250nm
y = -0.088x + 0.2779
R² = 0.1047
Absorbance @ 254nm
SSR

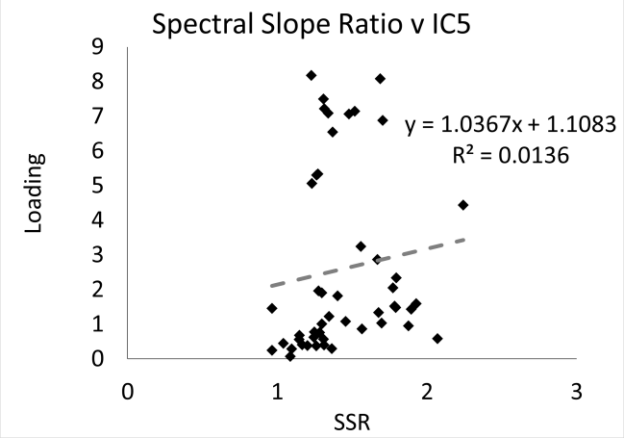
Influent

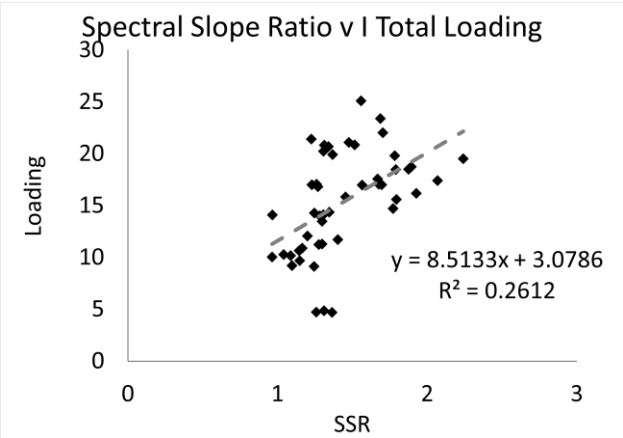

Spectral Slope Ratio v IC1
Loading
SSR
y = 2.1746x + 1.8155
R² = 0.1615

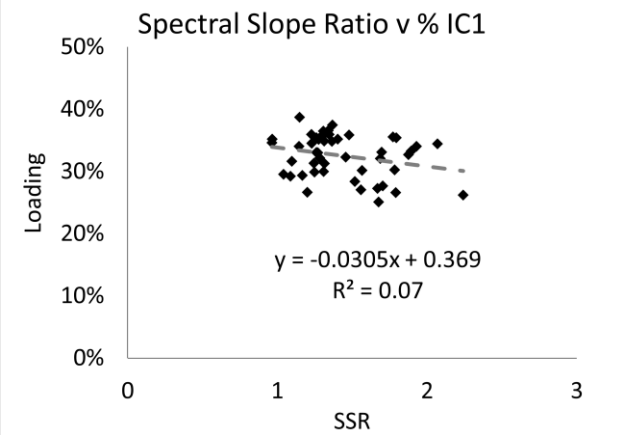

Spectral Slope Ratio v IC2
Loading
SSR
y = 0.7096x + 2.2069
R² = 0.0487

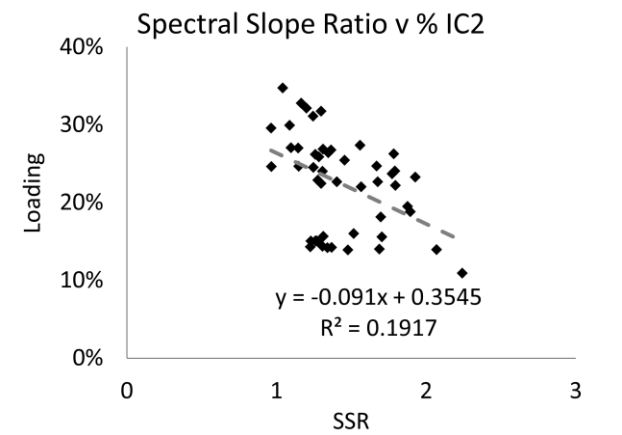

Spectral Slope Ratio v IC3
Loading
SSR
y = 0.7201x + 0.8107
R² = 0.1027

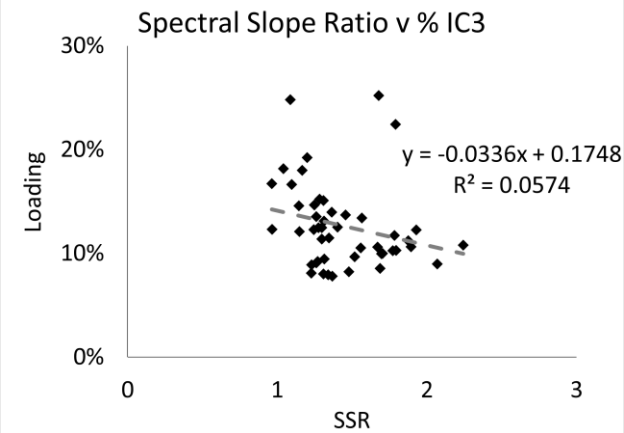

Spectral Slope Ratio v IC4
Loading
SSR
y = 3.8723x - 2.8628
R² = 0.5421

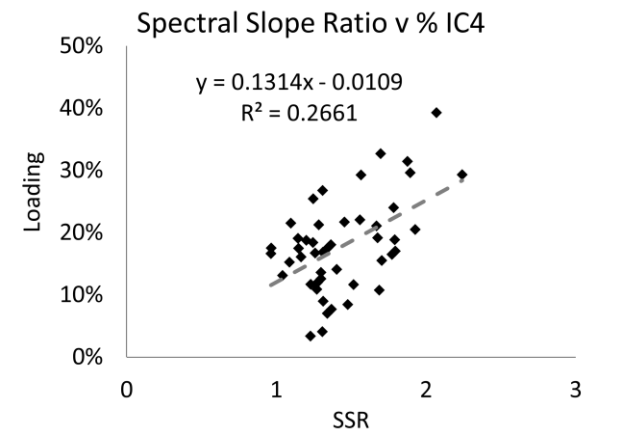

Spectral Slope Ratio v IC5
Loading
SSR
y = 1.0367x + 1.1083
R² = 0.0136

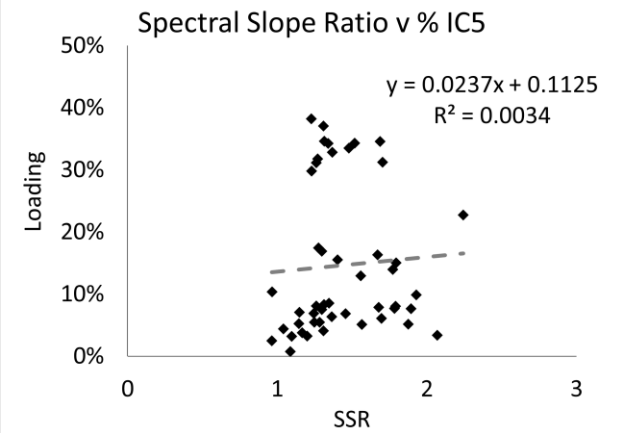

Spectral Slope Ratio v I Total Loading
Loading
SSR
y = 8.5133x + 3.0786
R² = 0.2612

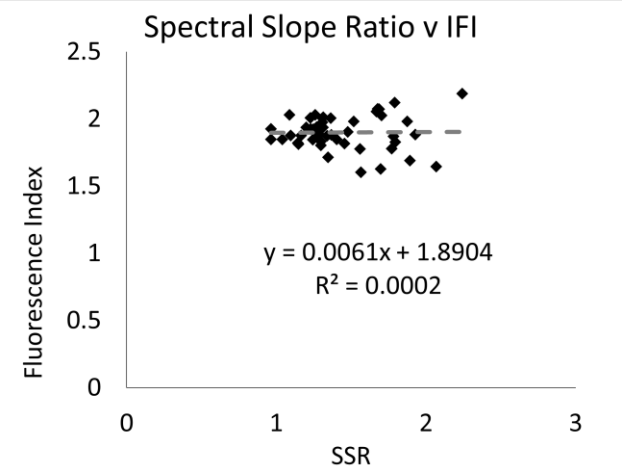

Spectral Slope Ratio v % IC1
Loading
SSR
y = -0.0305x + 0.369
R² = 0.07

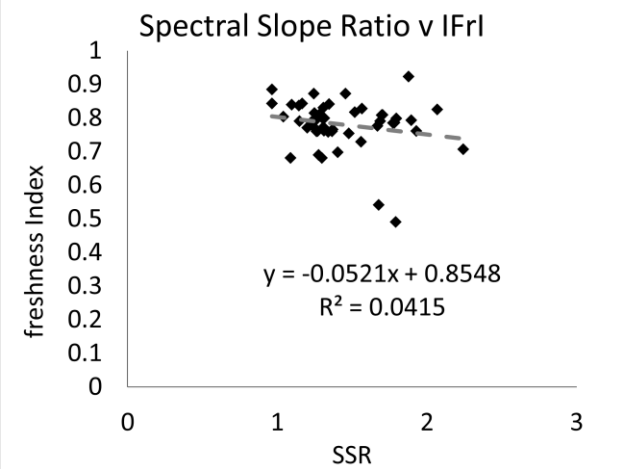

Spectral Slope Ratio v % IC2
Loading
SSR
y = -0.091x + 0.3545
R² = 0.1917

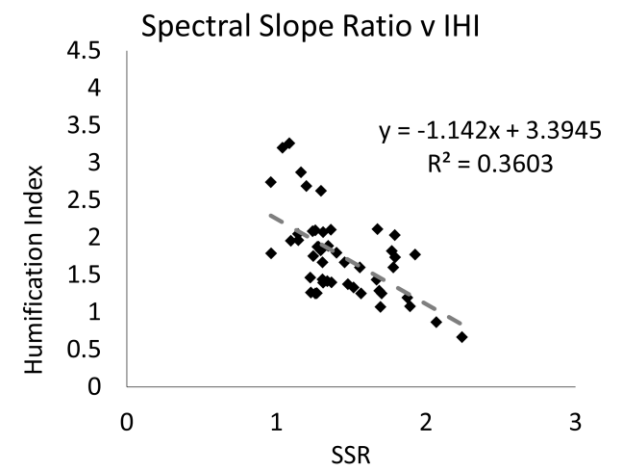

Spectral Slope Ratio v % IC3
Loading
SSR
y = -0.0336x + 0.1748
R² = 0.0574

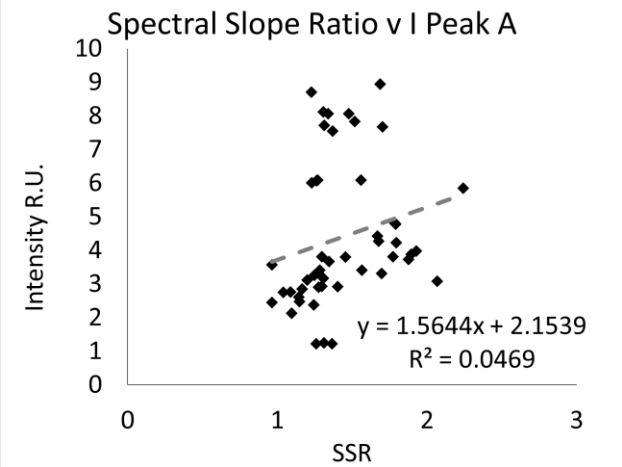

Spectral Slope Ratio v % IC4
Loading
SSR
y = 0.1314x - 0.0109
R² = 0.2661

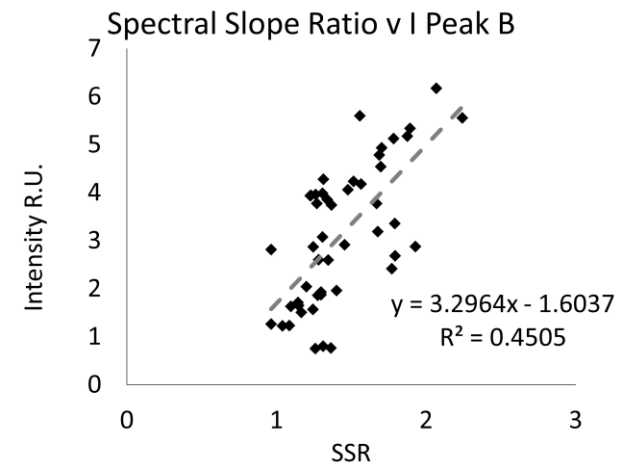

Spectral Slope Ratio v % IC5
Loading
SSR
y = 0.0237x + 0.1125
R² = 0.0034

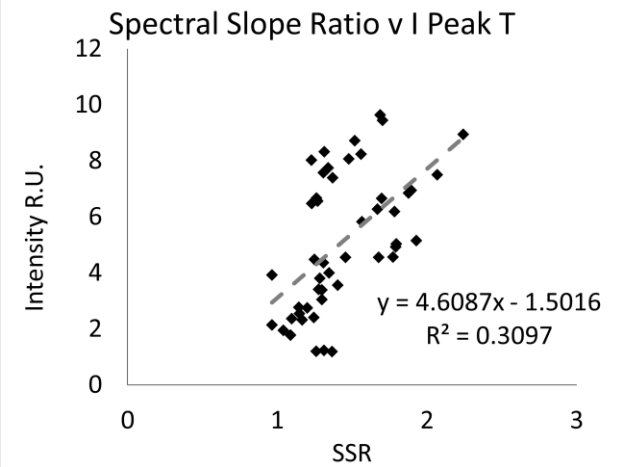

Spectral Slope Ratio v IFI
Fluorescence Index
SSR
y = 0.0061x + 1.8904
R² = 0.0002

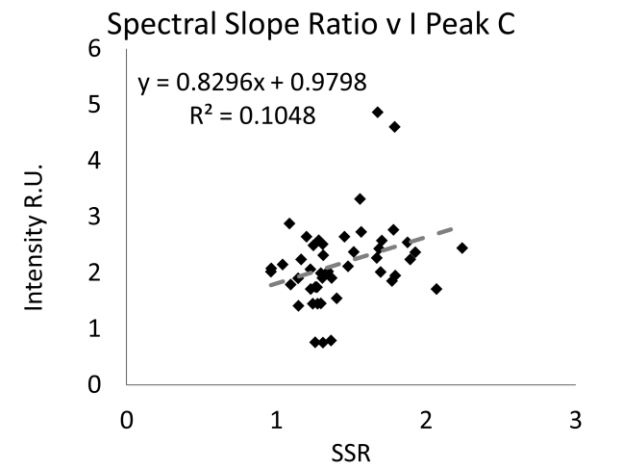

Spectral Slope Ratio v IFrI
freshness Index
SSR
y = -0.0521x + 0.8548
R² = 0.0415

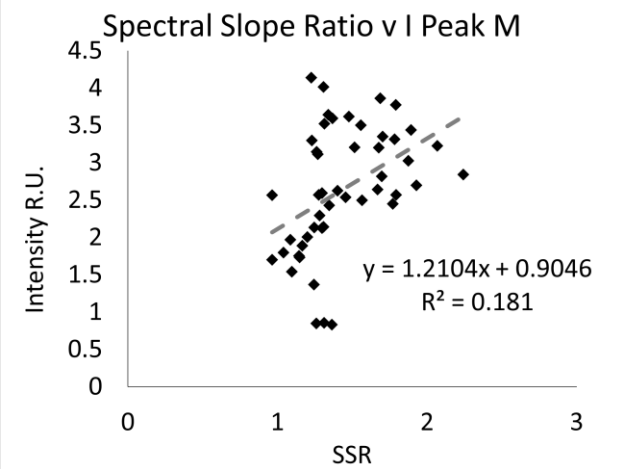

Spectral Slope Ratio v IHI
Humification Index
SSR
y = -1.142x + 3.3945
R² = 0.3603

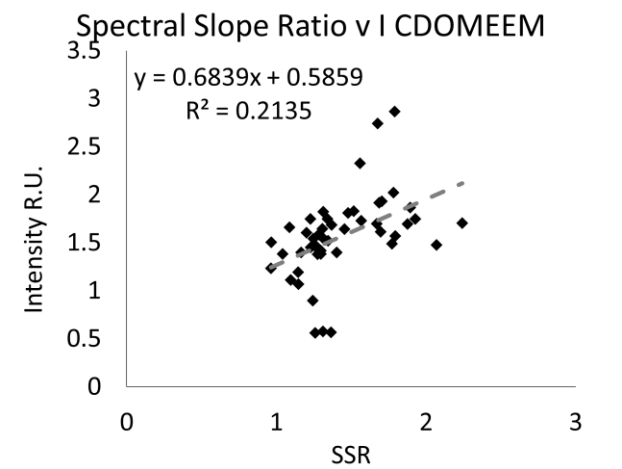

Spectral Slope Ratio v I Peak A
Intensity R.U.
SSR
y = 1.5644x + 2.1539
R² = 0.0469

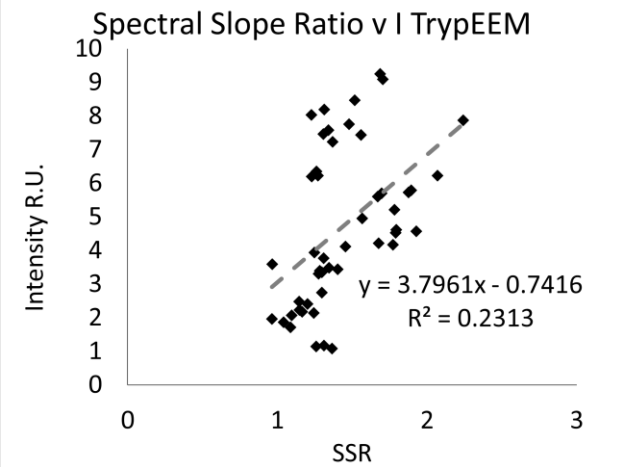

Spectral Slope Ratio v I Peak B
Intensity R.U.
SSR
y = 3.2964x - 1.6037
R² = 0.4505

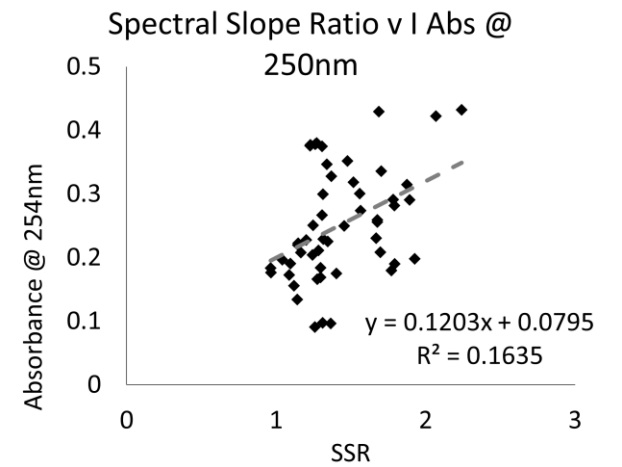

Spectral Slope Ratio v I Peak T
Intensity R.U.
SSR
y = 4.6087x - 1.5016
R² = 0.3097


Spectral Slope Ratio v I Peak C
Intensity R.U.
SSR
y = 0.8296x + 0.9798
R² = 0.1048


Spectral Slope Ratio v I Peak M
Intensity R.U.
SSR
y = 1.2104x + 0.9046
R² = 0.181


Spectral Slope Ratio v I CDOMEEM
Intensity R.U.
SSR
y = 0.6839x + 0.5859
R² = 0.2135


Spectral Slope Ratio v I TrypEEM
Intensity R.U.
SSR
y = 3.7961x - 0.7416
R² = 0.2313


Spectral Slope Ratio v I Abs @ 250nm
Absorbance @ 254nm
SSR
y = 0.1203x + 0.0795
R² = 0.1635

Appendix B - Raw data tables

Effluent

Grab Samples

Sample Name	Days	Filt time	TN	TP	NH4	NO3	OP	Total Coliforms	E. Coli	COD	TOC	Abs at 250nm	Spectral Slope Ratio
		min	mg/L	mg/L	mg/L	mg/L	ppb	MNP	MNP	mg/L	mg/L		
E160525.1	47	2	24.18	4.72	15.5	6.42	4339	4.1	0	32		0.15762	0.611443
E160525.2	47	15	24.57	4.65	18.24	4.15	4288	0	0	0		0.15921	0.527566
E160525.3	47	30	29.36	4.72	19.49	4.11	4469	2	0	0		0.19164	0.673904
E160527.1	49	0.5	21.39	4.13	0.22	18.65	4020	4.1	0	0		0.14748	0.460076
E160527.2	49	3	21.31	4.24	0.04	18.67	4050	0	0	22		0.14736	0.469436
E160527.3	49	12	21.21	4.25	0.04	18.38	4040	0	0	1		0.14029	0.451647
E160601.1	54	35	27.38	5.06	20.21	4.63	4857	6.3	0	0		0.16176	0.529408
E160601.2	54	48	27.65	5.34	20.83	4.87	4914	0	0	90		0.16002	0.578542
E160601.3	54	58	28.25	5.21	20.09	5.39	4855	0	0	80		0.1697	0.49552
E160606.1	59	0.12	14.32	4.60	0.03	11.56	4228	0	0	1		0.15614	0.588343
E160606.2	59	0.3	8.96	4.96	0.02	7.37	4578	1	0	0		0.13856	0.611522
E160606.3	59	3	9.02	4.89	0.02	7.43	4554	1	0	30		0.14771	0.625381
E160608.2	61	7	10.33	5.48	4.26	5.02	5121	0	0	40		0.13319	0.57522
E160608.3	61	14	10.77	5.63	4.25	5.41	5233	0	0	102		0.14025	0.655969
E160611.1	64	20	5.78	5.37	0.13	4.78	4922			17		0.12448	0.685144
E160611.2	64	28	5.65	5.49	0.05	4.79	4919			0		0.11742	0.63428
E160611.3	64	3	5.78	5.63	0.04	5.23	5068			10		0.11946	0.642016
E160614.1	67	0.12	4.12	4.42	0.06	3.99	3833	0	0	0		0.11817	0.724433
E160614.2	67	10	5.05	4.23	0.05	3.85	3687	1	0	0		0.11387	0.703182
E160614.3	67	22	4.42	4.26	0.04	4.33	3735	0	0	27		0.11213	0.706419

E160615.1	68	0.75	5.21	2.92	0.04	4.63	2823	3.1	0	26		0.12394	0.746791
E160615.2	68	6	4.76	3.25	0.69	3.99	3214	0	0	0		0.12567	0.733453
E160615.3	68	17	6.34	3.56	0.59	5.63	3470	0	0	26		0.1271	0.701777
E160621.2	74	28	8.41	4.62	1.02	6.99	4300	0	0	0	17.4	0.1409	0.659519
E160621.3	74	2	8.29	4.41	0.51	7.73	4193	0	0	14	17.4	0.1309	0.67003
E160622.1	75	3	6.10	2.83	0.03	5.95	2692	0	0	45	20.09	0.12964	0.741342
E160622.2	75	15	7.38	3.07	0.02	7.12	2795	0	0	11	19.25	0.12292	0.668167
E160622.3	75	22	7.33	2.95	0.15	6.73	2754	0	0	44	19.41	0.12309	0.667711
E160628.1	81	15	5.02	1.42	0.02	4.89	1289	0	0	51	22.29	0.11998	0.716138
E160628.2	81	1	4.94	1.36	0.02	4.78	1289	0	0	56	22.4	0.12212	0.696466
E160628.3	81	3	5.03	1.41	0.04	4.76	1317	0	0	49	22.29	0.11423	0.681723
E160629.1	82	3	3.73	3.02	0.05	3.26	2820	1	0	0	24.63	0.12736	0.743139
E160629.2	82	6	3.69	3.61	1.06	2.62	3333	1	1	0	23.22	0.11888	0.734943
E160629.3	82	13	4.85	3.91	1.58	3.18	3699	0	0	9	23.22	0.12353	0.754426
E160712.1	95	3	4.41	1.72	0.09	4.38	1626	5.2	1	17	6.212	0.12207	0.748157
E160712.2	95	5	4.66	1.83	0.04	4.69	1795	0	0	11	5.61	0.11279	0.668203
E160713.1	96	1	5.06	1.15	0.01	6.35	1062	1	0	76	5.462	0.11803	0.7022
E160713.3	96	11	7.68	1.62	0.11	7.56	1599	1	0	79	6.067	0.12157	0.626672
E160718.1	101	0.6	5.52	0.94	0.03	4.7	586	0	0	25	5.877	0.13139	0.746586
E160718.2	101	2	5.07	0.81	0.51	4.65	630	0	0	18	6.193	0.12659	0.722116
E160718.3	101	8	7.54	1.73	3.17	3.83	1605	1	0	22	6.415	0.13356	0.793643
E160720.1	103	4	5.62	2.76	0.43	4.76	2534	0	0	15	6.212	0.12214	0.694563
E160720.2	103	11	6.25	3.03	0.87	5.15	2836	1	0	0	6.061	0.12075	0.71325
E160720.3	103	16	6.6	2.92	0.43	6.04	2825	0	0	13	6.652	0.12143	0.668413
E160726.2	109	2	1.43	5.14	0.05	1.85	4690	1	0	4	4.58	0.10369	0.804241
E160726.3	109	3	1.27	5.12	0.02	1.72	4568	6.3	0	11	4.818	0.09829	0.800817
E160727.1	110	2	1.4	6.76	0.01	1.74	5861	1	0	55	5.251	0.09485	0.78798
E160727.2	110	7	1.52	6.6	0.01	2.13	5938	0	0	55	5.775	0.09057	0.790578
E160727.3	110	11	1.68	6.52	0.01	2.23	6603	0	0	55	5.841	0.09025	0.805242
E160808.1	122	1	2.08	7.98	0.15	1.48	7486	1	0	13	4.621	0.0916	0.79404
E160808.2	122	4	1.76	7.97	0.01	1.27	7588	1	0	0	4.434	0.08342	0.788428

E160808.3	122	8	1.67	7.96	0.01	1.22	7619	0	0	11	4.397	0.08453	0.777417
E160810.1	124	0.5	4.04	7.61	0.01	3.41	7222	1	0	23	4.42	0.07784	0.670156
E160810.2	124	3	4.48	7.51	0.4	3.56	7316	14.5	0	16	4.353	0.07771	0.705143
E160810.3	124	7	4.88	7.48	0.51	3.65	7137	0	0	17	4.424	0.07593	0.652259
E160817.1	131	0.5	3.68	5.32	0.01	3.11	4818	3.1	0	30	4.754	0.09018	0.74407
E160817.2	131	2	3.5	5.34	0.02	2.68	5053	6.3	0	0	5.137	0.08891	0.757194
E160817.3	131	25	3.01	5.14	0	2.47	4912	1	0	35	4.493	0.08577	0.756359
E160824.2	138	2	4.3	0.11	0.01	3.35	68	4.1	0	22	6.251	0.11956	0.711406
E160824.3	138	11	7.91	0.98	3.42	3.27	854	3.1	1	23	6.285	0.1178	0.776731
E160831.1	145	3						4.1	0	25	5.614	0.10971	0.694085
E160831.2	145	8						3.1	0	19	5.581	0.10708	0.698105
E160831.3	145	1						14.4	4.1	22	5.382	0.10804	0.688649

Table 12

	Total Model										
Sample Name	C1	C2	C3	C4	C5	Total Loading	% C1	% C2	% C3	% C4	% C5
E160525.1	3.136	2.06139	1.6118	1.2026	0.07505	8.0868485	0.3878	0.25490645	0.19931	0.1487	0.0093
E160525.2	3.068	1.839591	1.3758	1.1915	0.1325	7.6079255	0.4033	0.24179935	0.18084	0.1566	0.0174
E160525.3	4.208	2.737402	1.6317	1.0795	0.21983	9.8766777	0.4261	0.27715814	0.16521	0.1093	0.0223
E160527.1	2.5	1.589695	1.5783	0.7682	0.06896	6.5051579	0.3843	0.24437461	0.24262	0.1181	0.0106
E160527.2	2.597	1.655268	1.4163	0.7432	0.12694	6.5389913	0.3972	0.25313811	0.21659	0.1136	0.0194
E160527.3	2.489	1.582113	1.5091	0.7002	0.09411	6.3746984	0.3905	0.24818631	0.23673	0.1098	0.0148
E160601.1	3.001	2.022366	1.7506	1.0264	0.11968	7.9201211	0.3789	0.25534531	0.22104	0.1296	0.0151
E160601.2	2.977	2.154454	1.6767	0.9432	0.13654	7.8878758	0.3774	0.2731349	0.21257	0.1196	0.0173
E160601.3	2.989	2.039831	1.7082	0.9738	0.12031	7.8314273	0.3817	0.2604673	0.21812	0.1243	0.0154
E160606.1	2.648	1.702653	1.3295	1.0139	0.02204	6.7155664	0.3942	0.25353832	0.19797	0.151	0.0033
E160606.2	2.663	1.823702	1.4002	0.9654	0.02593	6.8785792	0.3872	0.26512775	0.20356	0.1403	0.0038
E160606.3	2.726	1.880118	1.4037	0.9917	0.04522	7.0470127	0.3869	0.26679648	0.19919	0.1407	0.0064

E160608.2	4.149	2.992205	2.4371	1.3708	0.09407	11.043434	0.3757	0.27094874	0.22069	0.1241	0.0085
E160608.3	4.451	3.012403	3.1195	1.5532	0	12.135648	0.3667	0.24822764	0.25705	0.128	0
E160611.1	3.51	2.509301	2.2928	1.2784	0	9.590197	0.366	0.26165267	0.23908	0.1333	0
E160611.2	3.781	2.834316	2.2951	1.2032	0.08351	10.196762	0.3708	0.2779624	0.22508	0.118	0.0082
E160611.3	3.778	2.773025	2.6651	1.2837	0	10.500232	0.3598	0.26409179	0.25381	0.1223	0
E160614.1	3.529	2.625636	2.475	1.211	0	9.840364	0.3586	0.2668231	0.25152	0.1231	0
E160614.2	3.621	2.743644	2.56	1.239	0	10.163468	0.3563	0.26995158	0.25189	0.1219	0
E160614.3	3.597	2.701424	2.3613	1.1768	0.00338	9.8401963	0.3656	0.27452946	0.23997	0.1196	0.0003
E160615.1	2.42	1.919774	1.2425	0.7783	0.07667	6.4372119	0.3759	0.29823064	0.19301	0.1209	0.0119
E160615.2	2.553	1.998632	1.5876	0.8124	0.02348	6.9748695	0.366	0.28654755	0.22762	0.1165	0.0034
E160615.3	2.551	2.018022	1.5421	0.8072	0.06226	6.9805442	0.3654	0.28909232	0.22092	0.1156	0.0089
E160621.2	2.498	1.818003	1.471	0.9206	0.04062	6.7481147	0.3702	0.26940905	0.21799	0.1364	0.006
E160621.3	2.558	2.009332	1.356	0.8359	0.12385	6.8827741	0.3716	0.29193642	0.19701	0.1215	0.018
E160622.1	2.46	1.876357	1.7176	0.9291	0	6.9834333	0.3523	0.26868689	0.24595	0.133	0
E160622.2	2.475	1.820207	1.5282	0.839	0.02654	6.6887796	0.37	0.27212842	0.22847	0.1254	0.004
E160622.3	2.469	1.836194	1.9098	0.9299	0	7.1450368	0.3456	0.25698874	0.26729	0.1301	0
E160628.1	2.673	1.946692	1.4488	0.8867	0.0354	6.9908305	0.3824	0.27846363	0.20725	0.1268	0.0051
E160628.2	2.805	2.135177	1.4345	0.8681	0.05504	7.2973859	0.3843	0.29259477	0.19658	0.119	0.0075
E160628.3	2.621	2.027754	1.3347	0.8175	0.10544	6.9062434	0.3795	0.29361178	0.19326	0.1184	0.0153
E160629.1	2.655	2.133854	1.5411	0.6747	0.16207	7.1665422	0.3704	0.29775219	0.21505	0.0941	0.0226
E160629.2	2.487	2.065388	1.4477	0.5047	0.1956	6.7001191	0.3711	0.30826137	0.21608	0.0753	0.0292
E160629.3	2.714	2.057701	1.6716	0.6922	0.099	7.2341607	0.3751	0.28444223	0.23107	0.0957	0.0137
E160712.1	3.254	2.674203	1.3943	0.8053	0.16944	8.2972272	0.3922	0.32230077	0.16804	0.0971	0.0204
E160712.2	3.22	2.557279	1.3275	0.7184	0.18972	8.0124031	0.4018	0.3191651	0.16568	0.0897	0.0237
E160713.1	3.889	3.070272	1.6175	1.0036	0.22196	9.8025439	0.3968	0.31321174	0.16501	0.1024	0.0226
E160713.3	3.932	3.078253	1.6061	0.9981	0.28216	9.8966183	0.3973	0.31104091	0.16228	0.1009	0.0285
E160718.1	2.402	1.946797	0.957	0.8053	0.07698	6.1883923	0.3882	0.31458853	0.15465	0.1301	0.0124
E160718.2	2.325	1.912694	0.8919	0.753	0.09235	5.9752455	0.3892	0.32010299	0.14926	0.126	0.0155
E160718.3	2.52	1.958586	0.9056	0.7712	0.09336	6.2489696	0.4033	0.31342547	0.14491	0.1234	0.0149
E160720.1	3.63	2.973609	1.6508	0.9159	0.23792	9.4081451	0.3858	0.31606753	0.17546	0.0974	0.0253
E160720.2	3.49	2.850431	1.6123	0.8544	0.26332	9.0705049	0.3848	0.31425273	0.17775	0.0942	0.029

E160720.3	3.753	2.998593	1.5206	2.9548	0.20577	11.432381	0.3282	0.26228948	0.13301	0.2585	0.018
E160726.2	2.78	2.551409	1.1019	0.0613	0.47373	6.9679125	0.3989	0.3661655	0.15814	0.0088	0.068
E160726.3	2.763	2.534996	1.0829	0.0648	0.46053	6.9065589	0.4001	0.36704186	0.1568	0.0094	0.0667
E160727.1	2.547	2.352537	1.0877	0.2884	0.38962	6.6656335	0.3822	0.35293519	0.16318	0.0433	0.0585
E160727.2	2.512	2.270482	1.0032	0.3002	0.34753	6.4336011	0.3905	0.35290995	0.15593	0.0467	0.054
E160727.3	2.475	2.23246	1.0011	0.2973	0.35858	6.3645418	0.3889	0.35076517	0.15729	0.0467	0.0563
E160808.1	1.879	1.735978	0.7931	0.1053	0.30541	4.8184203	0.3899	0.36027944	0.16459	0.0219	0.0634
E160808.2	1.816	1.687682	0.7883	0.1272	0.28822	4.7070269	0.3857	0.35854521	0.16748	0.027	0.0612
E160808.3	1.851	1.75239	0.8194	0.112	0.31372	4.8489592	0.3818	0.36139506	0.16899	0.0231	0.0647
E160810.1	1.605	1.480639	0.7167	0.2158	0.20561	4.2239143	0.38	0.35053729	0.16967	0.0511	0.0487
E160810.2	1.573	1.436403	0.7048	0.2328	0.20501	4.1520704	0.3789	0.34594869	0.16975	0.0561	0.0494
E160810.3	1.622	1.385613	0.6853	0.2546	0.18089	4.1284854	0.3929	0.3356227	0.166	0.0617	0.0438
E160817.1	1.856	1.603483	0.7862	0.3323	0.1946	4.7729451	0.3889	0.33595243	0.16472	0.0696	0.0408
E160817.2	1.929	1.598191	0.7859	0.3457	0.17845	4.8376498	0.3988	0.33036523	0.16246	0.0715	0.0369
E160817.3	1.842	1.569673	0.7587	0.3276	0.18968	4.6877733	0.393	0.33484406	0.16185	0.0699	0.0405
E160824.2	2.818	2.201687	1.0363	0.9473	0.08715	7.0901869	0.3974	0.31052598	0.14616	0.1336	0.0123
E160824.3	2.643	1.94553	0.9554	0.8236	0.19389	6.5617005	0.4028	0.29649781	0.1456	0.1255	0.0295
E160831.1	3.771	3.095308	1.5186	0.9351	0.27148	9.5914474	0.3932	0.32271541	0.15833	0.0975	0.0283
E160831.2	3.828	3.265613	1.612	0.783	0.32495	9.81336	0.3901	0.33277218	0.16427	0.0798	0.0331
E160831.3	3.803	3.305155	1.6931	0.8355	0.29812	9.9348932	0.3828	0.33268147	0.17042	0.0841	0.03

Table 13

	Total Model									
Sample Name	FI	FrI	HI	A	B	T	C	M	CDOMEEM	TrypEEM
				R.U.	R.U.	R.U.	R.U.	R.U.	R.U.	R.U.
E160525.1	2.01413	0.817478	2.7944	2.0859	0.9905	1.427824	1.8229	1.6019	1.138394	1.372369
E160525.2	1.938	0.862034	2.5467	1.9309	0.964	1.431136	1.532	1.5034	1.020507	1.384599
E160525.3	1.882157	0.838332	3.2537	2.7068	1.1373	1.579781	1.8522	2.0705	1.282318	1.559264
E160527.1	1.992599	0.772054	3.2568	1.7202	0.6469	0.986216	1.7325	1.4062	1.084948	1.031482

E160527.2	1.940004	0.800705	3.1455	1.7554	0.6866	1.025513	1.5487	1.4039	1.02039	1.059762
E160527.3	2.005798	0.78108	3.2783	1.6869	0.628	0.96306	1.6542	1.3968	1.047043	0.976813
E160601.1	2.007729	0.829493	2.9545	2.1079	0.9502	1.324121	1.9181	1.6956	1.219699	1.285289
E160601.2	2.010818	0.818638	3.1814	2.1176	0.9177	1.271481	1.8373	1.6942	1.182508	1.265172
E160601.3	2.035428	0.803305	3.0733	2.1138	0.919	1.26797	1.856	1.6872	1.184786	1.252168
E160606.1	1.982918	0.826064	2.8087	1.6888	0.8795	1.143335	1.4823	1.4196	0.957937	1.136348
E160606.2	1.912894	0.874431	2.9741	1.7559	0.7993	1.124076	1.5549	1.4314	1.007736	1.155965
E160606.3	1.911143	0.875666	2.9241	1.8461	0.8646	1.148993	1.5425	1.4734	0.998632	1.204766
E160608.2	1.977155	0.802292	3.2844	2.8853	1.1929	1.690368	2.6808	2.4187	1.690346	1.745706
E160608.3	2.083429	0.749781	3.2834	3.1459	1.2653	1.816022	3.4324	2.7104	2.021338	1.860504
E160611.1	2.083727	0.786251	3.0935	2.5096	0.9818	1.464091	2.5386	2.0709	1.535385	1.481019
E160611.2	1.974718	0.808071	3.3015	2.7255	1.0497	1.497244	2.5406	2.1757	1.566548	1.562988
E160611.3	2.074129	0.760547	3.3234	2.7683	1.0499	1.516115	2.9557	2.3224	1.732652	1.547739
E160614.1	2.044914	0.772545	3.3773	2.5732	0.9658	1.36634	2.7493	2.1544	1.651887	1.45872
E160614.2	2.062904	0.76661	3.4019	2.6653	0.9888	1.411517	2.8485	2.2355	1.701892	1.484472
E160614.3	2.01592	0.784744	3.4984	2.6468	0.9519	1.38442	2.6093	2.1433	1.602669	1.462518
E160615.1	1.990064	0.79708	3.6359	1.7852	0.7546	0.979035	1.4037	1.2836	0.903673	0.98704
E160615.2	2.101958	0.751169	3.7592	1.9186	0.7442	0.988609	1.7719	1.4728	1.102544	1.038984
E160615.3	2.034753	0.785271	3.7411	1.899	0.7543	1.019029	1.7159	1.4626	1.068044	1.046411
E160621.2	2.068214	0.816533	3.3528	1.7382	0.8208	1.090866	1.6238	1.4044	1.028779	1.119855
E160621.3	1.989961	0.867504	3.5682	1.8064	0.7937	1.134516	1.4957	1.4034	0.989214	1.135885
E160622.1	2.114738	0.761304	3.584	1.7737	0.7847	1.074628	1.9083	1.4894	1.149267	1.096516
E160622.2	2.094463	0.807217	3.5549	1.7459	0.6939	1.067932	1.7088	1.3898	1.045715	1.049623
E160622.3	2.1613	0.734562	3.5723	1.7985	0.715	1.128747	2.1284	1.5753	1.227158	1.117301
E160628.1	2.097361	0.753368	3.3622	1.8299	0.8315	1.044998	1.6273	1.4669	1.030026	1.075032
E160628.2	2.049708	0.759149	3.6403	1.9363	0.8025	1.077991	1.6103	1.5449	1.064073	1.132159
E160628.3	2.011686	0.789552	3.4601	1.8653	0.8019	1.058211	1.5096	1.4021	0.967187	1.086026
E160629.1	1.999689	0.767956	3.8571	1.9647	0.7459	0.972398	1.6899	1.5395	1.095764	1.035196
E160629.2	2.020774	0.775037	4.2999	1.8965	0.5713	0.876397	1.6083	1.436	1.037136	0.953261
E160629.3	2.05381	0.738186	3.988	1.948	0.6972	0.996772	1.8433	1.5862	1.165253	1.024228
E160712.1	1.92057	0.840549	4.2156	2.3247	0.8061	1.134473	1.6337	1.5987	1.083631	1.221094

E160712.2	1.888324	0.857844	4.1765	2.2543	0.7553	1.104542	1.5329	1.5741	1.063412	1.201519
E160713.1	1.879396	0.851203	3.6826	2.6539	0.9656	1.403503	1.863	1.9084	1.300034	1.508715
E160713.3	1.870153	0.866549	3.6406	2.7102	1.0216	1.532865	1.8361	1.9423	1.297157	1.557501
E160718.1	1.847652	0.893871	3.2508	1.6413	0.7071	0.946979	1.1137	1.1721	0.775257	1.038248
E160718.2	1.819822	0.890456	3.4587	1.5754	0.6865	0.906449	1.0431	1.1315	0.737288	0.991843
E160718.3	1.835778	0.920552	3.3479	1.6737	0.6809	0.973075	1.0742	1.1791	0.770958	1.05548
E160720.1	1.857009	0.879377	3.7366	2.519	0.918	1.352948	1.8597	1.907	1.288616	1.504482
E160720.2	1.866934	0.895415	3.8575	2.4463	0.859	1.32248	1.7901	1.8558	1.249219	1.449035
E160720.3	1.826559	0.884473	3.6928	2.4764	0.9043	1.358221	1.8023	1.8982	1.253882	1.504832
E160726.2	1.7659	0.759454	6.1752	2.2048	0.4722	0.691453	1.2466	1.3734	0.961283	0.804976
E160726.3	1.79251	0.780216	6.2148	2.1888	0.4594	0.706406	1.2315	1.3504	0.947677	0.782569
E160727.1	1.791451	0.801015	5.0191	2.068	0.6281	0.756241	1.2222	1.2946	0.913869	0.857063
E160727.2	1.761243	0.806123	4.8938	1.9794	0.5866	0.760783	1.1385	1.2441	0.861509	0.841111
E160727.3	1.761896	0.798847	4.9006	1.897	0.5811	0.774456	1.1275	1.2471	0.855081	0.858566
E160808.1	1.816844	0.771739	5.6046	1.507	0.4443	0.472207	0.895	0.9498	0.663154	0.554732
E160808.2	1.756417	0.775242	5.4117	1.4774	0.4091	0.466883	0.8807	0.9393	0.647312	0.534882
E160808.3	1.80656	0.779116	5.6184	1.5069	0.4317	0.49671	0.9144	0.9659	0.672474	0.56898
E160810.1	1.749442	0.790289	5.1465	1.2871	0.4277	0.47443	0.7996	0.8312	0.580025	0.537675
E160810.2	1.743838	0.799392	4.912	1.2897	0.4025	0.476457	0.7922	0.8229	0.563692	0.543548
E160810.3	1.831482	0.818251	4.7928	1.2417	0.4176	0.51635	0.769	0.8089	0.558777	0.542712
E160817.1	1.79284	0.813377	4.5782	1.4105	0.4982	0.593636	0.88	0.9384	0.637279	0.658896
E160817.2	1.806334	0.821549	4.5315	1.4119	0.4735	0.61177	0.8884	0.9419	0.645027	0.666653
E160817.3	1.801724	0.819352	4.5568	1.3699	0.4678	0.57614	0.8561	0.9164	0.623819	0.666734
E160824.2	1.863107	0.889098	3.6023	1.867	0.7569	1.179619	1.232	1.3045	0.866712	1.217683
E160824.3	1.874258	0.899217	3.228	1.7759	0.6978	1.133468	1.11	1.2242	0.803266	1.194934
E160831.1	1.903438	0.829924	4.1646	2.7058	1.0596	1.403695	1.7685	1.8722	1.237812	1.478773
E160831.2	1.83286	0.850584	4.6281	2.826	0.9178	1.358406	1.8615	1.9058	1.312912	1.463965
E160831.3	1.89545	0.822711	4.5925	2.9133	0.9038	1.334433	1.9447	1.9327	1.341237	1.457359

Table 14

	Effluent Model				
Sample Name	C1	C2	C3	C4	Total Loading
E160525.1	2.429	3.056655	1.5659	1.1531	8.204842
E160525.2	2.2	3.029618	1.3336	1.1793	7.742776
E160525.3	3.237	4.150519	1.5663	1.1292	10.08301
E160527.1	1.916	2.432988	1.5447	0.746	6.639399
E160527.2	1.992	2.556845	1.379	0.7617	6.689062
E160527.3	1.907	2.436805	1.4749	0.7011	6.519774
E160601.1	2.395	2.950144	1.7073	1.0141	8.06673
E160601.2	2.521	2.932887	1.6287	0.9494	8.031831
E160601.3	2.413	2.934802	1.6632	0.9692	7.979951
E160606.1	2.008	2.545597	1.2966	0.9483	6.798922
E160606.2	2.126	2.569301	1.3641	0.9034	6.963291
E160606.3	2.192	2.642497	1.3647	0.939	7.137744
E160608.2	3.495	4.025029	2.3744	1.322	11.21607
E160608.3	3.564	4.259789	3.0665	1.4272	12.31744
E160611.1	2.927	3.361491	2.2464	1.1793	9.713806
E160611.2	3.283	3.672934	2.2378	1.1568	10.35014
E160611.3	3.23	3.619887	2.6157	1.1764	10.64192
E160614.1	3.049	3.370438	2.4317	1.1179	9.968851
E160614.2	3.177	3.461081	2.5138	1.1413	10.2932
E160614.3	3.128	3.447919	2.3105	1.0801	9.966473
E160615.1	2.196	2.357159	1.2017	0.7664	6.521131
E160615.2	2.299	2.452572	1.549	0.7607	7.061291
E160615.3	2.316	2.476265	1.5032	0.7796	7.075144
E160621.2	2.1	2.427512	1.437	0.8638	6.828656
E160621.3	2.295	2.537689	1.3144	0.8349	6.982021
E160622.1	2.162	2.357141	1.6867	0.8525	7.058851
E160622.2	2.103	2.396195	1.4948	0.7774	6.771322

E160622.3	2.132	2.367197	1.8832	0.8518	7.233843
E160628.1	2.254	2.57918	1.4104	0.837	7.080163
E160628.2	2.452	2.71287	1.3921	0.8312	7.388105
E160628.3	2.326	2.573916	1.2915	0.8193	7.010852
E160629.1	2.462	2.635613	1.4933	0.7218	7.312402
E160629.2	2.379	2.493104	1.4006	0.583	6.855462
E160629.3	2.394	2.653011	1.6289	0.6939	7.370265
E160712.1	3.029	3.206569	1.3375	0.8512	8.424449
E160712.2	2.914	3.187063	1.2734	0.7764	8.150466
E160713.1	3.495	3.849441	1.5536	1.0639	9.962357
E160713.3	3.513	3.935643	1.5393	1.0908	10.07852
E160718.1	2.186	2.347374	0.9193	0.7912	6.243982
E160718.2	2.145	2.282513	0.8534	0.7531	6.034497
E160718.3	2.211	2.471478	0.867	0.7641	6.313277
E160720.1	3.376	3.619262	1.588	0.9847	9.568109
E160720.2	3.241	3.506256	1.5518	0.9399	9.238892
E160720.3	3.324	3.81516	1.4594	2.7742	11.37249
E160726.2	2.932	2.917638	1.0268	0.3573	7.233315
E160726.3	2.908	2.894657	1.0097	0.3507	7.163242
E160727.1	2.683	2.660673	1.0217	0.5127	6.87758
E160727.2	2.589	2.595888	0.9418	0.4978	6.624574
E160727.3	2.55	2.571046	0.939	0.5015	6.561447
E160808.1	1.99	1.965206	0.7425	0.2939	4.991579
E160808.2	1.933	1.896405	0.7388	0.304	4.872278
E160808.3	2.003	1.946559	0.7686	0.3054	5.023645
E160810.1	1.686	1.651427	0.6753	0.3319	4.344691
E160810.2	1.638	1.620063	0.6652	0.3495	4.272559
E160810.3	1.589	1.6535	0.6478	0.351	4.241357
E160817.1	1.832	1.886216	0.7433	0.4318	4.893412
E160817.2	1.834	1.945151	0.7437	0.4338	4.956229
E160817.3	1.794	1.86889	0.7178	0.424	4.804924

E160824.2	2.489	2.744833	0.9916	0.929	7.154661
E160824.3	2.233	2.650732	0.9129	0.8764	6.672722
E160831.1	3.519	3.757277	1.4498	1.0321	9.758318
E160831.2	3.705	3.841145	1.5381	0.9268	10.01077
E160831.3	3.741	3.79892	1.6185	0.9664	10.12466

Table 15

Online

Sample Name	EC	pH	DO	Neph	UVT	TOC	CDOM	Tryp	Temp
	mS/cm		mg/L	NTU		mg/L	R.U.	R.U.	°C
E160525.1	0.833	4.829	1.255	49.59	71.59	5.613	6952	48.4	23.95
E160525.2	0.83	4.886	0.749	64.03	71.59	5.111	6936	45.08	23.98
E160525.3	0.828	4.917	1.619	42.07	71.57	7.315	6892	44.12	24
E160527.1	0.043	4.428	8.32		71.6	5.474	5692	43.36	23.54
E160527.2	0.043	4.428	8.32		71.6	5.474	5692	43.36	23.54
E160527.3	0.033	6.932	10.2	71.21	71.6	4.78	5636	45.24	23.54
E160601.1	0.875	7.154	0.89		71.6	7.376	5696	42.44	24.54
E160601.2	0.878	7.185	1.761		71.6	7.376	5652	45.12	24.53
E160601.3	0.883	7.202	1.923		71.57	1.721	5652	44.28	24.54
E160606.1	0.744	6.59	0.03	89.5	71.6	6.78	2955.2	44.96	24.98
E160606.2	0.745	6.587	0.03	87.7	71.61	6.78	2948.8	44.52	24.98
E160606.3	0.744	6.584	0.03	88.9	71.59	6.78	2948.8	44.64	25
E160608.2	0.77	6.846	0.04	95.8	71.59	5.245	2710.8	43.76	24.77
E160608.3	0.769	6.82	0.03	97	71.61	5.245	2951.2	42.88	24.78
E160611.1	0.66	6.924	5.007	39.87	71.61	6.901	2358.8	44.24	25.35
E160611.2	0.659	6.936	4.855	33.51	71.6	6.901	2192.8	45.92	25.38
E160611.3	0.659	6.816	4.107	32.35	71.6	6.901	2111.6	45.52	25.51
E160614.1	0.665	6.935	5.048	25.87	71.63	7.21	1988	43.96	25.9

E160614.2	0.662	6.938	5.169	25.89	71.62	7.2	1808	46.24	25.88
E160614.3	0.662	6.949	5.665	29.36	71.62	7.2	1795.2	45.6	25.95
E160615.1	0.673	6.872	5.321		71.61	7.914	1955.2	44.6	26.12
E160615.2	0.671	6.827	5.22	44.33	71.61	7.914	1695.2	42.8	26.1
E160615.3	0.67	6.847	4.674	28.75	71.62	7	1471.6	41.36	26.1
E160621.2	0.713	6.368	3.642	30.04	71.6	6.481	1467.6	43.48	26.76
E160621.3	0.712	6.399	4.592	26.58	71.6	6.418	1475.2	41.12	26.76
E160622.1	0.679	6.688	5.503	28.89	71.61	6.176	1422.8	43.88	26.56
E160622.2	0.677	6.679	5.705		71.6	6.208	1322.4	43.68	26.55
E160622.3	0.677	6.586	5.968		71.62	6.208	1435.2	41.4	26.54
E160628.1	0.684	6.606	3.521	27.62	71.61	6.795	981.6	44.24	26.64
E160628.2	0.685	6.594	3.501	28.2	71.57	6.795	982.8	43.88	26.64
E160628.3	0.684	6.487	3.238	32.82	71.67	6.795	974.4	41.88	26.71
E160629.1	0.675	6.851	8.88	31.64	71.61	6.233	942.8	41.96	26.77
E160629.2	0.673	6.86	8.76	31.65	71.62	6.249	951.2	44.04	26.78
E160629.3	0.674	6.837	8.42		71.63	6.249	951.2	42.96	26.85
E160712.1	0.621	6.001	2.57	25.89	108	6.097	402.4	43.08	27.01
E160712.2	0.621	6.001	2.57	25.89	108	6.097	402.4	43.08	27.01
E160713.1									
E160713.3									
E160718.1	0.712		2.812	24.07	77.09	7.341	337	42.2	27.69
E160718.2	0.713		2.589	24.11	77.12	7.341	326.52	43.64	27.7
E160718.3	0.714		2.549	56.46	77.09	7.341	333.2	42.92	27.72
E160720.1	0.655		5.622	22.78	77.11	6.431	309.8	41.96	27.98
E160720.2	0.655		5.481	23.35	77.11	6.423	307.68	43.56	27.96
E160720.3	0.659		3.014	23.34	77.1	6.431	299.52	41.44	27.92
E160726.2	0.467		2.792	29.83	77.09	4.628	187.64	44.68	29.07
E160726.3	0.467		2.822	31.59	77.11	4.626	186.44	45.64	29.1
E160727.1	0.496		6.977	39.45	77.1	5.096	178.16	43.36	28.67
E160727.2	0.497		6.957	38.31	77.1	5.097	178.84	43.48	28.73
E160727.3	0.496		6.937	40.03	77.08	5.097	181.16	43.12	28.77

E160808.1	0.483	4.554	23.58	77.07	4.484	156.8	42.28	27.55
E160808.2	0.483	4.594	21.85	77.11	4.486	156.52	43.08	27.54
E160808.3	0.483	4.554	23	77.09	4.484	156.8	43.76	27.52
E160810.1	0.533	3.085	25.42	77.11	4.827	152.92	41.88	29.84
E160810.2	0.533	3.075	24.26	77.1	4.827	155.08	44.08	29.85
E160810.3	0.533	3.095	25.42	77.09	4.827	153.68	42.48	29.86
E160817.1	0.572	4.188	18.49	77.08	4.785	170.96	44.12	28.07
E160817.2	0.573	4.168	19.11	77.07	4.785	171.48	45.92	28.08
E160817.3	0.572	4.147	19.77	77.1	4.786	164.36	43.04	28.16
E160824.2	0.669	4.208	23.3	77.09	6.42	176.84	46.36	28.33
E160824.3	0.674	1.396	54.02	77.13	6.421	226.04	43.2	27.8
E160831.1	0.596	4.006	21.23	79.52	5.539	159.04	43.76	27.7
E160831.2	0.596	4.168	21.25	79.48	5.54	156.96	43.96	27.68
E160831.3	0.596	4.189	21.25	79.49	5.539	156.8	42.96	27.59

Table 16

Oxic Tank

O Sample	Days	TN	TP	TOC	Abs @ 250nm	Spectral Slope Ratio
		mg/L	mg/L	mg/L		
O160525.1	47	128.35	47.05		0.196096	0.757453
O160525.2	47	128.35	47.05		0.154408	0.69049
O160525.3	47	128.35	47.05		0.186291	0.779666
O160527.1	49	174.56	70.36		0.156996	0.713961
O160527.2	49	174.56	70.36		0.165148	0.732879
O160527.3	49	174.56	70.36		0.149061	0.74625
O160601.1	54	186.18	67.57		0.189484	0.717871

O160601.2	54	186.18	67.57		0.183275	0.701506
O160601.3	54	186.18	67.57		0.172405	0.728306
O160606.1	59	222.54	84.87		0.189928	0.935108
O160606.2	59	222.54	84.87		0.188924	0.809183
O160606.3	59	222.54	84.87		0.20661	0.886137
O160608.1	61	224.93	82.11		0.190614	1.042191
O160608.2	61	224.93	82.11		0.269323	0.822316
O160608.3	61	224.93	82.11		0.165888	0.91357
O160611.1	64	251.70	92.80		0.179525	1.023821
O160611.2	64	251.70	92.80		0.263336	0.884288
O160611.3	64	251.70	92.80		0.196738	0.992226
O160614.1	67	284.30	105.82		0.182151	1.013018
O160614.2	67	284.30	105.82		0.174828	0.892286
O160614.3	67	284.30	105.82		0.176375	1.117542
O160615.1	68	287.95	106.41		0.262929	0.885257
O160615.2	68	287.95	106.41		0.170504	0.929845
O160615.3	68	287.95	106.41		0.23099	0.905337
O160621.1	74	362.54	131.1	52.49	0.366547	0.77214
O160621.2	74	362.54	131.1	52.49	0.255402	1.084931
O160621.3	74	362.54	131.1	52.49	0.381077	0.693148
O160622.1	75	354.92	131.7	51.84	0.386127	0.754352
O160622.2	75	354.92	131.7	51.84	0.205113	1.045766
O160622.3	75	354.92	131.7	51.84	0.148252	1.013973
O160628.1	81	460.15	197	49.33	0.249366	0.857733
O160628.2	81	460.15	197	49.33	0.248998	0.96279
O160629.1	82	423.79	182	47.04	0.217283	0.973972
O160629.2	82	423.79	182	47.04	0.327315	0.894957
O160629.3	82	423.79	182	47.04	0.15626	1.04306
O160706.1	89	716.97	288.35	7.817	0.175808	1.350222
O160706.2	89	716.97	288.35	7.923	0.1797	1.375885
O160706.3	89	716.97	288.35	7.569	0.174035	1.322351

O160712.1	95	769.00	298.80	6.391	0.180627	1.363196
O160712.2	95	769.00	298.80	7.826	0.25949	1.702144
O160712.3	95	769.00	298.80	7.341	0.184426	1.393607
O160713.1	96	783.72	331.00	5.526	0.146862	1.091214
O160713.2		783.72	331.00	5.789	0.218763	1.407137
O160713.3	96	783.72	331.00	5.901	0.157033	1.18563
O160718.1	101	826.46	338.18	8.136	0.210599	1.288649
O160718.2	101	826.46	338.18	8.029	0.217214	1.190508
O160718.3	101	826.46	338.18	7.819	0.208064	1.15238
O160720.1	103	779.62	357.95	7.892	0.183439	1.254417
O160720.2	103	779.62	357.95	8.044	0.206948	1.233273
O160720.3	103	779.62	357.95	8.229	0.191839	1.181992
O160726.1	109	865.20	381.34	21.77	0.139545	1.279136
O160726.2	109	865.20	381.34	21.37	0.140124	1.254108
O160726.3	109	865.20	381.34	21.58	0.135162	1.260212
O160727.1	110	788.73	321.48	6.072	0.137594	1.253336
O160727.2	110	788.73	321.48	5.775	0.133599	1.292728
O160727.3	110	788.73	321.48	5.639	0.125695	1.228669
O160808.1	122	714.43	288.08	6.007	0.142444	1.390958
O160808.2	122	714.43	288.08	5.118	0.118962	1.283153
O160808.3	122	714.43	288.08	4.801	0.112803	1.167575
O160810.1	124	708.70	288.08	5.293	0.129292	1.502575
O160810.2	124	708.70	288.08	4.552	0.09881	1.151632
O160810.3	124	708.70	288.08	4.624	0.096435	1.186259
O160817.1	131	763.82	291.70	4.87	0.099961	1.032699
O160817.2	131	763.82	291.70	4.998	0.11206	1.20753
O160817.3	131	763.82	291.70	5.047	0.09624	1.018913
O160824.1	138			7.087	0.152259	1.077901
O160824.2	138			7.068	0.175224	1.023491
O160824.3	138			6.722	0.166095	1.128817
O160831.1	145			5.905	0.15823	0.942979

O160831.2	145	5.625	0.113963	0.977501
O160831.3	145	5.972	0.121073	0.992419

Table 17

O Sample	C1	C2	C3	C4	C5	Total Loading	% C1	% C2	% C3	% C4	% C5
O160525.1	5.48701	3.50643	2.51949	2.87225	0.056	14.44118	0.38	0.2428	0.1745	0.1989	0.0039
O160525.2	5.08236	3.76065	2.36112	2.30111	0.04965	13.55488	0.3749	0.2774	0.1742	0.1698	0.0037
O160525.3	5.72923	3.87104	2.66512	2.8859	0.04923	15.20052	0.3769	0.2547	0.1753	0.1899	0.0032
O160527.1	4.53143	3.45781	2.18233	2.10939	0.25715	12.53812	0.3614	0.2758	0.1741	0.1682	0.0205
O160527.2	4.7057	4.05786	2.29869	2.27266	0.26296	13.59787	0.3461	0.2984	0.169	0.1671	0.0193
O160527.3	4.31653	3.36076	2.0638	2.10871	0.20255	12.05236	0.3581	0.2788	0.1712	0.175	0.0168
O160601.1	5.28597	4.53627	2.74174	2.94133	0.20819	15.7135	0.3364	0.2887	0.1745	0.1872	0.0132
O160601.2	5.56675	4.81859	2.75643	2.70947	0.15867	16.00991	0.3477	0.301	0.1722	0.1692	0.0099
O160601.3	5.46958	4.62124	2.66642	2.95101	0.20935	15.9176	0.3436	0.2903	0.1675	0.1854	0.0132
O160606.1	4.77401	3.87478	2.80395	3.74848	0	15.20121	0.3141	0.2549	0.1845	0.2466	0
O160606.2	5.1999	4.72535	2.5849	3.01931	0.04241	15.57186	0.3339	0.3035	0.166	0.1939	0.0027
O160606.3	4.87875	3.90053	2.50567	3.72924	0	15.01419	0.3249	0.2598	0.1669	0.2484	0
O160608.1	4.49193	3.80002	2.69802	4.06635	0.02268	15.07901	0.2979	0.252	0.1789	0.2697	0.0015
O160608.2	5.28315	4.77149	2.74787	4.16593	0.10889	17.07733	0.3094	0.2794	0.1609	0.2439	0.0064
O160608.3	3.12361	2.54598	1.88626	2.27953	0.04439	9.879776	0.3162	0.2577	0.1909	0.2307	0.0045
O160611.1	4.12591	3.72911	2.06152	3.30992	0.18864	13.41511	0.3076	0.278	0.1537	0.2467	0.0141
O160611.2	4.95596	5.06935	2.37495	3.98142	0.1464	16.52808	0.2999	0.3067	0.1437	0.2409	0.0089
O160611.3	4.17009	3.76513	2.05849	3.61491	0.12901	13.73763	0.3036	0.2741	0.1498	0.2631	0.0094
O160614.1	3.93494	3.56823	2.02147	3.63065	0.12288	13.27816	0.2963	0.2687	0.1522	0.2734	0.0093
O160614.2	4.44528	4.71361	1.9857	2.53378	0.15907	13.83744	0.3213	0.3406	0.1435	0.1831	0.0115
O160614.3	3.96312	3.68699	1.94039	3.71444	0.13279	13.43773	0.2949	0.2744	0.1444	0.2764	0.0099
O160615.1	4.69123	4.41934	1.76397	3.18461	0.18613	14.24528	0.3293	0.3102	0.1238	0.2236	0.0131

O160615.2	4.78399	5.09582	1.99899	2.55019	0.20015	14.62914	0.327	0.3483	0.1366	0.1743	0.0137
O160615.3	4.6928	4.15731	2.59207	3.66137	0	15.10354	0.3107	0.2753	0.1716	0.2424	0
O160621.1	3.32651	2.55904	1.54927	3.45841	0	10.89323	0.3054	0.2349	0.1422	0.3175	0
O160621.2	4.40679	4.41546	1.68474	1.88556	0.10629	12.49884	0.3526	0.3533	0.1348	0.1509	0.0085
O160621.3	3.38949	2.57057	1.56556	3.36726	0	10.89287	0.3112	0.236	0.1437	0.3091	0
O160622.1	5.12229	4.12396	2.95027	6.31128	0	18.5078	0.2768	0.2228	0.1594	0.341	0
O160622.2	3.93973	4.11588	1.54437	1.93281	0.14603	11.67882	0.3373	0.3524	0.1322	0.1655	0.0125
O160622.3	2.50096	2.07068	1.01368	1.61745	0.05751	7.260278	0.3445	0.2852	0.1396	0.2228	0.0079
O160628.1	4.26564	3.55705	1.81628	5.14442	0	14.78339	0.2885	0.2406	0.1229	0.348	0
O160628.2	6.49905	7.41397	2.60761	3.81666	0.38028	20.71757	0.3137	0.3579	0.1259	0.1842	0.0184
O160629.1	2.71731	2.14484	1.19644	2.38515	0.18823	8.631962	0.3148	0.2485	0.1386	0.2763	0.0218
O160629.2	4.25774	4.24275	1.72446	2.83643	0.1768	13.23817	0.3216	0.3205	0.1303	0.2143	0.0134
O160629.3	2.57865	2.00412	0.99608	1.78248	0.14572	7.507042	0.3435	0.267	0.1327	0.2374	0.0194
O160706.1	3.41911	2.77082	1.35769	3.48002	0.16986	11.1975	0.3053	0.2474	0.1212	0.3108	0.0152
O160706.2	3.46572	2.74736	1.33616	3.6172	0.14897	11.3154	0.3063	0.2428	0.1181	0.3197	0.0132
O160706.3	3.46527	2.73266	1.34657	3.4115	0.15602	11.11202	0.3118	0.2459	0.1212	0.307	0.014
O160712.1	3.04615	2.44306	1.16751	2.9362	0.20748	9.800391	0.3108	0.2493	0.1191	0.2996	0.0212
O160712.2	3.66459	2.75747	1.3617	5.53387	0.21883	13.53646	0.2707	0.2037	0.1006	0.4088	0.0162
O160712.3	3.30768	2.53317	1.19544	3.1988	0.17279	10.40788	0.3178	0.2434	0.1149	0.3073	0.0166
O160713.1	3.63309	2.94649	1.35079	1.98389	0.28138	10.19564	0.3563	0.289	0.1325	0.1946	0.0276
O160713.2	4.1973	3.19593	1.54146	3.97767	0.27941	13.19178	0.3182	0.2423	0.1169	0.3015	0.0212
O160713.3	3.80708	3.00059	1.40347	2.37059	0.21859	10.80033	0.3525	0.2778	0.1299	0.2195	0.0202
O160718.1	2.54146	1.98704	0.88282	2.29795	0.08195	7.791225	0.3262	0.255	0.1133	0.2949	0.0105
O160718.2	2.67798	2.13114	0.94878	2.24327	0.09564	8.096811	0.3307	0.2632	0.1172	0.2771	0.0118
O160718.3	2.59831	2.02996	0.89791	2.0487	0.07744	7.652325	0.3395	0.2653	0.1173	0.2677	0.0101
O160720.1	3.67786	2.85649	1.59904	0.90349	0.22834	9.265215	0.397	0.3083	0.1726	0.0975	0.0246
O160720.2	3.86819	3.01729	1.54751	3.39297	0.22063	12.04659	0.3211	0.2505	0.1285	0.2817	0.0183
O160720.3	3.73004	2.96566	1.50937	2.94328	0.22577	11.37412	0.3279	0.2607	0.1327	0.2588	0.0198
O160726.1	2.79861	2.5583	1.05786	1.42306	0.42836	8.266182	0.3386	0.3095	0.128	0.1722	0.0518
O160726.2	2.79329	2.55035	1.02622	1.42794	0.40835	8.206142	0.3404	0.3108	0.1251	0.174	0.0498
O160726.3	2.83931	2.54786	1.03709	1.29124	0.40955	8.125062	0.3495	0.3136	0.1276	0.1589	0.0504

O160727.1	1.77432	1.58018	0.68727	1.08001	0.17809	5.299863	0.3348	0.2982	0.1297	0.2038	0.0336
O160727.2	1.72872	1.61421	0.71982	1.06468	0.21766	5.34509	0.3234	0.302	0.1347	0.1992	0.0407
O160727.3	1.81692	1.57395	0.70179	0.92787	0.19153	5.212061	0.3486	0.302	0.1346	0.178	0.0367
O160808.1	1.86371	1.74817	0.74776	1.25302	0.25455	5.867218	0.3176	0.298	0.1274	0.2136	0.0434
O160808.2	1.80262	1.66155	0.71382	0.93987	0.24039	5.358246	0.3364	0.3101	0.1332	0.1754	0.0449
O160808.3	1.76157	1.63876	0.68222	0.8031	0.23242	5.118077	0.3442	0.3202	0.1333	0.1569	0.0454
O160810.1	1.55313	1.41538	0.6563	1.36106	0.17925	5.165115	0.3007	0.274	0.1271	0.2635	0.0347
O160810.2	1.54295	1.4072	0.63336	0.80978	0.16018	4.553478	0.3389	0.309	0.1391	0.1778	0.0352
O160810.3	4.14921	2.99221	2.43714	1.37081	0.09407	11.04344	0.3757	0.2709	0.2207	0.1241	0.0085
O160817.1	3.17253	2.61249	1.21924	1.01638	0.23719	8.257825	0.3842	0.3164	0.1476	0.1231	0.0287
O160817.2	3.07366	2.6284	1.25478	1.35786	0.30515	8.619855	0.3566	0.3049	0.1456	0.1575	0.0354
O160817.3	3.0354	2.53521	1.23333	1.04172	0.24232	8.087987	0.3753	0.3135	0.1525	0.1288	0.03
O160824.1	2.65713	2.02633	0.95402	1.39602	0.09654	7.130045	0.3727	0.2842	0.1338	0.1958	0.0135
O160824.2	2.75076	2.1003	0.98226	1.46192	0.10381	7.399046	0.3718	0.2839	0.1328	0.1976	0.014
O160824.3	2.68316	2.07736	0.97302	1.49178	0.1344	7.359712	0.3646	0.2823	0.1322	0.2027	0.0183
O160831.1	3.75311	3.26345	1.47759	1.63338	0.31884	10.44636	0.3593	0.3124	0.1414	0.1564	0.0305
O160831.2	3.4993	3.01254	1.39666	1.26985	0.27192	9.450271	0.3703	0.3188	0.1478	0.1344	0.0288
O160831.3	3.75704	3.15015	1.42041	1.39083	0.25483	9.973266	0.3767	0.3159	0.1424	0.1395	0.0256

Table 18

O Sample	FI	FrI	HI	A	B	T	C	M	CDOM EEM	TrypEEM
				R.U.	R.U.	R.U.	R.U.	R.U.	R.U.	R.U.
O160525.1	1.94264	0.825674	2.350384	3.416096	2.323565	3.157368	2.873729	2.678	1.8676	2.879295
O160525.2	1.946668	0.83261	2.94883	3.477673	2.004877	2.557976	2.672468	2.5547	1.743	2.413726
O160525.3	2.010987	0.799348	2.45814	3.688345	2.460669	3.205571	3.041946	2.9054	1.96	2.887413
O160527.1	1.885463	0.842308	2.70954	3.224714	1.936985	2.586946	2.448244	2.3658	1.6225	2.383236
O160527.2	1.874222	0.846848	3.005394	3.532098	2.074782	2.756269	2.602627	2.5163	1.6835	2.512962
O160527.3	1.91372	0.84886	2.636553	3.013764	1.868309	2.491184	2.316508	2.2373	1.5345	2.270217

O160601.1	1.900784	0.866586	2.637375	3.916096	2.624589	3.344034	3.090182	2.8763	1.9703	3.047873
O160601.2	1.902801	0.861151	3.017001	4.060798	2.472348	3.177334	3.097189	3.0688	2.0014	2.948383
O160601.3	1.910972	0.859663	2.653594	4.028412	2.625253	3.407441	3.023054	2.9369	1.9417	3.087118
O160606.1	2.007358	0.798281	2.113755	3.418948	3.066065	3.782586	3.196193	2.6499	1.9288	3.374652
O160606.2	1.955905	0.85709	2.899768	3.929624	2.551004	3.279088	2.988835	2.7794	1.8588	2.988089
O160606.3	1.938377	0.862869	2.110085	3.385691	3.023931	3.844793	2.865349	2.554	1.7662	3.328154
O160608.1	2.025056	0.819184	1.931311	3.351413	3.273489	4.141727	3.04414	2.5485	1.8383	3.533597
O160608.2	1.939516	0.859487	2.271626	4.037026	3.48244	4.464775	3.11452	2.9308	1.9772	3.82083
O160608.3	2.021785	0.817674	2.268477	2.314939	1.950732	2.430187	2.101797	1.8427	1.277	2.129027
O160611.1	1.934194	0.86891	2.136166	3.165323	2.887802	3.601986	2.342371	2.2577	1.527	3.108157
O160611.2	1.919078	0.860563	2.471322	4.025715	3.317651	4.280177	2.792497	2.6549	1.7919	3.673955
O160611.3	1.947553	0.853629	2.042358	3.163256	3.0809	3.826426	2.341986	2.2226	1.5403	3.209586
O160614.1	1.888799	0.856594	1.939322	2.959647	3.059578	3.774589	2.317946	2.1384	1.4649	3.191627
O160614.2	1.886023	0.877276	3.187159	3.62576	2.277995	2.934725	2.337997	2.3595	1.576	2.629723
O160614.3	1.914068	0.875394	1.935895	2.998016	3.121328	3.885975	2.200596	2.1433	1.4556	3.29317
O160615.1	1.871284	0.864116	2.440688	3.55291	2.98951	3.42449	2.105463	2.3475	1.5211	3.050229
O160615.2	1.872696	0.865468	3.34024	3.932074	2.358265	3.004262	2.409168	2.4268	1.6463	2.748019
O160615.3	2.017685	0.7808	2.319798	3.590717	3.053956	3.797248	3.003236	2.5424	1.8751	3.263278
O160621.1	1.990383	0.860778	1.634242	2.257816	2.744706	3.429358	1.792424	1.7108	1.1821	2.909185
O160621.2	1.952771	0.872473	3.875611	3.437662	1.799645	2.246711	2.052332	2.1795	1.4444	2.150309
O160621.3	1.96063	0.866345	1.680712	2.238377	2.672111	3.357031	1.817131	1.7237	1.1887	2.84665
O160622.1	2.060235	0.780455	1.523417	3.690072	4.957901	6.339307	3.407067	2.7995	2.0995	5.254228
O160622.2	1.929102	0.867915	3.635962	3.20652	1.772229	2.313167	1.887462	1.9816	1.3045	2.142926
O160622.3	1.887769	0.883342	2.423066	1.705762	1.369725	1.78237	1.176808	1.2544	0.8244	1.589708
O160628.1	1.934905	0.852056	1.472002	2.945448	4.099528	5.029412	2.117569	2.0629	1.4202	4.130009
O160628.2	1.865151	0.832013	3.346992	5.637022	3.537556	4.574296	3.172723	3.3811	2.2679	4.078335
O160629.1	1.877063	0.855446	1.771196	1.82735	1.984864	2.626412	1.358052	1.4031	0.9429	2.259314
O160629.2	1.93042	0.84519	2.902247	3.324916	2.448087	3.228837	2.056444	2.1654	1.4485	2.860254
O160629.3	1.845098	0.89529	2.126148	1.737576	1.585769	1.991427	1.121801	1.2895	0.8215	1.766193
O160706.1	1.845459	0.92799	1.625654	2.316241	2.882454	3.616525	1.560464	1.6766	1.0835	3.092045
O160706.2	1.780738	0.921497	1.58991	2.268185	2.957189	3.707879	1.545131	1.665	1.0843	3.179767

O160706.3	1.822064	0.913793	1.632575	2.287039	2.793144	3.526387	1.553244	1.6684	1.0826	3.045438
O160712.1	1.817312	0.909191	1.672996	2.095851	2.486742	3.141788	1.339293	1.4959	0.9599	2.716207
O160712.2	1.8364	0.899017	1.122445	2.380464	4.535613	5.53715	1.591431	1.7268	1.1182	4.534418
O160712.3	1.830083	0.904891	1.659236	2.143206	2.625521	3.341642	1.386002	1.5425	0.9976	2.906697
O160713.1	1.755876	0.911251	2.41254	2.423372	1.832739	2.362824	1.550747	1.7823	1.1323	2.155445
O160713.2	1.80909	0.909724	1.600738	2.728845	3.226284	4.306096	1.785446	1.9999	1.2843	3.627914
O160713.3	1.80391	0.904988	2.243115	2.488439	1.999717	2.672702	1.612225	1.8407	1.175	2.457986
O160718.1	1.805528	0.966033	1.702557	1.633713	1.85558	2.370076	1.04163	1.2095	0.747	2.072973
O160718.2	1.79658	0.961868	1.799274	1.754552	1.84953	2.327676	1.108545	1.2956	0.8021	2.082408
O160718.3	1.845273	0.957005	1.892632	1.666259	1.693397	2.119109	1.058845	1.2414	0.7731	1.934854
O160720.1	1.808525	0.925668	1.903273	2.496788	2.477599	3.201595	1.73195	1.9193	1.2149	2.906812
O160720.2	1.818926	0.932016	1.729805	2.555261	2.865717	3.563137	1.745173	1.9664	1.2593	3.151263
O160720.3	1.78308	0.944856	1.886569	2.474931	2.567583	3.233627	1.704429	1.9069	1.2083	2.866946
O160726.1	1.768131	0.81099	2.701201	2.175922	1.516494	1.885623	1.190214	1.3794	0.9518	1.662396
O160726.2	1.679832	0.802954	2.676137	2.153965	1.509574	1.90804	1.170552	1.3471	0.9349	1.691029
O160726.3	1.726329	0.809301	2.790737	2.160248	1.361729	1.74378	1.185343	1.3497	0.9479	1.597485
O160727.1	1.749476	0.82554	2.488831	1.332116	1.046027	1.274545	0.785778	0.8772	0.5889	1.159389
O160727.2	1.733299	0.82644	2.498593	1.356212	1.056894	1.288908	0.804284	0.898	0.6086	1.155175
O160727.3	1.729503	0.834543	2.730372	1.316169	0.947011	1.175418	0.792789	0.8989	0.6035	1.060368
O160808.1	1.748393	0.816849	2.332473	1.474061	1.27684	1.469902	0.84723	0.9374	0.6409	1.31176
O160808.2	1.74501	0.825702	2.769369	1.387389	1.034856	1.181793	0.808245	0.8978	0.614	1.075337
O160808.3	1.737627	0.827629	2.904684	1.376634	0.936101	1.036416	0.785642	0.8645	0.5966	0.942356
O160810.1	1.772723	0.845725	1.983384	1.165851	1.292909	1.520278	0.729406	0.8025	0.5421	1.293366
O160810.2	1.715707	0.849486	2.756691	1.187583	0.880174	0.976014	0.713542	0.7886	0.5222	0.903206
O160810.3	1.69243	0.849448	2.68954	1.131727	0.868452	0.987895	0.689318	0.7515	0.5103	0.900548
O160817.1	1.760377	0.862107	3.362488	2.207054	1.1411	1.333782	1.382738	1.4991	1.033	1.348466
O160817.2	1.778902	0.841307	2.871481	2.248297	1.424697	1.663844	1.407846	1.5231	1.0378	1.629867
O160817.3	1.76826	0.860969	3.348799	2.231941	1.154199	1.307502	1.37835	1.4925	1.0249	1.324564
O160824.1	1.864324	0.925503	2.595495	1.715723	1.216326	1.565763	1.120733	1.2605	0.8036	1.477407
O160824.2	1.823131	0.924786	2.530327	1.765993	1.263341	1.638699	1.150824	1.301	0.8249	1.551869
O160824.3	1.859635	0.907733	2.444674	1.771187	1.30519	1.711034	1.136585	1.2813	0.8195	1.591193

O160831.1	1.766091	0.891532	3.073619	2.671039	1.614485	2.071472	1.682619	1.8972	1.2407	2.042461
O160831.2	1.74578	0.889644	3.457916	2.488059	1.289892	1.661451	1.59666	1.7439	1.1736	1.710663
O160831.3	1.811615	0.896997	3.438506	2.628304	1.407682	1.839763	1.653246	1.8398	1.212	1.805543

Table 19

Influent

Sample Name	Days	TN	TP	COD	TOC	CDOMEEM	TrypEEM	Abs @ 250nm	Spectral Slope Ratio
		mg/L	mg/L	mg/L	mg/L	R.U.	R.U.		
II160525.2	47	65.55	7.82	255		1.234362	1.960674	0.183734	0.963996
II160601.2	54	86.09	12.09	45		1.605845	2.406922	0.227667	1.200376
II160606.1	59	46.44	6.25	50		1.584957	3.391374	0.211105	1.282899
II160606.2	59	46.44	6.25	275		1.111587	2.067024	0.190788	1.095924
II160606.3	59	46.44	6.25	275		1.728253	4.951293	0.273621	1.565646
II160608.1	61	101.83	13.56	780		1.385511	1.865072	0.196748	1.040664
II160608.2	61	101.83	13.56	675		1.400558	2.178997	0.20789	1.165596
II160608.3	61	101.83	13.56	820		1.642972	4.117	0.249723	1.455326
II160611.1	64	74.25	9.64	255		1.552194	3.773926	0.266949	1.30807
II160611.2	64	72.95	9.32	435		1.542971	3.940118	0.250891	1.246996
II160611.3	64	72.95		470		2.327723	7.434858	0.30077	1.558253
II160614.1	67	61.25	7.44	220		2.865301	4.526589	0.281882	1.790772
II160614.2	67	61.25	7.44	260		1.65975	1.716042	0.17263	1.087002
II160614.3	67	61.25	7.44	65		2.740353	4.210447	0.259246	1.676717
II160615.2	68	79.19	9.44	310	76.76	1.235048	1.357795	0.176456	0.96502
II160615.3	68	79.19	9.44	310	76.76	1.505347	3.592395	0.256081	1.677108
II160621.1	74	63.06	7.55	70	68.74	1.695394	5.728335	0.314757	1.875438

II160621.2	74	63.06	7.55	200	63	1.193048	2.480859	0.219856	1.144554
II160621.3	74	63.06	7.55	285	63	0.899219	2.14032	0.204191	1.243496
II160622.3	75	56.07	6.7	390	59.31	1.615887	5.698161	0.208579	1.696434
II160628.1	81	54	6.94	480	59.82	1.416812	2.744502	0.184132	1.297776
II160628.2	81	54	6.94	220	59.82	1.068781	2.231539	0.222689	1.14757
II160628.3		54	6.94	665	59.82	1.522163	3.484171	0.225352	1.345616
II160629.1	82	59.27	8.14	400	81.98	2.02142	5.207855	0.291115	1.782538
II160629.2	82	59.27	8.14	265	81.98	1.477429	6.226298	0.422215	2.069061
Ii160629.3	82	59.27	8.14	665	81.98	1.866697	5.789896	0.290562	1.893445
II160706.3	89	49.01	5.30	405	19.33	1.206041	2.118198	0.1343	1.140987
II160712.1	95	48.10	5.09	150	20.52	1.74906	7.575443	0.346572	1.340149
II160712.2	95	48.10	5.09	220	21.03	1.809897	7.753547	0.351735	1.47772
II160712.3	95	48.10	5.09	215	19.79	1.686107	7.230277	0.32786	1.368358
II160713.1	96	56.64	5.99	505	22.59	1.645537	7.459934	0.375124	1.307554
II160713.2		56.64	5.99	500	21.16	1.916286	9.253668	0.429382	1.687137
II160713.3	96	56.64	5.99	485	20.53	1.748136	8.028364	0.375824	1.226763
II160718.1	101	58.45	6.78	200	26.38	1.451701	6.200971	0.377447	1.229607
II160718.2	101	58.45	6.78	240	26.98	1.458153	6.353826	0.378219	1.261286
II160718.3	101	58.45	6.78	285	26.74	1.455091	6.228682	0.38025	1.270397
II160720.1	103	50.59	6.54	225	20.72	1.932314	9.090957	0.335898	1.703729
II160720.2	103	50.59	6.54	195	19.39	1.82187	8.191634	0.299579	1.313278
II160720.3	103	50.59	6.54	40	19.31	1.829616	8.463843	0.318729	1.516245
II160726.1	109	36.46	3.52	105	11.3	1.384365	3.350386	0.16919	1.297417
II160726.2	109	36.46	3.52	105	11.25	1.400436	3.44069	0.174874	1.402393
II160726.3	109	36.46	3.52	85	11.5	1.379553	3.304464	0.166257	1.275388
II160808.1	122	34.28	4.53	35	7.071	0.567243	1.084873	0.096614	1.364433
II160808.2	122	34.28	4.53	0	6.998	0.563072	1.140529	0.090997	1.259834
II160808.3	122	34.28	4.53	30	7.259	0.578136	1.175371	0.097545	1.311554
II160824.1	138		315.19	445	32.38	1.703856	7.87012	0.432128	2.241561
II160824.2	138		315.19	440	31.99	1.699485	5.599591	0.230618	1.669384
II160831.1	145			100	11.21	1.488849	4.17276	0.17986	1.771742

II160831.2	145	10	11.49	1.570414	4.610991	0.190031	1.793786	
II160831.3	145	125	11.49	1.749128	4.572072	0.198308	1.927858	

Table 20

Sample Name	C1	C2	C3	C4	C5	Total Loading	% C1	% C2	% C3	% C4	% C5
II160525.2	3.46899	2.96654	1.67678	1.66611	0.24938	10.0278	0.34594	0.29583	0.16721	0.16615	0.02487
II160601.2	3.21493	3.87963	2.32063	2.26299	0.39041	12.06858	0.26639	0.32146	0.19229	0.18751	0.03235
II160606.1	4.502	3.62497	2.13141	2.97809	0.76512	14.0016	0.32153	0.2589	0.15223	0.2127	0.05465
II160606.2	2.90774	2.48506	1.52866	1.97853	0.29315	9.19313	0.3163	0.27032	0.16628	0.21522	0.03189
II160606.3	5.11914	3.73541	2.27499	4.96386	0.87128	16.96468	0.30175	0.22019	0.1341	0.2926	0.05136
II160608.1	3.03126	3.56589	1.86586	1.34899	0.45467	10.26667	0.29525	0.34733	0.18174	0.13139	0.04429
II160608.2	3.19735	3.56776	1.96111	1.75165	0.41038	10.88825	0.29365	0.32767	0.18011	0.16087	0.03769
II160608.3	5.1119	4.02691	2.16705	3.4334	1.08665	15.8259	0.32301	0.25445	0.13693	0.21695	0.06866
II160611.1	4.23349	3.39184	2.13065	3.7806	0.57554	14.11212	0.29999	0.24035	0.15098	0.2679	0.04078
II160611.2	4.26856	3.50108	2.09312	3.63005	0.78116	14.27397	0.29904	0.24528	0.14664	0.25431	0.05473
II160611.3	6.78295	6.86761	2.64323	5.53748	3.24757	25.07884	0.27047	0.27384	0.1054	0.2208	0.12949
II160614.1	4.91176	4.44389	4.14211	3.48437	1.48426	18.46639	0.26598	0.24065	0.22431	0.18869	0.08038
II160614.2	2.97099	3.04063	2.52009	1.54738	0.07887	10.15795	0.29248	0.29933	0.24809	0.15233	0.00776
II160614.3	4.27837	3.86504	4.29989	3.27026	1.34264	17.05621	0.25084	0.22661	0.2521	0.19173	0.07872
II160615.2	2.82188	3.04661	1.72758	0.76486	0.43428	8.795215	0.32084	0.34639	0.19642	0.08696	0.04938
II160615.3	4.96078	3.4693	1.73669	2.46849	1.46207	14.09732	0.3519	0.2461	0.12319	0.1751	0.10371
II160621.1	6.04606	3.60691	2.0782	5.81383	0.95374	18.49875	0.32684	0.19498	0.11234	0.31428	0.05156
II160621.2	3.61973	2.87493	1.55161	2.03225	0.56077	10.6393	0.34022	0.27022	0.14584	0.19101	0.05271
II160621.3	2.86055	2.84306	1.12226	1.68236	0.62997	9.138193	0.31303	0.31112	0.12281	0.1841	0.06894
II160622.3	5.63038	3.08573	1.69452	5.56441	1.03522	17.01026	0.331	0.1814	0.09962	0.32712	0.06086
II160628.1	4.82282	4.27786	1.53285	1.83225	1.01185	13.47764	0.35784	0.3174	0.11373	0.13595	0.07508
II160628.2	3.7481	2.38755	1.1731	1.69173	0.68742	9.687901	0.38688	0.24645	0.12109	0.17462	0.07096
II160628.3	5.16412	3.79121	1.64999	2.53095	1.22592	14.36219	0.35956	0.26397	0.11488	0.17622	0.08536

II160629.1	5.9961	5.20346	2.32361	4.76134	1.52602	19.81053	0.30267	0.26266	0.11729	0.24034	0.07703
II160629.2	5.99167	2.42686	1.5622	6.83663	0.58949	17.40684	0.34421	0.13942	0.08975	0.39276	0.03387
Ii160629.3	6.23467	3.52698	1.99505	5.55081	1.43397	18.74148	0.33267	0.18819	0.10645	0.29618	0.07651
II160706.3	3.81349	2.60133	1.61582	1.94397	0.30632	10.28094	0.37093	0.25302	0.15717	0.18908	0.0298
II160712.1	7.56766	2.93878	1.64514	1.45623	7.08921	20.69702	0.36564	0.14199	0.07949	0.07036	0.34252
II160712.2	7.55883	2.92946	1.73627	1.78393	7.06555	21.07405	0.35868	0.13901	0.08239	0.08465	0.33527
II160712.3	7.45777	2.83741	1.55453	1.52809	6.54281	19.92062	0.37437	0.14244	0.07804	0.07671	0.32844
II160713.1	7.37642	2.90664	1.61915	0.82322	7.49945	20.22488	0.36472	0.14372	0.08006	0.0407	0.3708
II160713.2	7.49644	3.27915	2.00115	2.51247	8.08452	23.37373	0.32072	0.14029	0.08562	0.10749	0.34588
II160713.3	7.68849	3.06319	1.73529	0.7261	8.18001	21.39308	0.35939	0.14319	0.08111	0.03394	0.38237
II160718.1	5.86362	2.55966	1.51448	1.98985	5.06727	16.99489	0.34502	0.15061	0.08911	0.11709	0.29816
II160718.2	5.62978	2.57313	1.54647	1.98739	5.30521	17.04198	0.33035	0.15099	0.09074	0.11662	0.3113
II160718.3	5.54823	2.53167	1.54979	1.83405	5.33851	16.80225	0.33021	0.15067	0.09224	0.10916	0.31773
II160720.1	6.08863	3.42818	2.20003	3.42046	6.88015	22.01746	0.27654	0.1557	0.09992	0.15535	0.31249
II160720.2	6.51057	3.26158	1.97073	1.87144	7.21556	20.82988	0.31256	0.15658	0.09461	0.08984	0.3464
II160720.3	5.91421	3.33277	2.01671	2.42615	7.14652	20.83636	0.28384	0.15995	0.09679	0.11644	0.34298
II160726.1	4.0148	2.53258	1.40914	1.4199	1.9095	11.28593	0.35574	0.2244	0.12486	0.12581	0.16919
II160726.2	4.12379	2.656	1.46896	1.65077	1.82142	11.72094	0.35183	0.2266	0.12533	0.14084	0.1554
II160726.3	3.95118	2.57511	1.40268	1.35201	1.96423	11.24521	0.35137	0.229	0.12474	0.12023	0.17467
II160808.1	1.63532	1.25525	0.65521	0.84699	0.29958	4.692343	0.34851	0.26751	0.13963	0.1805	0.06384
II160808.2	1.672	1.23691	0.63966	0.78855	0.38289	4.720009	0.35424	0.26206	0.13552	0.16707	0.08112
II160808.3	1.68894	1.30198	0.63526	0.81658	0.40246	4.845232	0.34858	0.26871	0.13111	0.16853	0.08306
II160824.1	5.10902	2.13075	2.10655	5.72251	4.43973	19.50855	0.26189	0.10922	0.10798	0.29333	0.22758
II160824.2	4.79263	4.33799	1.8624	3.70379	2.86748	17.56429	0.27286	0.24698	0.10603	0.21087	0.16326
II160831.1	5.22583	3.48514	1.50985	2.42237	2.05267	14.69586	0.3556	0.23715	0.10274	0.16483	0.13968
II160831.2	5.5189	3.4581	1.60337	2.65386	2.34443	15.57866	0.35426	0.22198	0.10292	0.17035	0.15049
II160831.3	5.50414	3.76264	1.98437	3.3176	1.59725	16.16601	0.34048	0.23275	0.12275	0.20522	0.0988

Table 21

Sample Name	FI	FrI	HI	A R.U.	B R.U.	T R.U.	C R.U.	M R.U.
II160525.2	1.92639	0.84305	2.73978	2.45165	1.26613	2.14003	2.0211	1.69985
II160601.2	1.93706	0.77072	2.68902	3.11428	2.04434	2.75432	2.64427	2.00579
II160606.1	1.88828	0.81213	1.87845	3.40761	2.60426	3.81325	2.58212	2.29549
II160606.2	1.87739	0.84002	1.95471	2.12894	1.63377	2.36279	1.79239	1.54115
II160606.3	1.60389	0.82804	1.25124	3.40903	4.17796	5.82306	2.73256	2.49962
II160608.1	1.84932	0.80434	3.20222	2.75278	1.229	1.95044	2.14804	1.79599
II160608.2	1.87775	0.84288	2.87503	2.85058	1.50507	2.32661	2.23941	1.88807
II160608.3	1.81699	0.87292	1.66868	3.80192	2.9183	4.55986	2.64515	2.53878
II160611.1	1.97552	0.83056	1.66719	3.16797	3.0767	4.36449	2.51172	2.14096
II160611.2	1.92353	0.81469	1.7522	3.26102	2.87225	4.47581	2.49272	2.1325
II160611.3	1.77742	0.72916	1.60064	6.08881	5.59902	8.24078	3.31989	3.50147
II160614.1	2.12208	0.49062	2.03247	4.77964	3.356	4.93179	4.60816	3.77572
II160614.2	2.0311	0.68101	3.26336	2.76327	1.23454	1.77578	2.87858	1.96802
II160614.3	2.07513	0.54182	2.11457	4.27196	3.18947	4.55251	4.86639	3.2048
II160615.2	1.9852	0.79503	4.05631	2.56858	1.02372	1.34346	1.93673	1.66837
II160615.3	1.84903	0.88507	1.78683	3.56714	2.81863	3.92856	2.08251	2.56689
II160621.1	1.98109	0.9234	1.19518	3.73448	5.17939	6.84819	2.54299	3.02564
II160621.2	1.82246	0.83683	2.04974	2.61434	1.71089	2.77695	1.90278	1.75474
II160621.3	1.84702	0.8726	2.08669	2.38116	1.57226	2.41223	1.4503	1.36713
II160622.3	1.62728	0.80852	1.06982	3.3132	4.54302	6.66083	2.01753	2.81929
II160628.1	1.83282	0.80161	2.62485	3.80969	1.93336	3.04603	1.99279	2.12622
II160628.2	1.81316	0.79077	1.9626	2.47794	1.65152	2.54822	1.41538	1.73256
II160628.3	1.71557	0.84157	1.88988	3.66691	2.59909	3.99877	2.02757	2.43142
II160629.1	1.87167	0.78602	1.59945	4.82908	5.12759	6.18885	2.77098	3.31328
II160629.2	1.64488	0.82519	0.86726	3.08027	6.17276	7.50657	1.71328	3.22896
Ii160629.3	1.68961	0.79372	1.07838	3.88487	5.33819	6.94363	2.24036	3.43877
II160706.3	1.82978	0.82273	2.15093	2.50856	1.7997	2.44784	1.93125	1.84892
II160712.1	1.87542	0.75853	1.41602	8.06155	3.85851	7.74321	2.01234	3.64373

II160712.2	1.90413	0.75392	1.37622	8.06886	4.06308	8.0657	2.11929	3.61828
II160712.3	1.88273	0.76556	1.39965	7.54944	3.74533	7.40071	1.91197	3.5938
II160713.1	2.00637	0.77279	1.44128	8.11703	3.98428	7.57508	1.90936	4.0159
II160713.2	2.07269	0.79116	1.28628	8.94939	4.78336	9.64191	2.43353	3.86236
II160713.3	2.00811	0.78843	1.46274	8.70636	3.9352	8.02082	2.06213	4.14145
II160718.1	1.9273	0.77903	1.26272	6.01103	3.94159	6.48243	1.71109	3.29836
II160718.2	1.91974	0.76029	1.25154	6.07482	3.96525	6.668	1.75135	3.14706
II160718.3	1.93879	0.76125	1.25575	6.09139	3.77343	6.56153	1.74636	3.11428
II160720.1	2.02564	0.80971	1.25167	7.67172	4.93574	9.44211	2.57502	3.35077
II160720.2	2.01319	0.79931	1.39758	7.71647	4.27815	8.32151	2.31277	3.52243
II160720.3	1.98235	0.81731	1.33092	7.83048	4.23804	8.72254	2.37166	3.20632
II160726.1	1.80444	0.68169	1.82821	2.92816	1.87801	3.38643	1.45454	2.59245
II160726.2	1.84743	0.69787	1.79492	2.92316	1.96145	3.56673	1.54855	2.62669
II160726.3	1.8699	0.68975	1.87623	2.90558	1.86236	3.41161	1.44897	2.57141
II160808.1	2.00627	0.76064	2.10319	1.21889	0.76835	1.19136	0.79245	0.83284
II160808.2	2.03064	0.79487	2.09553	1.22145	0.75533	1.1982	0.76343	0.84976
II160808.3	1.93629	0.76218	2.07261	1.24645	0.80609	1.23894	0.75612	0.85576
II160824.1	2.18781	0.70666	0.66676	5.8456	5.55926	8.94389	2.44284	2.84299
II160824.2	2.05617	0.7767	1.43596	4.4272	3.77411	6.27601	2.26567	2.64104
II160831.1	1.77897	0.78541	1.82223	3.8133	2.415	4.56089	1.85611	2.4502
II160831.2	1.82732	0.79866	1.7365	4.23231	2.68416	5.03525	1.95233	2.56898
II160831.3	1.88328	0.76159	1.77058	3.98303	2.87598	5.15095	2.37042	2.69893

Table 22

Appendix C - R Code

ANOVA on PARAFAC Outputs

```
R version 3.3.1 (2016-06-21) -- "Bug in Your Hair"
Copyright (C) 2016 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)

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'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> PFdata = read.csv(file.choose())
> attach(PFdata)
> corrc1.aov = aov(corrc1 ~ source)
```

```
> corrc2.aov = aov(corrc2 ~ source)
> corrc3.aov = aov(corrc3 ~ source)
> corrc4.aov = aov(corrc4 ~ source)
> totalfi.aov = aov(totalfi ~ source)
> TukeyHSD(corrc1.aov)
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = corrc1 ~ source)

$source
                     diff       lwr      upr     p adj
Influent-Effluent 1.7238174  1.205538 2.242097 0.0000000
Oxic-Effluent     1.9768199  1.464825 2.488815 0.0000000
Oxic-Influent     0.2530025 -0.262221 0.768226 0.4761646

> TukeyHSD(corrc2.aov)
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = corrc2 ~ source)

$source
```

```
                      diff       lwr       upr     p adj
Influent-Effluent  0.7288635  0.3398602 1.1178668 0.0000580
Oxic-Effluent      0.4905550  0.1062684 0.8748415 0.0083775
Oxic-Influent     -0.2383085 -0.6250182 0.1484011 0.3126583

> TukeyHSD(corrc3.aov)
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = corrc3 ~ source)

$source
                      diff       lwr       upr   p adj
Influent-Effluent  2.0133065  1.5614835  2.4651295 0.00000
Oxic-Effluent      0.7542399  0.3078954  1.2005844 0.00031
Oxic-Influent     -1.2590666 -1.7082255 -0.8099077 0.00000

> TukeyHSD(corrc4.aov)
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = corrc4 ~ source)
```

$source

	diff	lwr	upr	p adj
Influent-Effluent	3.273506100	2.3184239	4.2285883	0.0000000
Oxic-Effluent	0.001963098	-0.9415385	0.9454647	0.9999866
Oxic-Influent	-3.271543002	-4.2209938	-2.3220922	0.0000000

> TukeyHSD(totalfi.aov)

Tukey multiple comparisons of means

95% family-wise confidence level

Fit: aov(formula = totalfi ~ source)

$source

	diff	lwr	upr	p adj
Influent-Effluent	7.739493	6.362554	9.116433	0e+00
Oxic-Effluent	3.223578	1.863334	4.583821	4e-07
Oxic-Influent	-4.515916	-5.884736	-3.147095	0e+00

Detection Limit Analysis

First Try

R version 3.3.1 (2016-06-21) -- "Bug in Your Hair"
Copyright (C) 2016 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)

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```
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'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> RB=read.csv(file.choose())
> attach(RB)
> B543Ratio=B.5C4/B.5C3
> B443Ratio=B.4C4/B.4C3
> BR543Ratio=BR.5C4/BR.5C3
> BR443Ratio=BR.4C4/BR.4C3
> BS543Ratio=BS.5C4/BS.5C3
> BS443Ratio=BS.4C4/BS.4C3
> BRTCRatio=BR.T/BR.C
> BSTCRatio=BS.T/BR.C
> BSWW.BS543Ratio=lm(BS.WW~BS543Ratio)
> summary(BSWW.BS543Ratio)

Call:
lm(formula = BS.WW ~ BS543Ratio)

Residuals:
    Min      1Q  Median      3Q     Max
-14.3646  -1.7208   0.5191   3.2875   8.4963

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.5191     1.3588  -0.382    0.705
BS543Ratio  315.9733    11.8269  26.717   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.783 on 27 degrees of freedom
  (45 observations deleted due to missingness)
Multiple R-squared:  0.9636,    Adjusted R-squared:  0.9622
F-statistic: 713.8 on 1 and 27 DF,  p-value: < 2.2e-16

> predict(BSWW.BS543Ratio,interval="confidence")
         fit       lwr       upr
```

```
1   -0.5190868 -3.3071427   2.268969
2    1.4959579 -1.2000527   4.191969
3   -0.1818327 -2.9540941   2.590429
4    9.9629745  7.5816076  12.344341
5   -0.5190868 -3.3071427   2.268969
6   -0.5190868 -3.3071427   2.268969
7   12.4317863 10.1156831  14.747890
8   18.3646034 16.1461345  20.583072
9    2.8787822  0.2425386   5.515026
10   3.5293613  0.9202145   6.138508
11   9.3649251  6.9657603  11.764090
12   7.4767715  5.0166285   9.936915
13   4.3983717  1.8243511   6.972392
14   0.9836151 -1.7352593   3.702489
15  -0.4122495 -3.1952856   2.370787
16  18.6062014 16.3898138  20.822589
17   9.8616913  7.4773631  12.246020
18   5.4739881  2.9416832   8.006293
19  18.2619716 16.0425722  20.481371
20  30.5602945 28.2547457  32.865843
21  20.0759512 17.8689041  22.282998
22  23.2556804 21.0491290  25.462232
23  26.9678452 24.7279312  29.207759
24  42.5119416 39.7909383  45.232945
25  36.7125059 34.2265289  39.198483
26  34.1363146 31.7355377  36.537092
27 101.7208349 95.1939150 108.247755
28  91.5036564 85.7092922  97.298021
29 101.6153162 95.0960238 108.134609
> BSWW.BS443Ratio=lm(BS.WW~BS443Ratio)
> summary(BSWW.BS443Ratio)

Call:
lm(formula = BS.WW ~ BS443Ratio)

Residuals:
    Min      1Q  Median      3Q     Max
-11.1175  -2.7356   0.4607   4.1443   8.1174

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -110.78       4.34  -25.52   <2e-16 ***
BS443Ratio    339.65      10.87   31.24   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 4.97 on 27 degrees of freedom
  (45 observations deleted due to missingness)
Multiple R-squared:  0.9731,    Adjusted R-squared:  0.9721
F-statistic: 976.1 on 1 and 27 DF,  p-value: < 2.2e-16

> predict(BSWW.BS443Ratio,interval="confidence")
         fit        lwr        upr
1    1.861886 -0.4374766   4.161248
2    3.754965  1.5237847   5.986145
3   -1.407756 -3.8353881   1.019877
4   11.124262  9.1068168  13.141708
5   -6.117408 -8.7496812  -3.485135
6   -3.557691 -6.0760930  -1.039290
7    9.469788  7.4123198  11.527257
8   15.117501 13.1748925  17.060109
9    2.038077 -0.2547402   4.330895
10   5.539325  3.3678498   7.710800
11   7.893352  5.7932223   9.993481
12   6.882956  4.7532851   9.012626
13   6.382811  4.2379079   8.527713
14   3.524245  1.2850133   5.763476
15   3.555901  1.3177780   5.794023
16  17.098290 15.1805413  19.016039
17  10.670048  8.6421157  12.697980
18   6.643814  4.5069097   8.780718
19  20.204161 18.3079991  22.100323
20  26.904238 24.9803872  28.828090
21  19.054686 17.1530551  20.956317
22  24.941538 23.0362519  26.846823
23  28.400873 26.4572309  30.344514
24  42.991497 40.6385553  45.344439
25  35.855672 33.7469250  37.964420
26  34.744676 32.6670081  36.822344
27 102.735584 97.0882413 108.382926
28  92.211833 87.2102590  97.213408
29 101.480877 95.9110987 107.050655
> BSWW.BSHI=lm(BS.WW~BS.HI)
> summary(BSWW.BSHI)

Call:
lm(formula = BS.WW ~ BS.HI)

Residuals:
   Min     1Q  Median     3Q    Max
-19.519  -9.320   0.784   5.867  33.435
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  472.955     38.933   12.15 1.87e-12 ***
BS.HI        -77.116      6.642  -11.61 5.26e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.37 on 27 degrees of freedom
  (45 observations deleted due to missingness)
Multiple R-squared:  0.8331,    Adjusted R-squared:  0.8269
F-statistic: 134.8 on 1 and 27 DF,  p-value: 5.262e-12

> predict(BSWW.BSHI,interval="confidence")
          fit       lwr       upr
1   -0.7838371  -6.952329   5.384654
2    8.2595308   2.978413  13.540648
3  -14.6619019 -22.635423  -6.688380
4    0.3272471  -5.716489   6.370983
5  -14.0206841 -21.903103  -6.138265
6  -10.3180469 -17.686470  -2.949623
7   22.5343562  17.817521  27.251191
8   17.0111696  12.223503  21.798836
9    9.4286060   4.237301  14.619911
10  17.4178011  12.642112  22.193491
11  15.5932417  10.755684  20.430800
12  25.5185057  20.756397  30.280615
13   6.6444949   1.228779  12.060211
14   8.5222642   3.261904  13.782624
15  16.4843917  11.679655  21.289129
16  22.0658007  17.350753  26.780849
17   4.1329881  -1.514368   9.780345
18  19.3925821  14.659949  24.125215
19  23.5753422  18.849344  28.301341
20  29.0503314  24.161125  33.939537
21  10.5411554   5.429029  15.653282
22  26.3918419  21.605560  31.178124
23  27.7932671  22.958142  32.628392
24  49.3199065  42.536707  56.103106
25  38.8003883  33.202608  44.398168
26   6.5648343   1.142177  11.987492
27  95.5650077  81.689921 109.440095
28  80.0653523  68.728189  91.402515
29  88.7840627  76.029534 101.538592
> BSWW.BSB=lm(BS.WW~BS.B)
> summary(BSWW.BSB)
```

```
Call:
lm(formula = BS.WW ~ BS.B)

Residuals:
    Min      1Q  Median      3Q     Max
-9.7869 -3.8548  0.3829  2.6628 14.4099

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -193.219      8.222  -23.50   <2e-16 ***
BS.B         401.717     15.231   26.38   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.855 on 27 degrees of freedom
  (45 observations deleted due to missingness)
Multiple R-squared:  0.9626,    Adjusted R-squared:  0.9613
F-statistic: 695.7 on 1 and 27 DF,  p-value: < 2.2e-16

> predict(BSWW.BSB,interval="confidence")
          fit         lwr         upr
1   -2.2368134  -5.1438883   0.6702616
2    3.8548234   1.2263218   6.4833249
3  -10.2679398 -13.6101720  -6.9257077
4    1.3939050  -1.3406731   4.1284830
5   -0.8890528  -3.7300411   1.9519355
6    0.7125929  -2.0529763   3.4781622
7    8.8975770   6.4537550  11.3413990
8    7.4003777   4.9067329   9.8940225
9   13.7868747  11.4721623  16.1015871
10   3.2068538   0.5513494   5.8623583
11   3.9211067   1.2953285   6.5468849
12  14.3014742  11.9971176  16.6058308
13   0.5848469  -2.1866075   3.3563013
14   5.3371591   2.7677782   7.9065401
15   9.1297694   6.6932667  11.5662721
16  14.1556509  11.8484256  16.4628763
17   9.6170522   7.1955436  12.0385607
18  12.3121716   9.9642521  14.6600911
19  22.6937443  20.4616322  24.9258563
20  29.7105353  27.3948004  32.0262702
21  26.3899425  24.1297701  28.6501148
22  25.1767571  22.9298092  27.4237050
23  29.9587964  27.6378055  32.2797873
24  44.3499066  41.5083123  47.1915008
25  38.6153962  36.0263278  41.2044647
```

```
26  25.5901239  23.3391057  27.8411421
27  91.0916892  85.2524608  96.9309177
28  97.6681984  91.3531480 103.9832489
29 103.5364805  96.7924249 110.2805361
> BSWW.BSTC=lm(BS.WW~BS.TCRatio)
Error in eval(expr, envir, enclos) : object 'BS.TCRatio' not found
> BSWW.BSTC=lm(BS.WW~BSTCRatio)
> predict(BSWW.BSTC,interval="confidence")
       fit       lwr      upr
1  14.79180  4.8062163 24.77738
2  11.30525  3.5738557 19.03664
3  12.48721  7.0542422 17.92019
4  13.87695  6.7072394 21.04665
5  12.43235  6.9617511 17.90295
6  11.02360  2.4438510 19.60336
7  13.27565  7.4179915 19.13331
8  12.45351  6.9984462 17.90858
9  12.25860  6.6136608 17.90353
10 11.02631  2.4550321 19.59759
11 12.35951  6.8258219 17.89319
12 13.49744  7.2313885 19.76348
13 12.74004  7.3662569 18.11382
14 10.91050  1.9725440 19.84845
15 14.21851  6.0765259 22.36049
16 11.17549  3.0617500 19.28923
17 13.11110  7.4843066 18.73789
18 14.82650  4.7233289 24.92967
19 12.31699  6.7397446 17.89424
20 12.38702  6.8788986 17.89514
21 12.41357  6.9281302 17.89901
22 12.22338  6.5333585 17.91341
23 13.15021  7.4746402 18.82578
24 16.67894 -0.1845413 33.54241
25 11.61378  4.7186045 18.50896
26 11.44580  4.1093765 18.78222
> summary(BSWW.BSTC)

Call:
lm(formula = BS.WW ~ BSTCRatio)

Residuals:
   Min     1Q  Median     3Q    Max
-14.792  -8.881  -4.926   7.606  28.554

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)    5.903     13.444   0.439    0.665
BSTCRatio     10.344     20.097   0.515    0.611

Residual standard error: 13.27 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.01092,   Adjusted R-squared:  -0.03029
F-statistic: 0.2649 on 1 and 24 DF,  p-value: 0.6115

> BSTCRatio=BS.T/BS.C
> BSWW.BSTC=lm(BS.WW~BSTCRatio)
> summary(BSWW.BSTC)

Call:
lm(formula = BS.WW ~ BSTCRatio)

Residuals:
    Min      1Q  Median      3Q     Max
-13.0133  -2.8325   0.8611   3.2814   8.7691

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -232.219      7.934  -29.27   <2e-16 ***
BSTCRatio    400.449     12.432   32.21   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.824 on 27 degrees of freedom
  (45 observations deleted due to missingness)
Multiple R-squared:  0.9746,    Adjusted R-squared:  0.9737
F-statistic:  1038 on 1 and 27 DF,  p-value: < 2.2e-16

> predict(BSWW.BSTC,interval="confidence")
         fit         lwr        upr
1    0.9524518  -1.31231755   3.217221
2    4.8260368   2.69599129   6.956082
3    0.1384797  -2.15696797   2.433927
4    0.9720753  -1.29196391   3.236115
5    4.8324564   2.70261747   6.962295
6    2.8463731   0.64990402   5.042842
7   17.0133419  15.15095500  18.875729
8    9.4816191   7.48497153  11.478267
9    6.0856012   3.99495488   8.176247
10   4.2039030   2.05355867   6.354247
11   1.3077068  -0.94391636   3.559330
12   2.7186475   0.51771357   4.919581
13  12.4141684  10.48281126  14.345526
```

```
14   2.2539597   0.03660577   4.471314
15  11.6375677   9.69045116  13.584684
16   6.8297467   4.76126721   8.898226
17   8.5451758   6.52448336  10.565868
18   8.5083592   6.48669128  10.530027
19  22.1337078  20.29546977  23.971946
20  22.2737531  20.43536690  24.112139
21  19.1388834  17.29346806  20.984299
22  24.1121055  22.26776908  25.956442
23  21.2308646  19.39254324  23.069186
24  46.2431833  43.83116056  48.655206
25  34.1696268  32.16789397  36.171360
26  36.2562171  34.19822144  38.314213
27  98.3164417  93.10276927 103.530114
28 105.8662705 100.20001466 111.532526
29  94.6912761  89.69303717  99.689515
> BSWW.BSTryp=lm(BS.WW~BS.TrypEEM)
> summary(BSWW.BSTryp)

Call:
lm(formula = BS.WW ~ BS.TrypEEM)

Residuals:
    Min      1Q  Median      3Q     Max
-13.230  -7.939  -2.955   5.364  27.507

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -524.53      40.60  -12.92 4.51e-13 ***
BS.TrypEEM    585.27      43.45   13.47 1.69e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10.9 on 27 degrees of freedom
  (45 observations deleted due to missingness)
Multiple R-squared:  0.8705,    Adjusted R-squared:  0.8657
F-statistic: 181.4 on 1 and 27 DF,  p-value: 1.689e-13

> predict(BSWW.BSTryp,interval="confidence")
         fit        lwr        upr
1  -12.349624 -18.997649  -5.701599
2    1.463402  -3.711594   6.638398
3    3.541706  -1.450949   8.534362
4  -24.485258 -32.658643 -16.311873
5   14.804698  10.519125  19.090272
6    9.186078   4.614101  13.758055
```

```
7    2.938875  -2.105303   7.983053
8   13.076387   8.718583  17.434192
9   13.632397   9.299443  17.965350
10   9.865580   5.335868  14.395293
11  15.350758  11.084881  19.616635
12   8.677476   4.072596  13.282356
13  15.938957  11.692576  20.185339
14  10.954773   6.488635  15.420911
15   6.733785   1.993588  11.473982
16  17.813001  13.616563  22.009440
17  18.754705  14.576220  22.933191
18  13.796858   9.470965  18.122752
19  23.741816  19.576531  27.907101
20  30.168698  25.820150  34.517246
21  33.230260  28.721689  37.738832
22  29.632588  25.307494  33.957682
23  13.819099   9.494150  18.144048
24  40.562560  35.513783  45.611336
25  27.952855  23.691939  32.213770
26  12.492870   8.107377  16.878363
27  94.635925  82.777845 106.494005
28  91.178717  79.812409 102.545026
29  92.890055  81.280700 104.499411
> BRWW.BRTC=lm(BR.WW~BRTCRatio)
> summary(BRWW.BRTC)

Call:
lm(formula = BR.WW ~ BRTCRatio)

Residuals:
   Min     1Q  Median     3Q    Max
-14.597  -6.215   1.410   7.186  22.411

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   -33.19      11.99  -2.767 0.010720 *
BRTCRatio      53.77      13.41   4.009 0.000515 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10.17 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.4011,    Adjusted R-squared:  0.3762
F-statistic: 16.07 on 1 and 24 DF,  p-value: 0.0005147

> predict(BRWW.BRTC,interval="confidence")
```

```
         fit       lwr       upr
1   8.0722414  2.875787 13.268696
2  15.4101790 11.248327 19.572031
3  -0.7595777 -9.506033  7.986877
4  10.2628609  5.666708 14.859014
5  14.9915279 10.855616 19.127439
6  12.8873586  8.712355 17.062362
7   9.0893273  4.194688 13.983967
8  20.5966646 15.334404 25.858925
9  11.9303328  7.646086 16.214580
10 11.2220094  6.822994 15.621025
11 -0.6778515 -9.387211  8.031508
12 21.1243639 15.688778 26.559949
13  6.8328665  1.224344 12.441389
14 13.6774349  9.550265 17.804605
15  2.6452183 -4.601981  9.892418
16 24.3125532 17.687787 30.937320
17  7.7691556  2.476070 13.062241
18 15.2528382 11.102029 19.403648
19 18.3470350 13.716436 22.977634
20 11.5229233  7.176030 15.869817
21 24.0286673 17.517754 30.539581
22 19.3753293 14.479822 24.270837
23 13.2536919  9.105755 17.401629
24 17.5891126 13.123558 22.054667
25 30.6225979 21.233479 40.011717
26 30.6211394 21.232696 40.009583
> BRWW.BRB=lm(BR.WW~BR.B)
> summary(BRWW.BRB)

Call:
lm(formula = BR.WW ~ BR.B)

Residuals:
   Min     1Q  Median     3Q    Max
-16.437  -7.901  -2.976   9.417  29.510

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   -8.642      9.024  -0.958    0.348
BR.B          28.493     10.879   2.619    0.015 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 11.59 on 24 degrees of freedom
  (48 observations deleted due to missingness)
```

```
Multiple R-squared:  0.2223,    Adjusted R-squared:  0.1899
F-statistic:  6.86 on 1 and 24 DF,  p-value: 0.01504

> predict(BRWW.BRB,interval="confidence")
        fit       lwr      upr
1   6.557729 -1.0955382 14.21100
2  18.436640 12.6922346 24.18105
3   3.918595 -5.4646794 13.30187
4   8.309525  1.6924949 14.92656
5  15.635436 10.8147219 20.45615
6  18.442453 12.6954034 24.18950
7   9.029722  2.7998592 15.25958
8  15.815286 10.9600714 20.67050
9  13.362241  8.6206684 18.10381
10 14.080557  9.3871448 18.77397
11  8.271002  1.6325317 14.90947
12 13.489492  8.7613518 18.21763
13 11.680111  6.5758110 16.78441
14 18.017390 12.4570388 23.57774
15  7.312402  0.1197099 14.50509
16 24.136268 15.0291053 33.24343
17 10.411333  4.8370627 15.98560
18  9.374662  3.3201539 15.42917
19 17.663760 12.2478396 23.07968
20 11.799384  6.7313567 16.86741
21 20.177808 13.5464293 26.80919
22 17.543575 12.1743324 22.91282
23 11.939371  6.9120089 16.96673
24 10.489975  4.9489179 16.03103
25 27.601936 16.0680108 39.13586
26 26.503348 15.7544755 37.25222
> BRWW.BRHI=lm(BR.WW~BR.HI)
> summary(BRWW.BRHI)

Call:
lm(formula = BR.WW ~ BR.HI)

Residuals:
   Min     1Q  Median     3Q    Max
-14.320  -9.984  -1.363   6.935  24.274

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   37.623     10.974   3.428   0.0022 **
BR.HI         -6.143      2.815  -2.182   0.0391 *
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.01 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.1656,    Adjusted R-squared:  0.1308
F-statistic: 4.763 on 1 and 24 DF,  p-value: 0.03909

> predict(BRWW.BRHI,interval="confidence")
        fit       lwr      upr
1  12.352369   7.177989 17.52675
2  16.229280  11.014816 21.44374
3  -1.592648 -17.325671 14.14038
4  14.227091   9.367167 19.08702
5  18.320211  12.109390 24.53103
6  15.545825  10.529313 20.56234
7   8.928244   1.945194 15.91129
8  17.792834  11.879654 23.70601
9  16.550945  11.218691 21.88320
10 15.255493  10.299900 20.21108
11  3.890681  -7.028682 14.81004
12 16.838704  11.388831 22.28858
13 10.757892   4.892349 16.62344
14 15.950195  10.825479 21.07491
15  9.968642   3.654847 16.28244
16 18.933363  12.345859 25.52087
17  9.665607   3.165132 16.16608
18 15.002538  10.088120 19.91696
19 19.095025  12.403367 25.78668
20 11.232405   5.605811 16.85900
21 22.419363  13.277002 31.56172
22 14.516803   9.649358 19.38425
23 12.442868   7.297241 17.58850
24 15.725601  10.664264 20.78694
25 20.819806  12.917643 28.72197
26 19.130862  12.415862 25.84586
> BRWW.BR543Ratio=lm(BR.WW~BR.543Ratio)
Error in eval(expr, envir, enclos) : object 'BR.543Ratio' not found
> BRWW.BR543Ratio=lm(BR.WW~BR543Ratio)
> summary(BRWW.BR543Ratio)

Call:
lm(formula = BR.WW ~ BR543Ratio)

Residuals:
    Min      1Q  Median      3Q     Max
-15.0850  -9.2327  -0.2471   7.0483  23.3049
```

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.6984     5.8006   -0.12   0.9052
BR543Ratio   24.8527     8.9072    2.79   0.0102 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 11.42 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.2449,    Adjusted R-squared:  0.2135
F-statistic: 7.785 on 1 and 24 DF,  p-value: 0.01016

> BRWW.BR443Ratio=lm(BR.WW~BR.443Ratio)
Error in eval(expr, envir, enclos) : object 'BR.443Ratio' not found
> BRWW.BR443Ratio=lm(BR.WW~BR443Ratio)
> summary(BRWW.BR443Ratio)

Call:
lm(formula = BR.WW ~ BR443Ratio)

Residuals:
    Min      1Q  Median      3Q     Max
-15.2318  -7.6309   0.3579   5.7970  20.7912

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  -16.173      8.777  -1.843  0.07777 .
BR443Ratio    40.525     11.365   3.566  0.00156 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10.63 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.3463,    Adjusted R-squared:  0.3191
F-statistic: 12.72 on 1 and 24 DF,  p-value: 0.001565

> predict(BRWW.BR443Ratio,interval="confidence")
         fit        lwr       upr
1   9.65364904   4.6018288 14.705469
2  16.72602337  12.1885497 21.263497
3  -1.82144455 -12.0595865  8.416697
4  11.56258751   6.9922730 16.132902
5  18.06737529  13.2265310 22.908220
6  12.84757156   8.4722018 17.222941
7   7.31969029   1.4457806 13.193600
```

```
8  21.23182491  15.3223294 27.141320
9  13.48129351   9.1579705 17.804617
10 10.86540420   6.1434467 15.587362
11  0.06115003  -9.1995447  9.321845
12 21.11824822  15.2536315 26.982865
13  8.41862604   2.9579426 13.879309
14 12.41066435   7.9820430 16.839286
15  4.62863328  -2.3990866 11.656353
16 22.19122220  15.8880077 28.494437
17  6.96441035   0.9485881 12.980233
18 15.44704998  11.0883217 19.805778
19 18.86563805  13.7962109 23.935065
20 11.29421913   6.6691099 15.919328
21 24.85741402  17.3519993 32.362829
22 18.36092490  13.4398294 23.282020
23 12.06652491   7.5863455 16.546704
24 19.20881262  14.0315378 24.386087
25 25.74238354  17.8117999 33.672967
26 28.43010325  19.1541747 37.706032
> predict(BRWW.BR543Ratio,interval="confidence")
        fit         lwr      upr
1   9.815424   4.1549906 15.47586
2  17.020519  11.9577304 22.08331
3   0.102104 -11.3258181 11.53003
4  12.050299   7.1538832 16.94671
5  18.802473  13.0745263 24.53042
6  14.731472  10.0935190 19.36943
7   7.603978   0.8659009 14.34206
8  21.084965  14.2235448 27.94639
9  15.626813  10.8897442 20.36388
10 13.455554   8.7969865 18.11412
11  1.925263  -8.2839316 12.13446
12 19.796854  13.6061177 25.98759
13  9.239525   3.3230563 15.15599
14 13.936782   9.3085295 18.56504
15  5.320151  -2.7307858 13.37109
16 20.685493  14.0394353 27.33155
17  7.733545   1.0648666 14.40222
18 13.606178   8.9600084 18.25235
19 19.254750  13.3231394 25.18636
20 12.733558   7.9796154 17.48750
21 21.924056  14.5920639 29.25605
22 17.586313  12.3390000 22.83363
23 11.511339   6.4695275 16.55315
24 16.695149  11.7255979 21.66470
25 23.270628  15.1412391 31.40002
```

```
26 24.486812  15.6027022 33.37092
> BRTOC.BR443Ratio=lm(BR.TOC~BR443Ratio)
> summary(BRTOC.BR443Ratio)

Call:
lm(formula = BR.TOC ~ BR443Ratio)

Residuals:
   Min     1Q  Median     3Q    Max
-1.3983 -0.4114  0.1070  0.4969  0.8779

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.4949     0.4995   6.996 3.11e-07 ***
BR443Ratio    2.7086     0.6468   4.188 0.000327 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6048 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.4222,    Adjusted R-squared:  0.3981
F-statistic: 17.54 on 1 and 24 DF,  p-value: 0.0003275

> predict(BRTOC.BR443Ratio,interval="confidence")
       fit      lwr      upr
1  5.221080 4.933574 5.508587
2  5.693770 5.435535 5.952004
3  4.454130 3.871462 5.036798
4  5.348666 5.088563 5.608770
5  5.783421 5.507921 6.058920
6  5.434549 5.185541 5.683558
7  5.065088 4.730795 5.399381
8  5.994920 5.658602 6.331238
9  5.476905 5.230858 5.722952
10 5.302069 5.033336 5.570803
11 4.579955 4.052916 5.106995
12 5.987329 5.653565 6.321093
13 5.138536 4.827761 5.449312
14 5.405348 5.153309 5.657388
15 4.885228 4.485270 5.285186
16 6.059042 5.700317 6.417768
17 5.041342 4.698973 5.383712
18 5.608288 5.360227 5.856350
19 5.836773 5.548265 6.125282
20 5.330729 5.067508 5.593951
21 6.237240 5.810096 6.664384
```

```
22 5.803040 5.522973 6.083107
23 5.382347 5.127374 5.637321
24 5.859710 5.565063 6.154356
25 6.296388 5.845046 6.747729
26 6.476024 5.948117 7.003931
> BRTOC.BR543Ratio=lm(BR.TOC~BR543Ratio)
> summary(BRTOC.BR543Ratio)

Call:
lm(formula = BR.TOC ~ BR543Ratio)

Residuals:
    Min      1Q  Median      3Q     Max
-1.27531 -0.43129  0.01689  0.45233  0.85172

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   4.2565     0.2902  14.665 1.77e-13 ***
BR543Ratio    2.1149     0.4457   4.745 7.94e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5715 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.4841,    Adjusted R-squared:  0.4626
F-statistic: 22.52 on 1 and 24 DF,  p-value: 7.937e-05

> predict(BRTOC.BR543Ratio,interval="confidence")
       fit      lwr      upr
1  5.151254 4.868019 5.434489
2  5.764403 5.511072 6.017733
3  4.324658 3.752831 4.896484
4  5.341440 5.096435 5.586446
5  5.916046 5.629433 6.202659
6  5.569606 5.337534 5.801679
7  4.963062 4.625904 5.300220
8  6.110284 5.766955 6.453614
9  5.645799 5.408767 5.882831
10 5.461027 5.227923 5.694131
11 4.479807 3.968963 4.990652
12 6.000667 5.690897 6.310437
13 5.102246 4.806199 5.398292
14 5.501979 5.270392 5.733566
15 4.768710 4.365860 5.171560
16 6.076289 5.743736 6.408843
17 4.974088 4.640403 5.307773
```

```
18 5.473845 5.241361 5.706328
19 5.954534 5.657730 6.251338
20 5.399585 5.161709 5.637462
21 6.181690 5.814814 6.548566
22 5.812551 5.549988 6.075115
23 5.295575 5.043295 5.547856
24 5.736714 5.488049 5.985379
25 6.296282 5.889507 6.703058
26 6.399779 5.955239 6.844319
> BRTOC.BRHI=lm(BR.TOC~BR.HI)
> summary(BRTOC.BRHI)

Call:
lm(formula = BR.TOC ~ BR.HI)

Residuals:
    Min      1Q  Median      3Q     Max
-1.20227 -0.40808  0.05259  0.54947  1.01856

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   7.6657     0.5736  13.364  1.3e-12 ***
BR.HI        -0.5616     0.1471  -3.817 0.000835 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6276 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.3778,    Adjusted R-squared:  0.3519
F-statistic: 14.57 on 1 and 24 DF,  p-value: 0.0008346

> predict(BRTOC.BRHI,interval="confidence")
       fit      lwr      upr
1  5.355253 5.084777 5.625729
2  5.709723 5.437152 5.982294
3  4.080245 3.257846 4.902644
4  5.526661 5.272622 5.780699
5  5.900899 5.576246 6.225552
6  5.647234 5.385010 5.909458
7  5.042182 4.677163 5.407201
8  5.852680 5.543586 6.161775
9  5.739133 5.460405 6.017861
10 5.620688 5.361649 5.879728
11 4.581592 4.010813 5.152370
12 5.765443 5.480567 6.050320
13 5.209468 4.902864 5.516073
```

```
14 5.684206 5.416326 5.952086
15 5.137306 4.807271 5.467342
16 5.956960 5.612617 6.301303
17 5.109599 4.769806 5.449393
18 5.597561 5.340673 5.854448
19 5.971741 5.621954 6.321528
20 5.252853 4.958739 5.546967
21 6.275689 5.797798 6.753579
22 5.553149 5.298717 5.807581
23 5.363527 5.094554 5.632500
24 5.663671 5.399104 5.928238
25 6.129439 5.716376 6.542502
26 5.975017 5.624010 6.326025
> BRTOC.BRB=lm(BR.TOC~BR.B)
> summary(BRTOC.BRB)

Call:
lm(formula = BR.TOC ~ BR.B)

Residuals:
    Min      1Q  Median      3Q     Max
-0.6814 -0.3862 -0.1445  0.3052  0.8589

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.1779     0.3717   8.550 9.54e-09 ***
BR.B          2.9264     0.4481   6.531 9.38e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4775 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.6399,    Adjusted R-squared:  0.6249
F-statistic: 42.65 on 1 and 24 DF,  p-value: 9.38e-07

> predict(BRTOC.BRB,interval="confidence")
       fit      lwr      upr
1  4.738942 4.423705 5.054180
2  5.958958 5.722347 6.195570
3  4.467892 4.081395 4.854388
4  4.918859 4.646304 5.191414
5  5.671262 5.472697 5.869827
6  5.959555 5.722835 6.196276
7  4.992827 4.736219 5.249434
8  5.689734 5.489748 5.889720
9  5.437795 5.242490 5.633100
```

```
10 5.511569 5.318248 5.704891
11 4.914903 4.641465 5.188341
12 5.450865 5.256113 5.645616
13 5.265033 5.054787 5.475279
14 5.915899 5.686869 6.144930
15 4.816451 4.520184 5.112717
16 6.544335 6.169211 6.919458
17 5.134724 4.905120 5.364328
18 5.028254 4.778869 5.277638
19 5.879580 5.656499 6.102661
20 5.277283 5.068531 5.486035
21 6.137784 5.864638 6.410930
22 5.867237 5.646078 6.088395
23 5.291660 5.084584 5.498737
24 5.142801 4.914565 5.371037
25 6.900274 6.425192 7.375356
26 6.787444 6.344699 7.230190
> BRTOC.BRTC=lm(BR.TOC~BRTCRatio)
> summary(BRTOC.BRTC)

Call:
lm(formula = BR.TOC ~ BRTCRatio)

Residuals:
    Min      1Q  Median      3Q     Max
-1.2928 -0.3846 -0.0150  0.4328  0.8565

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.3194     0.6628   3.500  0.00184 **
BRTCRatio     3.6377     0.7412   4.908 5.25e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5621 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.5009,    Adjusted R-squared:  0.4801
F-statistic: 24.09 on 1 and 24 DF,  p-value: 5.248e-05

> predict(BRTOC.BRTC,interval="confidence")
       fit      lwr      upr
1  5.110392 4.823241 5.397543
2  5.606780 5.376800 5.836760
3  4.512948 4.029627 4.996268
4  5.258581 5.004602 5.512560
5  5.578460 5.349913 5.807006
```

```
6  5.436119 5.205413 5.666826
7  5.179195 4.908722 5.449668
8  5.957629 5.666842 6.248417
9  5.371380 5.134636 5.608123
10 5.323464 5.080379 5.566549
11 4.518476 4.037206 4.999747
12 5.993327 5.692961 6.293692
13 5.026552 4.716631 5.336474
14 5.489566 5.261502 5.717629
15 4.743271 4.342798 5.143745
16 6.208997 5.842919 6.575076
17 5.089889 4.797399 5.382380
18 5.596137 5.366767 5.825506
19 5.805449 5.549567 6.061332
20 5.343820 5.103615 5.584025
21 6.189793 5.830007 6.549580
22 5.875010 5.604489 6.145531
23 5.460901 5.231690 5.690112
24 5.754178 5.507416 6.000940
25 6.635852 6.117018 7.154685
26 6.635753 6.116957 7.154549
> BRTOC.BRTC=lm(BR.TOCAdded~BRTCRatio)
> summary(BRTOC.BRTC)

Call:
lm(formula = BR.TOCAdded ~ BRTCRatio)

Residuals:
    Min      1Q  Median      3Q     Max
-0.93219 -0.45513  0.09514  0.48884  1.08123

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -2.4770     0.7146  -3.466    0.002 **
BRTCRatio     3.8376     0.7991   4.802 6.86e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.606 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:   0.49,     Adjusted R-squared:  0.4688
F-statistic: 23.06 on 1 and 24 DF,  p-value: 6.865e-05

> predict(BRTOC.BRTC,interval="confidence")
        fit        lwr       upr
1   0.4674222  0.15782272 0.7770216
```

```
2   0.9910883  0.74312945 1.2390472
3  -0.1628537 -0.68395854 0.3582511
4   0.6237540  0.34991993 0.8975881
5   0.9612116  0.71479824 1.2076250
6   0.8110492  0.56230680 1.0597916
7   0.5400057  0.24838810 0.8316233
8   1.3612178  1.04769772 1.6747379
9   0.7427518  0.48750078 0.9980029
10  0.6922029  0.43011406 0.9542917
11 -0.1570214 -0.67591609 0.3618734
12  1.3988767  1.07503004 1.7227233
13  0.3789751  0.04482513 0.7131251
14  0.8674324  0.62153983 1.1133250
15  0.0801269 -0.35165381 0.5119076
16  1.6263993  1.23170248 2.0210961
17  0.4457927  0.13043605 0.7611493
18  0.9798598  0.73255884 1.2271608
19  1.2006747  0.92478841 1.4765611
20  0.7136774  0.45469391 0.9726608
21  1.6061400  1.21822644 1.9940535
22  1.2740582  0.98238885 1.5657275
23  0.8371923  0.59006245 1.0843222
24  1.1465862  0.88053303 1.4126394
25  2.0767107  1.51731662 2.6361047
26  2.0766066  1.51725273 2.6359605
> BRTOC.BRTryp=lm(BR.TOCAdded~BR.TrypEEM)
> summary(BRTOC.BRTryp)

Call:
lm(formula = BR.TOCAdded ~ BR.TrypEEM)

Residuals:
    Min      1Q  Median      3Q     Max
-1.0759 -0.6033 -0.1567  0.5235  1.4241

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.6961     0.5435  -1.281  0.21253
BR.TrypEEM    1.3451     0.4404   3.054  0.00545 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7202 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.2799,    Adjusted R-squared:  0.2499
F-statistic: 9.328 on 1 and 24 DF,  p-value: 0.005453
```

```
> predict(BRTOC.BRTryp,interval="confidence")
        fit          lwr       upr
1  0.2538183 -0.2750912108 0.7827277
2  1.2397056  0.8715448757 1.6078663
3  0.4336677  0.0009515257 0.8663839
4  0.4485958  0.0232804809 0.8739111
5  0.8954310  0.6038276553 1.1870344
6  1.2005978  0.8479577135 1.5532379
7  0.6029312  0.2463229620 0.9595394
8  1.0872681  0.7713183058 1.4032180
9  0.8314562  0.5355293128 1.1273831
10 1.2182120  0.8587389126 1.5776852
11 0.4589222  0.0386610294 0.8791834
12 0.8006007  0.5003774481 1.1008239
13 0.7020645  0.3793645651 1.0247645
14 1.3010077  0.9061795469 1.6958358
15 0.3123521 -0.1840317431 0.8087360
16 1.5852916  1.0420528657 2.1285304
17 0.5423285  0.1606596339 0.9239974
18 0.4780497  0.0670014113 0.8890980
19 1.1210641  0.7956225233 1.4465056
20 0.9531000  0.6599344610 1.2462655
21 1.2166423  0.8577888570 1.5754957
22 1.1453353  0.8122768582 1.4783937
23 0.7494676  0.4391567677 1.0597785
24 0.4261755 -0.0102957774 0.8626467
25 1.7424504  1.1070360053 2.3778648
26 1.8334014  1.1428004365 2.5240025
> BRTOC.BRB=lm(BR.TOCAdded~BR.B)
> summary(BRTOC.BRB)

Call:
lm(formula = BR.TOCAdded ~ BR.B)

Residuals:
   Min      1Q  Median      3Q     Max
-1.0886 -0.4160 -0.1473  0.4471  1.2507

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.9721     0.5286  -1.839   0.0783 .
BR.B          2.3407     0.6372   3.673   0.0012 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 0.679 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.3599,    Adjusted R-squared:  0.3332
F-statistic: 13.49 on 1 and 24 DF,  p-value: 0.001198

> predict(BRTOC.BRB,interval="confidence")
         fit         lwr       upr
1  0.27657502 -0.17172448 0.7248745
2  1.25243593  0.91595033 1.5889215
3  0.05976828 -0.48986849 0.6094050
4  0.42048631  0.03288565 0.8080870
5  1.02231503  0.73993580 1.3046943
6  1.25291344  0.91627298 1.5895539
7  0.47965096  0.11472913 0.8445728
8  1.03708981  0.75268969 1.3214899
9  0.83557047  0.55782704 1.1133139
10 0.89458063  0.61965826 1.1695030
11 0.41732162  0.02846508 0.8061782
12 0.84602423  0.56906762 1.1229808
13 0.69738230  0.39839168 0.9963729
14 1.21799422  0.89228984 1.5436986
15 0.33857197 -0.08274880 0.7598927
16 1.72066434  1.18720114 2.2541275
17 0.59315130  0.26663159 0.9196710
18 0.50798801  0.15333781 0.8626382
19 1.18894324  0.87169909 1.5061874
20 0.70718065  0.41031475 1.0040465
21 1.39547412  1.00703297 1.7839153
22 1.17906999  0.86456003 1.4935799
23 0.71868073  0.42419681 1.0131646
24 0.59961176  0.27503757 0.9241859
25 2.00537139  1.32975762 2.6809852
26 1.91512166  1.28549328 2.5447500
> BRTOC.BRHI=lm(BR.TOCAdded~BR.HI)
> summary(BRTOC.BRHI)

Call:
lm(formula = BR.TOCAdded ~ BR.HI)

Residuals:
   Min     1Q  Median     3Q    Max
-0.9635 -0.6377 -0.1137  0.4202  1.7924

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.5352     0.6970   3.637  0.00131 **
```

```
BR.HI        -0.4276     0.1788  -2.392  0.02495 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7626 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.1925,    Adjusted R-squared:  0.1588
F-statistic: 5.721 on 1 and 24 DF,  p-value: 0.02495

> predict(BRTOC.BRHI,interval="confidence")
         fit        lwr       upr
1   0.7761660  0.44750869 1.1048234
2   1.0460361  0.71483281 1.3772394
3  -0.1945406 -1.19384361 0.8047625
4   0.9066646  0.59798034 1.2153490
5   1.1915849  0.79709670 1.5860732
6   0.9984611  0.67983097 1.3170912
7   0.5378142  0.09427685 0.9813516
8   1.1548745  0.77929131 1.5304576
9   1.0684271  0.72974220 1.4071120
10  0.9782512  0.66349045 1.2930120
11  0.1871516 -0.50640567 0.8807089
12  1.0884579  0.74230225 1.4346135
13  0.6651752  0.29261772 1.0377327
14  1.0266091  0.70110628 1.3521120
15  0.6102359  0.20920706 1.0112647
16  1.2342662  0.81585248 1.6526800
17  0.5891417  0.17625571 1.0020277
18  0.9606432  0.64849763 1.2727888
19  1.2455194  0.82049020 1.6705487
20  0.6982058  0.34082555 1.0555861
21  1.4769251  0.89623640 2.0576138
22  0.9268313  0.61766937 1.2359933
23  0.7824657  0.45563454 1.1092968
24  1.0109753  0.68949800 1.3324526
25  1.3655807  0.86366468 1.8674967
26  1.2480140  0.82150222 1.6745257
> BRTOC.BR543Ratio=lm(BR.TOCAdded~BR543Ratio)
> summary(BRTOC.BR543Ratio)

Call:
lm(formula = BR.TOCAdded ~ BR543Ratio)

Residuals:
    Min      1Q  Median      3Q     Max
-1.00584 -0.57371  0.01744  0.39328  1.60435
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.1610     0.3604  -0.447  0.65903
BR543Ratio    1.7778     0.5535   3.212  0.00373 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7097 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.3007,    Adjusted R-squared:  0.2715
F-statistic: 10.32 on 1 and 24 DF,  p-value: 0.003729

> predict(BRTOC.BR543Ratio,interval="confidence")
          fit         lwr       upr
1   0.59106863  0.23934929 0.9427880
2   1.10648563  0.79190179 1.4210695
3  -0.10377435 -0.81386511 0.6063164
4   0.75094058  0.44669458 1.0551866
5   1.23395780  0.87804341 1.5898722
6   0.94273849  0.65455244 1.2309245
7   0.43287274  0.01419238 0.8515531
8   1.39723606  0.97089159 1.8235805
9   1.00678673  0.71244201 1.3011314
10  0.85146563  0.56199866 1.1409326
11  0.02664546 -0.60771787 0.6610088
12  1.30509090  0.92042041 1.6897614
13  0.54987171  0.18224320 0.9175002
14  0.88589030  0.59830700 1.1734736
15  0.26949901 -0.23075781 0.7697558
16  1.36865977  0.95569720 1.7816223
17  0.44214131  0.02777316 0.8565095
18  0.86224047  0.57354391 1.1509370
19  1.26631148  0.89774212 1.6348808
20  0.79981759  0.50442435 1.0952108
21  1.45726046  1.00167634 1.9128446
22  1.14695974  0.82091021 1.4730093
23  0.71238602  0.39910566 1.0256664
24  1.08321025  0.77441988 1.3920006
25  1.55358760  1.04845604 2.0587192
26  1.64058741  1.08856015 2.1926147
> BRTOC.BR544Ratio=lm(BR.TOCAdded~BR443Ratio)
> summary(BRTOC.BR443Ratio)

Call:
lm(formula = BR.TOC ~ BR443Ratio)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-1.3983 -0.4114  0.1070  0.4969  0.8779

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.4949     0.4995   6.996 3.11e-07 ***
BR443Ratio    2.7086     0.6468   4.188 0.000327 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6048 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.4222,    Adjusted R-squared:  0.3981
F-statistic: 17.54 on 1 and 24 DF,  p-value: 0.0003275

> predict(BRTOC.BR443Ratio,interval="confidence")
       fit      lwr      upr
1  5.221080 4.933574 5.508587
2  5.693770 5.435535 5.952004
3  4.454130 3.871462 5.036798
4  5.348666 5.088563 5.608770
5  5.783421 5.507921 6.058920
6  5.434549 5.185541 5.683558
7  5.065088 4.730795 5.399381
8  5.994920 5.658602 6.331238
9  5.476905 5.230858 5.722952
10 5.302069 5.033336 5.570803
11 4.579955 4.052916 5.106995
12 5.987329 5.653565 6.321093
13 5.138536 4.827761 5.449312
14 5.405348 5.153309 5.657388
15 4.885228 4.485270 5.285186
16 6.059042 5.700317 6.417768
17 5.041342 4.698973 5.383712
18 5.608288 5.360227 5.856350
19 5.836773 5.548265 6.125282
20 5.330729 5.067508 5.593951
21 6.237240 5.810096 6.664384
22 5.803040 5.522973 6.083107
23 5.382347 5.127374 5.637321
24 5.859710 5.565063 6.154356
25 6.296388 5.845046 6.747729
26 6.476024 5.948117 7.003931
>
```

Second Try

```
R version 3.3.1 (2016-06-21) -- "Bug in Your Hair"
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Platform: x86_64-w64-mingw32/x64 (64-bit)

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Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> RB=read.csv(file.choose())
> attach(RB)
> B543Ratio=B.5C4/B.5C3
> B443Ratio=B.4C4/B.4C3
> BR543Ratio=BR.5C4/BR.5C3
> BR443Ratio=BR.4C4/BR.4C3
> BS543Ratio=BS.5C4/BS.5C3
> BS443Ratio=BS.4C4/BS.4C3
> BRTCRatio=BR.T/BR.C
> BSTCRatio=BS.T/BS.C
> BRTOC.BRTC=lm(BR.TOCAdded~BRTCRatio)
> summary(BRTOC.BRTC)

Call:
lm(formula = BR.TOCAdded ~ BRTCRatio)

Residuals:
    Min      1Q  Median      3Q     Max
-0.93219 -0.45513  0.09514  0.48884  1.08123

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -2.4770     0.7146  -3.466    0.002 **
BRTCRatio     3.8376     0.7991   4.802 6.86e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 0.606 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:   0.49,     Adjusted R-squared:  0.4688
F-statistic: 23.06 on 1 and 24 DF,  p-value: 6.865e-05

> predict(BRTOC.BRTC,interval="confidence")
         fit        lwr       upr
1   0.4674222  0.15782272 0.7770216
2   0.9910883  0.74312945 1.2390472
3  -0.1628537 -0.68395854 0.3582511
4   0.6237540  0.34991993 0.8975881
5   0.9612116  0.71479824 1.2076250
6   0.8110492  0.56230680 1.0597916
7   0.5400057  0.24838810 0.8316233
8   1.3612178  1.04769772 1.6747379
9   0.7427518  0.48750078 0.9980029
10  0.6922029  0.43011406 0.9542917
11 -0.1570214 -0.67591609 0.3618734
12  1.3988767  1.07503004 1.7227233
13  0.3789751  0.04482513 0.7131251
14  0.8674324  0.62153983 1.1133250
15  0.0801269 -0.35165381 0.5119076
16  1.6263993  1.23170248 2.0210961
17  0.4457927  0.13043605 0.7611493
18  0.9798598  0.73255884 1.2271608
19  1.2006747  0.92478841 1.4765611
20  0.7136774  0.45469391 0.9726608
21  1.6061400  1.21822644 1.9940535
22  1.2740582  0.98238885 1.5657275
23  0.8371923  0.59006245 1.0843222
24  1.1465862  0.88053303 1.4126394
25  2.0767107  1.51731662 2.6361047
26  2.0766066  1.51725273 2.6359605
> BRTOC.BRHI=lm(BR.TOCAdded~BRHI)
Error in eval(expr, envir, enclos) : object 'BRHI' not found
> BRTOC.BRHI=lm(BR.TOCAdded~BR.HI)
> summary(BRTOC.BRHI)

Call:
lm(formula = BR.TOCAdded ~ BR.HI)

Residuals:
    Min      1Q  Median      3Q     Max
-0.9635 -0.6377 -0.1137  0.4202  1.7924
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.5352     0.6970   3.637  0.00131 **
BR.HI        -0.4276     0.1788  -2.392  0.02495 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7626 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.1925,    Adjusted R-squared:  0.1588
F-statistic: 5.721 on 1 and 24 DF,  p-value: 0.02495

> predict(BRTOC.BRHI,interval="confidence")
         fit         lwr       upr
1   0.7761660  0.44750869 1.1048234
2   1.0460361  0.71483281 1.3772394
3  -0.1945406 -1.19384361 0.8047625
4   0.9066646  0.59798034 1.2153490
5   1.1915849  0.79709670 1.5860732
6   0.9984611  0.67983097 1.3170912
7   0.5378142  0.09427685 0.9813516
8   1.1548745  0.77929131 1.5304576
9   1.0684271  0.72974220 1.4071120
10  0.9782512  0.66349045 1.2930120
11  0.1871516 -0.50640567 0.8807089
12  1.0884579  0.74230225 1.4346135
13  0.6651752  0.29261772 1.0377327
14  1.0266091  0.70110628 1.3521120
15  0.6102359  0.20920706 1.0112647
16  1.2342662  0.81585248 1.6526800
17  0.5891417  0.17625571 1.0020277
18  0.9606432  0.64849763 1.2727888
19  1.2455194  0.82049020 1.6705487
20  0.6982058  0.34082555 1.0555861
21  1.4769251  0.89623640 2.0576138
22  0.9268313  0.61766937 1.2359933
23  0.7824657  0.45563454 1.1092968
24  1.0109753  0.68949800 1.3324526
25  1.3655807  0.86366468 1.8674967
26  1.2480140  0.82150222 1.6745257
> BRTOC.BR443Ratio=lm(BR.TOCAdded~BR443Ratio)
> summary(BRTOC.BR443Ratio)

Call:
lm(formula = BR.TOCAdded ~ BR443Ratio)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-0.96140 -0.53907  0.01453  0.42292  1.45600

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.1929     0.5446  -2.190  0.03846 *
BR443Ratio    2.7988     0.7052   3.969  0.00057 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6594 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.3963,    Adjusted R-squared:  0.3711
F-statistic: 15.75 on 1 and 24 DF,  p-value: 0.0005699

> predict(BRTOC.BR443Ratio,interval="confidence")
          fit         lwr       upr
1   0.59081440  0.27734712 0.9042817
2   1.07924856  0.79769667 1.3608005
3  -0.20168149 -0.83696193 0.4335989
4   0.72265001  0.43906033 1.0062397
5   1.17188535  0.87150921 1.4722615
6   0.81139391  0.53990063 1.0828872
7   0.42962594  0.06514771 0.7941042
8   1.39042940  1.02374305 1.7571157
9   0.85516018  0.58689641 1.1234239
10  0.67450095  0.38150178 0.9675001
11 -0.07166526 -0.64629473 0.5029642
12  1.38258553  1.01868393 1.7464871
13  0.50552092  0.16668353 0.8443583
14  0.78122011  0.50642255 1.0560177
15  0.24377546 -0.19229712 0.6798480
16  1.45668754  1.06557079 1.8478043
17  0.40508950  0.03180554 0.7783735
18  0.99091977  0.72045909 1.2613804
19  1.22701518  0.91245538 1.5415750
20  0.70411588  0.41712617 0.9911056
21  1.64082077  1.17510706 2.1065345
22  1.19215855  0.88680279 1.4975143
23  0.75745306  0.47945630 1.0354498
24  1.25071560  0.92946381 1.5719674
25  1.70193877  1.20984317 2.1940344
26  1.88755877  1.31198402 2.4631335
> BRTOC.BR543Ratio=lm(BR.TOCAdded~BR543Ratio)
> summary(BRTOC.BR543Ratio)
```

```
Call:
lm(formula = BR.TOCAdded ~ BR543Ratio)

Residuals:
    Min      1Q  Median      3Q     Max
-1.00584 -0.57371  0.01744  0.39328  1.60435

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.1610     0.3604  -0.447  0.65903
BR543Ratio    1.7778     0.5535   3.212  0.00373 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7097 on 24 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.3007,    Adjusted R-squared:  0.2715
F-statistic: 10.32 on 1 and 24 DF,  p-value: 0.003729

> predict(BRTOC.BR543Ratio,interval="confidence")
          fit         lwr       upr
1   0.59106863  0.23934929 0.9427880
2   1.10648563  0.79190179 1.4210695
3  -0.10377435 -0.81386511 0.6063164
4   0.75094058  0.44669458 1.0551866
5   1.23395780  0.87804341 1.5898722
6   0.94273849  0.65455244 1.2309245
7   0.43287274  0.01419238 0.8515531
8   1.39723606  0.97089159 1.8235805
9   1.00678673  0.71244201 1.3011314
10  0.85146563  0.56199866 1.1409326
11  0.02664546 -0.60771787 0.6610088
12  1.30509090  0.92042041 1.6897614
13  0.54987171  0.18224320 0.9175002
14  0.88589030  0.59830700 1.1734736
15  0.26949901 -0.23075781 0.7697558
16  1.36865977  0.95569720 1.7816223
17  0.44214131  0.02777316 0.8565095
18  0.86224047  0.57354391 1.1509370
19  1.26631148  0.89774212 1.6348808
20  0.79981759  0.50442435 1.0952108
21  1.45726046  1.00167634 1.9128446
22  1.14695974  0.82091021 1.4730093
23  0.71238602  0.39910566 1.0256664
24  1.08321025  0.77441988 1.3920006
```

25 1.55358760 1.04845604 2.0587192
26 1.64058741 1.08856015 2.1926147

Regressions of Grab Sample Data in R

```
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Platform: x86_64-w64-mingw32/x64 (64-bit)

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'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> RSource=read.csv(file.choose())
> attach(RSource)
> E5C1.Days=lm(E.5C1~Days)
> summary(E5C1.Days)

Call:
lm(formula = E.5C1 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-1.0812 -0.4666 -0.2076  0.5534  1.4225

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.621386   0.369894   9.790 3.36e-14 ***
Days        -0.005933   0.002794  -2.123   0.0377 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6769 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.06778,   Adjusted R-squared:  0.05275
F-statistic: 4.508 on 1 and 62 DF,  p-value: 0.03774
```

```
> E5C2.Days=lm(E.5C2~Days)
> summary(E5C2.Days)

Call:
lm(formula = E.5C2 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-0.8788 -0.3447 -0.1353  0.4495  1.0088

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.016161   0.282459   7.138 1.24e-09 ***
Days        0.001523   0.002134   0.714    0.478
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5169 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.008149,  Adjusted R-squared:  -0.007848
F-statistic: 0.5094 on 1 and 62 DF,  p-value: 0.4781

> E5C3.Days=lm(E.5C3~Days)
> summary(E5C3.Days)

Call:
lm(formula = E.5C3 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-0.5100 -0.2984 -0.1239  0.2107  1.3730

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.741630   0.234273  11.703  < 2e-16 ***
Days        -0.009951   0.001770  -5.623 4.78e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4287 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.3377,    Adjusted R-squared:  0.327
F-statistic: 31.61 on 1 and 62 DF,  p-value: 4.785e-07

> E5C4.Days=lm(E.5C4~Days)
```

```
> summary(E5C4.Days)

Call:
lm(formula = E.5C4 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-0.59875 -0.21058 -0.03402  0.21072  2.25096

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.739840   0.219438   7.929 5.26e-11 ***
Days        -0.007296   0.001658  -4.401 4.33e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4016 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.238,     Adjusted R-squared:  0.2257
F-statistic: 19.37 on 1 and 62 DF,  p-value: 4.326e-05

> E5C5.Days=lm(E.5C5~Days)
> summary(E5C5.Days)

Call:
lm(formula = E.5C5 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-0.20802 -0.08102 -0.01732  0.05745  0.26184

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.2130852  0.0530081   -4.02  0.00016 ***
Days         0.0028715  0.0004005    7.17 1.09e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.097 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.4533,    Adjusted R-squared:  0.4445
F-statistic: 51.42 on 1 and 62 DF,  p-value: 1.089e-09

> E4C1.Days=lm(E.4C1~Days)
> summary(E4C1.Days)
```

```
Call:
lm(formula = E.4C1 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-0.9881 -0.4085 -0.1381  0.4854  1.1471

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.4482670  0.3213145   7.620 1.81e-10 ***
Days        0.0007907  0.0024274   0.326    0.746
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.588 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.001708,  Adjusted R-squared:  -0.01439
F-statistic: 0.1061 on 1 and 62 DF,  p-value: 0.7457

> E4C2.Days=lm(E.4C2~Days)
> summary(E4C2.Days)

Call:
lm(formula = E.4C2 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-1.0656 -0.4711 -0.1612  0.4691  1.3143

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.357825   0.360909   9.304 2.25e-13 ***
Days        -0.004124   0.002727  -1.512    0.135
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6604 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.03558,   Adjusted R-squared:  0.02003
F-statistic: 2.288 on 1 and 62 DF,  p-value: 0.1355

> E4C3.Days=lm(E.4C3~Days)
> summary(E4C3.Days)

Call:
lm(formula = E.4C3 ~ Days)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-0.5113 -0.2891 -0.1198  0.1945  1.3634

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.716527   0.231470  11.736  < 2e-16 ***
Days        -0.010135   0.001749  -5.796 2.46e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4236 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.3514,    Adjusted R-squared:  0.3409
F-statistic: 33.59 on 1 and 62 DF,  p-value: 2.46e-07

> E4C4.Days=lm(E.4C4~Days)
> summary(E4C4.Days)

Call:
lm(formula = E.4C4 ~ Days)

Residuals:
     Min       1Q   Median       3Q      Max
-0.38892 -0.20276 -0.04526  0.17191  2.00543

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.459124   0.188975   7.721 1.21e-10 ***
Days        -0.004862   0.001428  -3.406  0.00116 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3458 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.1576,    Adjusted R-squared:  0.144
F-statistic:  11.6 on 1 and 62 DF,  p-value: 0.001163

> IC1.Days=lm(I.C1~Days)
> summary(IC1.Days)

Call:
lm(formula = I.C1 ~ Days)

Residuals:
```

```
   Min      1Q  Median      3Q     Max
-3.5042 -1.0623  0.0969  1.0594  2.7595

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.835870   1.146016   3.347  0.00159 **
Days        0.008097   0.008771   0.923  0.36053
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.603 on 48 degrees of freedom
  (23 observations deleted due to missingness)
Multiple R-squared:  0.01745,   Adjusted R-squared:  -0.003024
F-statistic: 0.8523 on 1 and 48 DF,  p-value: 0.3605

> IC2.Days=lm(I.C2~Days)
> summary(IC2.Days)

Call:
lm(formula = I.C2 ~ Days)

Residuals:
   Min      1Q  Median      3Q     Max
-1.5685 -0.4871 -0.0935  0.2804  3.3501

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.782021   0.633818   7.545 1.08e-09 ***
Days        -0.012277   0.004851  -2.531   0.0147 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8867 on 48 degrees of freedom
  (23 observations deleted due to missingness)
Multiple R-squared:  0.1177,    Adjusted R-squared:  0.09936
F-statistic: 6.406 on 1 and 48 DF,  p-value: 0.01471

> IC3.Days=lm(I.C3~Days)
> summary(IC3.Days)

Call:
lm(formula = I.C3 ~ Days)

Residuals:
   Min      1Q  Median      3Q     Max
-0.8840 -0.2760 -0.1418  0.2260  2.2486
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.076596   0.433219   7.102 5.14e-09 ***
Days        -0.009673   0.003316  -2.917  0.00536 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.606 on 48 degrees of freedom
  (23 observations deleted due to missingness)
Multiple R-squared:  0.1506,    Adjusted R-squared:  0.1329
F-statistic: 8.511 on 1 and 48 DF,  p-value: 0.005356

> IC4.Days=lm(I.C4~Days)
> summary(IC4.Days)

Call:
lm(formula = I.C4 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-2.0473 -1.0782 -0.6103  0.7554  4.1367

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.669557   1.108278   3.311  0.00177 **
Days        -0.008013   0.008482  -0.945  0.34953
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.55 on 48 degrees of freedom
  (23 observations deleted due to missingness)
Multiple R-squared:  0.01825,   Adjusted R-squared:  -0.002199
F-statistic: 0.8925 on 1 and 48 DF,  p-value: 0.3495

> IC5.Days=lm(I.C5~Days)
> summary(IC5.Days)

Call:
lm(formula = I.C5 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-3.3505 -1.3513 -0.9419  1.2663  5.4322

Coefficients:
```

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.93686    1.76489  -1.097   0.2779
Days         0.03470    0.01351   2.569   0.0134 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.469 on 48 degrees of freedom
  (23 observations deleted due to missingness)
Multiple R-squared:  0.1209,    Adjusted R-squared:  0.1026
F-statistic:   6.6 on 1 and 48 DF,  p-value: 0.01336

> OC1.Days=lm(O.C1~Days)
> summary(OC1.Days)

Call:
lm(formula = O.C1 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-1.5944 -0.4803  0.1184  0.5060  2.5625

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.113062   0.444155   16.02  < 2e-16 ***
Days        -0.026471   0.003346   -7.91 2.67e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.836 on 70 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.472,     Adjusted R-squared:  0.4644
F-statistic: 62.57 on 1 and 70 DF,  p-value: 2.674e-11

> OC2.Days=lm(O.C2~Days)
> summary(OC2.Days)

Call:
lm(formula = O.C2 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-1.4267 -0.6444 -0.0189  0.5728  4.0539

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  6.106708   0.471656  12.947  < 2e-16 ***
```

```
Days        -0.022889   0.003554  -6.441 1.28e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8877 on 70 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.3721,    Adjusted R-squared:  0.3631
F-statistic: 41.48 on 1 and 70 DF,  p-value: 1.285e-08

> OC3.Days=lm(O.C3~Days)
> summary(OC3.Days)

Call:
lm(formula = O.C3 ~ Days)

Residuals:
     Min       1Q   Median       3Q      Max
-0.87441 -0.34030 -0.02858  0.29940  1.36384

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.78374    0.24289  15.578  < 2e-16 ***
Days        -0.01663    0.00183  -9.086 1.84e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4572 on 70 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.5412,    Adjusted R-squared:  0.5346
F-statistic: 82.56 on 1 and 70 DF,  p-value: 1.837e-13

> OC4.Days=lm(O.C4~Days)
> summary(OC4.Days)

Call:
lm(formula = O.C4 ~ Days)

Residuals:
    Min      1Q  Median      3Q     Max
-1.4038 -0.6822 -0.1575  0.5587  3.4397

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.681789   0.517535  10.979  < 2e-16 ***
Days        -0.024651   0.003899  -6.322  2.1e-08 ***
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9741 on 70 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.3634,    Adjusted R-squared:  0.3543
F-statistic: 39.97 on 1 and 70 DF,  p-value: 2.099e-08

> OC5.Days=lm(O.C5~Days)
> summary(OC5.Days)

Call:
lm(formula = O.C5 ~ Days)

Residuals:
     Min       1Q   Median       3Q      Max
-0.161324 -0.072731  0.000778  0.040815  0.229586

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0604112  0.0516999  -1.168    0.247
Days         0.0017982  0.0003895   4.616 1.72e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.09731 on 70 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.2334,    Adjusted R-squared:  0.2224
F-statistic: 21.31 on 1 and 70 DF,  p-value: 1.723e-05

> EA.Days=lm(E.A~Days)
> summary(EA.Days)

Call:
lm(formula = E.A ~ Days)

Residuals:
   Min     1Q  Median     3Q    Max
-0.7280 -0.3514 -0.1239  0.4365  1.0335

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.338994   0.256141   9.132 4.42e-13 ***
Days        -0.002266   0.001935  -1.171    0.246
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 0.4687 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.02163,   Adjusted R-squared:  0.00585
F-statistic: 1.371 on 1 and 62 DF,  p-value: 0.2462

> E5C1.E4C1=lm(E.5C1~E.4C1)
> summary(E5C1.E4C1)

Call:
lm(formula = E.5C1 ~ E.4C1)

Residuals:
    Min      1Q  Median      3Q     Max
-0.49762 -0.17697  0.01254  0.14550  0.59731

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.04624    0.15018   0.308    0.759
E.4C1        1.10213    0.05743  19.192   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2661 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.8559,    Adjusted R-squared:  0.8536
F-statistic: 368.3 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C1.E4C2=lm(E.5C1~E.4C2)
> summary(E5C1.E4C2)

Call:
lm(formula = E.5C1 ~ E.4C2)

Residuals:
    Min      1Q  Median      3Q     Max
-0.22442 -0.03771  0.01289  0.05497  0.10854

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.07182    0.04210  -1.706    0.093 .
E.4C2        1.03617    0.01450  71.446   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0768 on 62 degrees of freedom
  (9 observations deleted due to missingness)
```

```
Multiple R-squared:  0.988,     Adjusted R-squared:  0.9878
F-statistic:  5105 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C1.E4C3=lm(E.5C1~E.4C3)
> summary(E5C1.E4C3)

Call:
lm(formula = E.5C1 ~ E.4C3)

Residuals:
   Min      1Q  Median      3Q     Max
-0.8675 -0.3543 -0.1196  0.2969  1.1933

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.4249     0.1648   8.644 3.04e-12 ***
E.4C3         1.0152     0.1097   9.254 2.74e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4543 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:   0.58,     Adjusted R-squared:  0.5732
F-statistic: 85.63 on 1 and 62 DF,  p-value: 2.738e-13

> E5C1.E4C4=lm(E.5C1~E.4C4)
> summary(E5C1.E4C4)

Call:
lm(formula = E.5C1 ~ E.4C4)

Residuals:
   Min      1Q  Median      3Q     Max
-1.6886 -0.3048 -0.1563  0.4177  0.9566

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.7485     0.1505  11.618  < 2e-16 ***
E.4C4         1.3311     0.1651   8.061  3.1e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4899 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.5118,    Adjusted R-squared:  0.5039
F-statistic: 64.99 on 1 and 62 DF,  p-value: 3.096e-11
```

```
> E5C2.E4C1=lm(E.5C2~E.4C1)
> summary(E5C2.E4C1)

Call:
lm(formula = E.5C2 ~ E.4C1)

Residuals:
     Min       1Q   Median       3Q      Max
-0.091684 -0.023099  0.008382  0.023749  0.105741

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.030577   0.021465  -1.425    0.159
E.4C1        0.879551   0.008208 107.158   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03803 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.9946,    Adjusted R-squared:  0.9945
F-statistic: 1.148e+04 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C2.E4C2=lm(E.5C2~E.4C2)
> summary(E5C2.E4C2)

Call:
lm(formula = E.5C2 ~ E.4C2)

Residuals:
    Min      1Q  Median      3Q     Max
-0.51863 -0.08737  0.04357  0.09697  0.39490

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.18423    0.10470    1.76   0.0834 .
E.4C2        0.71758    0.03607   19.90   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.191 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.8646,    Adjusted R-squared:  0.8624
F-statistic: 395.9 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C2.E4C3=lm(E.5C2~E.4C3)
```

```
> summary(E5C2.E4C3)

Call:
lm(formula = E.5C2 ~ E.4C3)

Residuals:
    Min      1Q  Median      3Q     Max
-0.6969 -0.2945 -0.1215  0.2902  0.9826

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.4315     0.1559   9.183 3.61e-13 ***
E.4C3         0.5536     0.1037   5.336 1.42e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4296 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.3147,    Adjusted R-squared:  0.3037
F-statistic: 28.47 on 1 and 62 DF,  p-value: 1.423e-06

> E5C2.E4C4=lm(E.5C2~E.4C4)
> summary(E5C2.E4C4)

Call:
lm(formula = E.5C2 ~ E.4C4)

Residuals:
    Min      1Q  Median      3Q     Max
-0.6476 -0.3434 -0.1393  0.3203  0.9939

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.5975     0.1346  11.868  < 2e-16 ***
E.4C4         0.7385     0.1477   5.001 4.98e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4381 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.2874,    Adjusted R-squared:  0.2759
F-statistic: 25.01 on 1 and 62 DF,  p-value: 4.98e-06

> E5C3.E4C1=lm(E.5C3~E.4C1)
> summary(E5C3.E4C1)
```

```
Call:
lm(formula = E.5C3 ~ E.4C1)

Residuals:
    Min      1Q  Median      3Q     Max
-0.59728 -0.33842 -0.01052  0.27525  1.09844

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.04637    0.23350   0.199    0.843
E.4C1        0.55406    0.08929   6.205 4.99e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4137 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.3831,    Adjusted R-squared:  0.3732
F-statistic: 38.51 on 1 and 62 DF,  p-value: 4.992e-08

> E5C3.E4C2=lm(E.5C3~E.4C2)
> summary(E5C3.E4C2)

Call:
lm(formula = E.5C3 ~ E.4C2)

Residuals:
    Min      1Q  Median      3Q     Max
-0.59037 -0.28779 -0.02882  0.24452  0.85305

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.13218    0.20075  -0.658    0.513
E.4C2        0.56308    0.06916   8.142 2.24e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3662 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.5167,    Adjusted R-squared:  0.5089
F-statistic:  66.3 on 1 and 62 DF,  p-value: 2.243e-11

> E5C3.E4C3=lm(E.5C3~E.4C3)
> summary(E5C3.E4C3)

Call:
lm(formula = E.5C3 ~ E.4C3)
```

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.022794 -0.009521 -0.004035  0.008978  0.033917

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.046897   0.004662   10.06 1.19e-14 ***
E.4C3       1.001303   0.003103  322.69  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01285 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.9994,    Adjusted R-squared:  0.9994
F-statistic: 1.041e+05 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C3.E4C4=lm(E.5C3~E.4C4)
> summary(E5C3.E4C4)

Call:
lm(formula = E.5C3 ~ E.4C4)

Residuals:
   Min      1Q  Median      3Q     Max
-1.6296 -0.1848 -0.0334  0.1410  1.1423

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.7342     0.1266   5.799 2.43e-07 ***
E.4C4         0.8709     0.1389   6.269 3.88e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4121 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.388,     Adjusted R-squared:  0.3781
F-statistic:  39.3 on 1 and 62 DF,  p-value: 3.885e-08

> E5C4.E4C1=lm(E.5C4~E.4C1)
> summary(E5C4.E4C1)

Call:
lm(formula = E.5C4 ~ E.4C1)

Residuals:
```

```
    Min      1Q  Median      3Q     Max
-0.98171 -0.20892  0.09808  0.22104  1.88539

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.08934    0.23237  -0.384 0.701951
E.4C1        0.34862    0.08886   3.923 0.000221 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4117 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.1989,    Adjusted R-squared:  0.186
F-statistic: 15.39 on 1 and 62 DF,  p-value: 0.0002213

> E5C4.E4C2=lm(E.5C4~E.4C2)
> summary(E5C4.E4C2)

Call:
lm(formula = E.5C4 ~ E.4C2)

Residuals:
    Min      1Q  Median      3Q     Max
-1.00879 -0.22421  0.08425  0.17636  1.74283

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.37879    0.19992  -1.895   0.0628 .
E.4C2        0.41695    0.06887   6.054 9.01e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3647 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.3716,    Adjusted R-squared:  0.3614
F-statistic: 36.66 on 1 and 62 DF,  p-value: 9.005e-08

> E5C4.E4C4=lm(E.5C4~E.4C4)
> summary(E5C4.E4C4)

Call:
lm(formula = E.5C4 ~ E.4C4)

Residuals:
    Min      1Q  Median      3Q     Max
-0.22492 -0.04846  0.01782  0.06242  0.10712
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.20136    0.02463  -8.177 1.95e-11 ***
E.4C4        1.20229    0.02702  44.501  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.08015 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.9696,    Adjusted R-squared:  0.9692
F-statistic:  1980 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C4.E4C3=lm(E.5C4~E.4C3)
> summary(E5C4.E4C3)

Call:
lm(formula = E.5C4 ~ E.4C3)

Residuals:
    Min      1Q  Median      3Q     Max
-0.6033 -0.1640 -0.0339  0.1005  2.1270

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.01155    0.12575  -0.092    0.927
E.4C3        0.57512    0.08369   6.872 3.58e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3466 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.4324,    Adjusted R-squared:  0.4232
F-statistic: 47.22 on 1 and 62 DF,  p-value: 3.581e-09

> E5C5.E4C1=lm(E.5C5~E.4C1)
> summary(E5C5.E4C1)

Call:
lm(formula = E.5C5 ~ E.4C1)

Residuals:
     Min       1Q   Median       3Q      Max
-0.20500 -0.09555 -0.01999  0.07007  0.38780

Coefficients:
```

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.03602    0.07235   0.498   0.6203
E.4C1        0.04741    0.02767   1.714   0.0916 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1282 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.04523,   Adjusted R-squared:  0.02983
F-statistic: 2.937 on 1 and 62 DF,  p-value: 0.09156

> E5C5.E4C2=lm(E.5C5~E.4C2)
> summary(E5C5.E4C2)

Call:
lm(formula = E.5C5 ~ E.4C2)

Residuals:
     Min       1Q   Median       3Q      Max
-0.16756 -0.09432 -0.02947  0.05741  0.40884

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.135977   0.071869   1.892   0.0632 .
E.4C2       0.007414   0.024758   0.299   0.7656
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1311 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.001444,  Adjusted R-squared:  -0.01466
F-statistic: 0.08968 on 1 and 62 DF,  p-value: 0.7656

> E5C5.E4C3=lm(E.5C5~E.4C3)
> summary(E5C5.E4C3)

Call:
lm(formula = E.5C5 ~ E.4C3)

Residuals:
     Min       1Q   Median       3Q      Max
-0.14953 -0.07619 -0.02843  0.06135  0.36870

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.33806    0.04081   8.284 1.28e-11 ***
```

```
E.4C3       -0.12840    0.02716  -4.728 1.35e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1125 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.265,     Adjusted R-squared:  0.2531
F-statistic: 22.35 on 1 and 62 DF,  p-value: 1.351e-05

> E5C5.E4C4=lm(E.5C5~E.4C4)
> summary(E5C5.E4C4)

Call:
lm(formula = E.5C5 ~ E.4C4)

Residuals:
     Min       1Q   Median       3Q      Max
-0.15428 -0.09774 -0.02619  0.07634  0.34635

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.27224    0.03698   7.361 5.09e-10 ***
E.4C4       -0.13849    0.04058  -3.413  0.00114 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1204 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.1582,    Adjusted R-squared:  0.1446
F-statistic: 11.65 on 1 and 62 DF,  p-value: 0.001137

> E5C1.EA=lm(E.5C1~E.A)
> summary(E5C1.EA)

Call:
lm(formula = E.5C1 ~ E.A)

Residuals:
    Min      1Q  Median      3Q     Max
-0.3395 -0.1195 -0.0010  0.1252  0.4055

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.07793    0.09735   -0.80    0.426
E.A          1.43366    0.04637   30.92   <2e-16 ***
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.173 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.9391,    Adjusted R-squared:  0.9381
F-statistic:   956 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C1.EB=lm(E.5C1~E.B)
> summary(E5C1.EB)

Call:
lm(formula = E.5C1 ~ E.B)

Residuals:
    Min      1Q  Median      3Q     Max
-0.52893 -0.27648 -0.01884  0.16957  1.13460

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.6538     0.1634   4.002  0.00017 ***
E.B           2.8683     0.2052  13.978  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3441 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.7591,    Adjusted R-squared:  0.7552
F-statistic: 195.4 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C1.ET=lm(E.5C1~E.T)
> summary(E5C1.ET)

Call:
lm(formula = E.5C1 ~ E.T)

Residuals:
    Min      1Q  Median      3Q     Max
-0.48662 -0.21311 -0.05706  0.18674  0.91715

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.8029     0.1288   6.233 4.47e-08 ***
E.T           1.9073     0.1145  16.664  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 0.2995 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.8175,    Adjusted R-squared:  0.8145
F-statistic: 277.7 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C1.EC=lm(E.5C1~E.C)
> summary(E5C1.EC)

Call:
lm(formula = E.5C1 ~ E.C)

Residuals:
    Min      1Q  Median      3Q     Max
-0.8649 -0.3169 -0.1138  0.2976  1.1421

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.26963    0.16188   7.843 7.41e-11 ***
E.C          0.96994    0.09348  10.376 3.51e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4238 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6346,    Adjusted R-squared:  0.6287
F-statistic: 107.7 on 1 and 62 DF,  p-value: 3.511e-15

> E5C1.EM=lm(E.5C1~E.M)
> summary(E5C1.EM)

Call:
lm(formula = E.5C1 ~ E.M)

Residuals:
     Min       1Q   Median       3Q      Max
-0.45730 -0.15872 -0.05914  0.17377  0.49952

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.43851    0.10907    4.02  0.00016 ***
E.M          1.57940    0.06877   22.96  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2274 on 62 degrees of freedom
  (9 observations deleted due to missingness)
```

```
Multiple R-squared:  0.8948,    Adjusted R-squared:  0.8931
F-statistic: 527.4 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C1.EFI=lm(E.5C1~E.FI)
> summary(E5C1.EFI)

Call:
lm(formula = E.5C1 ~ E.FI)

Residuals:
    Min      1Q  Median      3Q     Max
-1.0640 -0.5082 -0.1081  0.4854  1.4337

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.5095     1.4333  -0.355   0.7234
E.FI          1.7448     0.7416   2.353   0.0218 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6717 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.08196,   Adjusted R-squared:  0.06715
F-statistic: 5.535 on 1 and 62 DF,  p-value: 0.02183

> E5C1.EFrI=lm(E.5C1~E.FrI)
> summary(E5C1.EFrI)

Call:
lm(formula = E.5C1 ~ E.FrI)

Residuals:
    Min      1Q  Median      3Q     Max
-1.2574 -0.3681 -0.1855  0.5100  1.7195

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    1.228      1.546   0.794    0.430
E.FrI          2.005      1.900   1.055    0.295

Residual standard error: 0.6948 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.01764,   Adjusted R-squared:  0.001796
F-statistic: 1.113 on 1 and 62 DF,  p-value: 0.2954

> E5C1.EHI=lm(E.5C1~E.HI)
```

```
> summary(E5C1.EHI)

Call:
lm(formula = E.5C1 ~ E.HI)

Residuals:
    Min      1Q  Median      3Q     Max
-0.9973 -0.4947 -0.1511  0.5814  1.4170

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.96756    0.37459  10.592 1.54e-15 ***
E.HI        -0.28445    0.09362  -3.038  0.00348 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.654 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.1296,    Adjusted R-squared:  0.1156
F-statistic: 9.232 on 1 and 62 DF,  p-value: 0.003479

> E5C1.ECDOMEEM=lm(E.5C1~E.CDOMEEM)
> summary(E5C1.ECDOMEEM)

Call:
lm(formula = E.5C1 ~ E.CDOMEEM)

Residuals:
     Min       1Q   Median       3Q      Max
-0.67777 -0.25306 -0.07656  0.18897  0.95334

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.7456     0.1499   4.973 5.51e-06 ***
E.CDOMEEM     1.9568     0.1335  14.654  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3318 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.776,     Adjusted R-squared:  0.7723
F-statistic: 214.7 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C1.ETrypEEM=lm(E.5C1~E.TrypEEM)
> summary(E5C1.ETrypEEM)
```

```
Call:
lm(formula = E.5C1 ~ E.TrypEEM)

Residuals:
    Min      1Q  Median      3Q     Max
-0.36188 -0.16059 -0.04897  0.14446  0.80997

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.57509    0.11154   5.156  2.8e-06 ***
E.TrypEEM    2.01912    0.09496  21.263  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2434 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.8794,    Adjusted R-squared:  0.8775
F-statistic: 452.1 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C2.ETrypEEM=lm(E.5C2~E.TrypEEM)
> summary(E5C2.ETrypEEM)

Call:
lm(formula = E.5C2 ~ E.TrypEEM)

Residuals:
    Min      1Q  Median      3Q     Max
-0.67805 -0.21253 -0.06557  0.22402  0.73931

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.8572     0.1566   5.472 8.49e-07 ***
E.TrypEEM     1.1992     0.1334   8.992 7.66e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3419 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.566,     Adjusted R-squared:  0.559
F-statistic: 80.86 on 1 and 62 DF,  p-value: 7.66e-13

> E5C3.ETrypEEM=lm(E.5C3~E.TrypEEM)
> summary(E5C3.ETrypEEM)

Call:
lm(formula = E.5C3 ~ E.TrypEEM)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-0.59028 -0.19012  0.01654  0.18052  0.68793

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.04483    0.13720  -0.327    0.745
E.TrypEEM    1.33102    0.11681  11.395   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2995 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6768,    Adjusted R-squared:  0.6716
F-statistic: 129.9 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C4.ETrypEEM=lm(E.5C4~E.TrypEEM)
> summary(E5C4.ETrypEEM)

Call:
lm(formula = E.5C4 ~ E.TrypEEM)

Residuals:
    Min      1Q  Median      3Q     Max
-0.51211 -0.10366  0.03792  0.10261  1.73237

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.4750     0.1269  -3.743    4e-04 ***
E.TrypEEM     1.1280     0.1080  10.440 2.75e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.277 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6374,    Adjusted R-squared:  0.6316
F-statistic:   109 on 1 and 62 DF,  p-value: 2.751e-15

> E5C5.ETrypEEM=lm(E.5C5~E.TrypEEM)
> summary(E5C5.ETrypEEM)

Call:
lm(formula = E.5C5 ~ E.TrypEEM)

Residuals:
```

```
    Min       1Q   Median       3Q      Max
-0.16173 -0.10079 -0.03460  0.06885  0.37612

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.31841    0.05620   5.665 4.06e-07 ***
E.TrypEEM   -0.14289    0.04785  -2.986  0.00404 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1227 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.1258,    Adjusted R-squared:  0.1117
F-statistic: 8.919 on 1 and 62 DF,  p-value: 0.004038

> E5C2.ECDOMEEM=lm(E.5C2~E.CDOMEEM)
> summary(E5C2.ECDOMEEM)

Call:
lm(formula = E.5C2 ~ E.CDOMEEM)

Residuals:
    Min       1Q   Median       3Q      Max
-0.62998 -0.24450 -0.09418  0.28271  0.77761

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.9164     0.1602   5.722 3.27e-07 ***
E.CDOMEEM     1.2013     0.1426   8.421 7.37e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3545 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.5335,    Adjusted R-squared:  0.526
F-statistic: 70.92 on 1 and 62 DF,  p-value: 7.373e-12

> E5C2.EHI=lm(E.5C2~E.HI)
> summary(E5C2.EHI)

Call:
lm(formula = E.5C2 ~ E.HI)

Residuals:
   Min      1Q  Median      3Q     Max
-0.8277 -0.3789 -0.1633  0.4257  1.0920
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.208442   0.297244   7.430 3.87e-10 ***
E.HI        0.001018   0.074288   0.014    0.989
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.519 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  3.027e-06, Adjusted R-squared:  -0.01613
F-statistic: 0.0001877 on 1 and 62 DF,  p-value: 0.9891

> E5C2.EFrI=lm(E.5C2~E.FrI)
> summary(E5C2.EFrI)

Call:
lm(formula = E.5C2 ~ E.FrI)

Residuals:
    Min      1Q  Median      3Q     Max
-0.8352 -0.4127 -0.1374  0.4757  1.0778

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    1.021      1.145   0.892    0.376
E.FrI          1.466      1.407   1.042    0.301

Residual standard error: 0.5145 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.01722,   Adjusted R-squared:  0.001371
F-statistic: 1.086 on 1 and 62 DF,  p-value: 0.3013

> E5C2.EFI=lm(E.5C2~E.FI)
> summary(E5C2.EFI)

Call:
lm(formula = E.5C2 ~ E.FI)

Residuals:
    Min      1Q  Median      3Q     Max
-0.8179 -0.3897 -0.1741  0.4353  1.0958

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.03745    1.10724   1.840   0.0705 .
```

```
E.FI        0.09068    0.57291   0.158   0.8747
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5189 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.000404,  Adjusted R-squared:  -0.01572
F-statistic: 0.02506 on 1 and 62 DF,  p-value: 0.8747

> E5C2.EM=lm(E.5C2~E.M)
> summary(E5C2.EM)

Call:
lm(formula = E.5C2 ~ E.M)

Residuals:
    Min       1Q   Median       3Q      Max
-0.49839 -0.22274 -0.05428  0.23670  0.69310

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.6886     0.1477   4.663 1.70e-05 ***
E.M           0.9952     0.0931  10.690 1.06e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3078 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6483,    Adjusted R-squared:  0.6426
F-statistic: 114.3 on 1 and 62 DF,  p-value: 1.064e-15

> E5C2.EC=lm(E.5C2~E.C)
> summary(E5C2.EC)

Call:
lm(formula = E.5C2 ~ E.C)

Residuals:
   Min      1Q  Median      3Q     Max
-0.6756 -0.2740 -0.1287  0.3078  0.9295

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.31294    0.15712   8.356 9.56e-12 ***
E.C          0.54966    0.09073   6.058 8.87e-08 ***
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4113 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.3718,    Adjusted R-squared:  0.3617
F-statistic:  36.7 on 1 and 62 DF,  p-value: 8.872e-08

> E5C3.EC=lm(E.5C3~E.C)
> summary(E5C3.EC)

Call:
lm(formula = E.5C3 ~ E.C)

Residuals:
     Min       1Q   Median       3Q      Max
-0.090232 -0.009699  0.009164  0.018634  0.048247

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.035657   0.010895  -3.273  0.00174 **
E.C          0.913568   0.006292 145.206  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02852 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.9971,    Adjusted R-squared:  0.997
F-statistic: 2.108e+04 on 1 and 62 DF,  p-value: < 2.2e-16

> E5C4.EB=lm(E.5C4~E.B)
> summary(E5C4.EB)

Call:
lm(formula = E.5C4 ~ E.B)

Residuals:
    Min      1Q  Median      3Q     Max
-0.36298 -0.11237  0.00192  0.06216  1.92218

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.5134     0.1335  -3.844 0.000287 ***
E.B           1.7096     0.1677  10.193 7.09e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 0.2812 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6263,    Adjusted R-squared:  0.6202
F-statistic: 103.9 on 1 and 62 DF,  p-value: 7.094e-15

> E5C5.EA=lm(E.5C5~E.A)
> summary(E5C5.EA)

Call:
lm(formula = E.5C5 ~ E.A)

Residuals:
    Min      1Q  Median      3Q     Max
-0.17454 -0.09426 -0.02727  0.06037  0.40584

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.12413    0.07370   1.684   0.0971 .
E.A          0.01602    0.03510   0.457   0.6496
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.131 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.00335,   Adjusted R-squared:  -0.01272
F-statistic: 0.2084 on 1 and 62 DF,  p-value: 0.6496

> E5C2.EA=lm(E.5C2~E.A)
> summary(E2C5.EA)
Error in summary(E2C5.EA) : object 'E2C5.EA' not found
> summary(E5C2.EA)

Call:
lm(formula = E.5C2 ~ E.A)

Residuals:
    Min      1Q  Median      3Q     Max
-0.34502 -0.11861  0.00854  0.13053  0.33881

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.07940    0.08994   0.883    0.381
E.A          1.04199    0.04284  24.324   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 0.1598 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.9052,    Adjusted R-squared:  0.9036
F-statistic: 591.7 on 1 and 62 DF,  p-value: < 2.2e-16

>  EAsplit <- cut(E.A, 2, labels=c("early", "Late"))
> E5C3.EAsplit=lm(E.5C3~EAsplit)
> visreg(E5C3.EAsplit, "EAsplit", type="conditional")
Error: could not find function "visreg"
> library(visreg)
> visreg(E5C3.EAsplit, "EAsplit", type="conditional")
> visreg(fit, "E.5C3", by="EAsplit", overlay=TRUE, partial=FALSE)
Error in setupF(fit, xvar, parent.frame()) : object 'fit' not found
> visreg(E5C3.EAsplit, "E.5C3", by="EAsplit", overlay=TRUE, partial=FALSE)
>
> visreg(E5C3.EAsplit, "EAsplit", by="E.5C3", overlay=TRUE, partial=FALSE)
Warning messages:
1: In axis(side = 1, at = c(0.222222222222222, 0.777777777777778),  :
  "ax" is not a graphical parameter
2: In axis(side = 1, at = c(0.222222222222222, 0.777777777777778),  :
  "ax" is not a graphical parameter
3: In axis(side = 1, at = c(0.222222222222222, 0.777777777777778),  :
  "ax" is not a graphical parameter
> visreg(E5C3.EAsplit, "E.5C3", by="EAsplit", overlay=TRUE, partial=FALSE)
> visreg(E5C3.EAsplit, "EAsplit", type="conditional")
> E5C4.EA=lm(E.5C4~E.A)
>
> summary(E5C4.EA)

Call:
lm(formula = E.5C4 ~ E.A)

Residuals:
    Min      1Q  Median      3Q     Max
-1.01356 -0.15686  0.08366  0.19284  1.93602

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.2448     0.2202  -1.112    0.271
E.A           0.5102     0.1049   4.865  8.2e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3913 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.2763,    Adjusted R-squared:  0.2646
```

```
F-statistic: 23.67 on 1 and 62 DF,  p-value: 8.205e-06

> E5C4.EB=lm(E.5C4~E.B)
> summary(E5C4.EB)

Call:
lm(formula = E.5C4 ~ E.B)

Residuals:
    Min      1Q  Median      3Q     Max
-0.36298 -0.11237  0.00192  0.06216  1.92218

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.5134     0.1335  -3.844 0.000287 ***
E.B           1.7096     0.1677  10.193 7.09e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2812 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6263,    Adjusted R-squared:  0.6202
F-statistic: 103.9 on 1 and 62 DF,  p-value: 7.094e-15

> E5C4.ET=lm(E.5C4~E.T)
> summary(E5C4.ET)

Call:
lm(formula = E.5C4 ~ E.T)

Residuals:
    Min      1Q  Median      3Q     Max
-0.43727 -0.08230  0.00296  0.07951  1.84239

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.3972     0.1179  -3.368  0.00131 **
E.T           1.1114     0.1048  10.606 1.46e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2742 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6447,    Adjusted R-squared:  0.639
F-statistic: 112.5 on 1 and 62 DF,  p-value: 1.461e-15
```

```
> E5C1.EA=lm(E.4C1~E.A)
> summary(E4C1.EA)
Error in summary(E4C1.EA) : object 'E4C1.EA' not found
> E4C1.EA=lm(E.4C1~E.A)
> summary(E4C1.EA)

Call:
lm(formula = E.4C1 ~ E.A)

Residuals:
     Min       1Q   Median       3Q      Max
-0.309640 -0.111284  0.008975  0.115512  0.257575

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.08477    0.08076    1.05    0.298
E.A          1.20436    0.03847   31.31   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1435 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.9405,    Adjusted R-squared:  0.9395
F-statistic: 980.2 on 1 and 62 DF,  p-value: < 2.2e-16

> E4C1.EB=lm(E.4C1~E.B)
> summary(E4C1.EB)

Call:
lm(formula = E.4C1 ~ E.B)

Residuals:
   Min      1Q  Median      3Q     Max
-0.7489 -0.3093 -0.1047  0.2638  1.0663

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.1219     0.2067   5.428 1.01e-06 ***
E.B           1.8596     0.2596   7.163 1.12e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4353 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.4528,    Adjusted R-squared:  0.444
F-statistic: 51.31 on 1 and 62 DF,  p-value: 1.123e-09
```

```
> E4C1.ET=lm(E.4C1~E.T)
> summary(E4C1.ET)

Call:
lm(formula = E.4C1 ~ E.T)

Residuals:
    Min      1Q  Median      3Q     Max
-0.7934 -0.2865 -0.1091  0.2381  0.9303

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.2022     0.1790   6.715 6.67e-09 ***
E.T           1.2518     0.1591   7.870 6.66e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4162 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.4997,    Adjusted R-squared:  0.4917
F-statistic: 61.93 on 1 and 62 DF,  p-value: 6.663e-11

> E4C1.EC=lm(E.4C1~E.C)
> summary(E4C1.Ec)
Error in summary(E4C1.Ec) : object 'E4C1.Ec' not found
> summary(E4C1.EC)

Call:
lm(formula = E.4C1 ~ E.C)

Residuals:
    Min      1Q  Median      3Q     Max
-0.7441 -0.2910 -0.1574  0.3444  1.0056

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.46730    0.17132   8.565 4.17e-12 ***
E.C          0.66172    0.09893   6.689 7.40e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4485 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.4192,    Adjusted R-squared:  0.4098
F-statistic: 44.74 on 1 and 62 DF,  p-value: 7.403e-09
```

```
> E4C1.EM=lm(E.4C1~E.M)
> summary(E4C1.EM)

Call:
lm(formula = E.4C1 ~ E.M)

Residuals:
    Min      1Q  Median      3Q     Max
-0.48798 -0.23558 -0.06851  0.23116  0.72009

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.75584    0.15486   4.881 7.74e-06 ***
E.M          1.17186    0.09764  12.002  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3228 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6991,    Adjusted R-squared:  0.6942
F-statistic:   144 on 1 and 62 DF,  p-value: < 2.2e-16

> E4C1.ECDOMEEM=lm(E.4C1~E.CDOMEEM)
> summary(E4C1.ECDOMEEM)

Call:
lm(formula = E.4C1 ~ E.CDOMEEM)

Residuals:
   Min     1Q  Median     3Q    Max
-0.6430 -0.2686 -0.1056  0.3265  0.8208

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1.0112     0.1713   5.904 1.61e-07 ***
E.CDOMEEM     1.4264     0.1525   9.351 1.87e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3791 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.5851,    Adjusted R-squared:  0.5784
F-statistic: 87.43 on 1 and 62 DF,  p-value: 1.87e-13

> E4C1.ETrypEEM=lm(E.4C1~E.TrypEEM)
```

```
> summary(E4C1.EtrypEEM)
Error in summary(E4C1.EtrypEEM) : object 'E4C1.EtrypEEM' not found
> summary(E4C1.ETrypEEM)

Call:
lm(formula = E.4C1 ~ E.TrypEEM)

Residuals:
    Min      1Q  Median      3Q     Max
-0.70682 -0.24224 -0.06213  0.24429  0.87956

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.9657     0.1701   5.676 3.90e-07 ***
E.TrypEEM     1.4021     0.1448   9.680 5.15e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3713 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6018,    Adjusted R-squared:  0.5954
F-statistic: 93.71 on 1 and 62 DF,  p-value: 5.153e-14

> E4C2.ETrypEEM=lm(E.4C2~E.TrypEEM)
> summary(E4C2.ETrypEEM)

Call:
lm(formula = E.4C2 ~ E.TrypEEM)

Residuals:
    Min      1Q  Median      3Q     Max
-0.43542 -0.20545 -0.06965  0.18725  0.97675

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.7198     0.1327   5.425 1.02e-06 ***
E.TrypEEM     1.8642     0.1129  16.505  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2896 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.8146,    Adjusted R-squared:  0.8116
F-statistic: 272.4 on 1 and 62 DF,  p-value: < 2.2e-16

> E4C2.ECDOMEEM=lm(E.4C2~E.CDOMEEM)
```

```
> summary(E4C2.ECDOMEEM)

Call:
lm(formula = E.4C2 ~ E.CDOMEEM)

Residuals:
    Min      1Q  Median      3Q     Max
-0.72545 -0.26403 -0.09453  0.30020  0.95882

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.8890     0.1636   5.434 9.83e-07 ***
E.CDOMEEM     1.7957     0.1457  12.324  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3621 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.7101,    Adjusted R-squared:  0.7054
F-statistic: 151.9 on 1 and 62 DF,  p-value: < 2.2e-16

> E4C2.EM=lm(E.4C2~E.M)
> summary(E4C2.EM)

Call:
lm(formula = E.4C2 ~ E.M)

Residuals:
    Min      1Q  Median      3Q     Max
-0.52398 -0.19264 -0.09088  0.21256  0.55985

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.5778     0.1288   4.487 3.19e-05 ***
E.M           1.4685     0.0812  18.086  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2684 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.8407,    Adjusted R-squared:  0.8381
F-statistic: 327.1 on 1 and 62 DF,  p-value: < 2.2e-16

> E4C2.EA=lm(E.4C2~E.A)
> summary(E4C2.EA)
```

```
Call:
lm(formula = E.4C2 ~ E.A)

Residuals:
    Min      1Q  Median      3Q     Max
-0.22594 -0.11742 -0.00879  0.09771  0.41137

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.005528   0.084400  -0.065    0.948
E.A          1.383428   0.040200  34.414   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.15 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.9503,    Adjusted R-squared:  0.9495
F-statistic:  1184 on 1 and 62 DF,  p-value: < 2.2e-16

> E4C3.EA=lm(E.4C3~E.A)
> summary(E4C3.EA)

Call:
lm(formula = E.4C3 ~ E.A)

Residuals:
    Min      1Q  Median      3Q     Max
-0.69187 -0.26913  0.01508  0.24583  0.73727

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.30070    0.19466  -1.545    0.127
E.A          0.83597    0.09272   9.016 6.96e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3459 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.5673,    Adjusted R-squared:  0.5604
F-statistic:  81.3 on 1 and 62 DF,  p-value: 6.964e-13

> E4C3.EB=lm(E.4C3~E.B)
> summary(E4C3.Eb)
Error in summary(E4C3.Eb) : object 'E4C3.Eb' not found
> summary(E4C3.EB)
```

```
Call:
lm(formula = E.4C3 ~ E.B)

Residuals:
    Min      1Q  Median      3Q     Max
-0.58575 -0.17529 -0.07222  0.21260  0.66003

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.1318     0.1454  -0.907    0.368
E.B           2.0082     0.1826  10.998 3.33e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3062 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6611,    Adjusted R-squared:  0.6557
F-statistic:   121 on 1 and 62 DF,  p-value: 3.326e-16

> E4C3.ET=lm(E.4C3~E.T)
> summary(E4C3.ET)

Call:
lm(formula = E.4C3 ~ E.T)

Residuals:
    Min      1Q  Median      3Q     Max
-0.57165 -0.17488 -0.02308  0.16399  0.69049

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.004112   0.127739   0.032    0.974
E.T         1.306079   0.113501  11.507   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.297 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6811,    Adjusted R-squared:  0.676
F-statistic: 132.4 on 1 and 62 DF,  p-value: < 2.2e-16

> E4C3.EC=lm(E.4C3~E.C)
> summary(E4C3.EC)

Call:
lm(formula = E.4C3 ~ E.C)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-0.10234 -0.01684  0.01009  0.02483  0.05253

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.080722   0.013688  -5.897 1.66e-07 ***
E.C          0.911325   0.007904 115.298  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03583 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.9954,    Adjusted R-squared:  0.9953
F-statistic: 1.329e+04 on 1 and 62 DF,  p-value: < 2.2e-16

> E4C3.EM=lm(E.4C3~E.M)
> summary(E4C3.Em)
Error in summary(E4C3.Em) : object 'E4C3.Em' not found
> summary(E4C3.EM)

Call:
lm(formula = E.4C3 ~ E.M)

Residuals:
    Min      1Q  Median      3Q     Max
-0.46980 -0.14185  0.02064  0.10858  0.42152

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.36507    0.09536  -3.828 0.000303 ***
E.M          1.15967    0.06013  19.286  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1988 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.8571,    Adjusted R-squared:  0.8548
F-statistic: 371.9 on 1 and 62 DF,  p-value: < 2.2e-16

> E4C4.EA=lm(E.4C4~E.A)
> summary(E4C4.Ea)
Error in summary(E4C4.Ea) : object 'E4C4.Ea' not found
> summary(E4C4.EA)
```

```
Call:
lm(formula = E.4C4 ~ E.A)

Residuals:
    Min      1Q  Median      3Q     Max
-0.67756 -0.11367  0.00784  0.11105  1.73720

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.14165    0.16982  -0.834    0.407
E.A          0.47594    0.08089   5.884 1.75e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3018 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.3583,    Adjusted R-squared:  0.348
F-statistic: 34.62 on 1 and 62 DF,  p-value: 1.746e-07

> E4C4.EB=lm(E.4C4~E.B)
> summary(E4C4.EB)

Call:
lm(formula = E.4C4 ~ E.B)

Residuals:
    Min      1Q  Median      3Q     Max
-0.21539 -0.06762 -0.03636  0.01486  1.75261

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.2325     0.1111  -2.093   0.0405 *
E.B           1.3868     0.1395   9.938  1.9e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.234 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6143,    Adjusted R-squared:  0.6081
F-statistic: 98.76 on 1 and 62 DF,  p-value: 1.898e-14

> E4C4.ET=lm(E.4C4~E.T)
> summary(E4C4.ET)

Call:
lm(formula = E.4C4 ~ E.T)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-0.18113 -0.06178 -0.01171  0.02315  1.68535

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.14794    0.09654  -1.532     0.13
E.T          0.91057    0.08577  10.616 1.41e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2245 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.6451,    Adjusted R-squared:  0.6394
F-statistic: 112.7 on 1 and 62 DF,  p-value: 1.409e-15

> E4C4.Ec=lm(E.4C4~E.C)
> E4C4.EC=lm(E.4C4~E.C)
> summary(E4C4.EC)

Call:
lm(formula = E.4C4 ~ E.C)

Residuals:
    Min      1Q  Median      3Q     Max
-0.33142 -0.14049 -0.03420  0.06188  1.87146

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.14110    0.10988   1.284    0.204
E.C          0.42258    0.06345   6.660 8.31e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2877 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.417,     Adjusted R-squared:  0.4076
F-statistic: 44.36 on 1 and 62 DF,  p-value: 8.307e-09

> E4C4.EM=lm(E.4C4~E.M)
> summary(E4C4.EM)

Call:
lm(formula = E.4C4 ~ E.M)
```

```
Residuals:
    Min      1Q  Median      3Q     Max
-0.45270 -0.12701 -0.02170  0.05216  1.70733

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.14435    0.12708  -1.136     0.26
E.M          0.63806    0.08013   7.963 4.59e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2649 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.5056,    Adjusted R-squared:  0.4977
F-statistic: 63.41 on 1 and 62 DF,  p-value: 4.586e-11

> E4C4.EHI=lm(E.4C4~E.HI)
> summary(E4C4.EHI)

Call:
lm(formula = E.4C4 ~ E.HI)

Residuals:
   Min      1Q  Median      3Q     Max
-0.2966 -0.1460 -0.0740  0.1235  1.8857

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.86163    0.16921  11.002 3.28e-16 ***
E.HI        -0.26352    0.04229  -6.232 4.50e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2954 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.3851,    Adjusted R-squared:  0.3752
F-statistic: 38.83 on 1 and 62 DF,  p-value: 4.504e-08

> ETN.Days=lm(E.TN~Days)
> summary(ETN.Days)

Call:
lm(formula = E.TN ~ Days)

Residuals:
   Min     1Q Median     3Q    Max
```

```
-7.702 -4.204 -2.028  3.147 14.007

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 31.56042    3.47364   9.086 9.58e-13 ***
Days        -0.18621    0.02717  -6.853 5.17e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.69 on 58 degrees of freedom
  (13 observations deleted due to missingness)
Multiple R-squared:  0.4474,    Adjusted R-squared:  0.4379
F-statistic: 46.97 on 1 and 58 DF,  p-value: 5.17e-09

> ETN.FO=lm(E.TN~FlowOut)
> summary(ETN.FlowOut)
Error in summary(ETN.FlowOut) : object 'ETN.FlowOut' not found
> summary(ETN.FO)

Call:
lm(formula = E.TN ~ FlowOut)

Residuals:
   Min     1Q Median     3Q    Max
-7.946 -4.036 -1.404  2.752 13.692

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 68.1453923  8.4119690   8.101 4.15e-11 ***
FlowOut     -0.0057171  0.0008006  -7.141 1.70e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.584 on 58 degrees of freedom
  (13 observations deleted due to missingness)
Multiple R-squared:  0.4679,    Adjusted R-squared:  0.4587
F-statistic:    51 on 1 and 58 DF,  p-value: 1.696e-09

> ETP.FO=lm(E.TP~FlowOut)
> summary(ETP.FO)

Call:
lm(formula = E.TP ~ FlowOut)

Residuals:
    Min      1Q  Median      3Q     Max
```

```
-4.2482 -1.2592  0.2755  1.1651  3.6630

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 3.1051995  3.0232011   1.027    0.309
FlowOut     0.0001041  0.0002877   0.362    0.719

Residual standard error: 2.007 on 58 degrees of freedom
  (13 observations deleted due to missingness)
Multiple R-squared:  0.00225,   Adjusted R-squared:  -0.01495
F-statistic: 0.1308 on 1 and 58 DF,  p-value: 0.7189

> ECOD.FO=lm(E.COD~FlowOut)
> summary(ECOD.FO)

Call:
lm(formula = E.COD ~ FlowOut)

Residuals:
    Min      1Q  Median      3Q     Max
-24.269 -23.009  -6.245   7.189  77.929

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 28.7661584 33.1855764   0.867    0.389
FlowOut     -0.0004899  0.0031201  -0.157    0.876

Residual standard error: 24.73 on 62 degrees of freedom
  (9 observations deleted due to missingness)
Multiple R-squared:  0.0003975, Adjusted R-squared:  -0.01573
F-statistic: 0.02465 on 1 and 62 DF,  p-value: 0.8757

> ETOC.FO=lm(E.TOC~FlowOut)
> summary(ETOC.FO)

Call:
lm(formula = E.TOC ~ FlowOut)

Residuals:
   Min     1Q Median     3Q    Max
-6.584 -3.573 -1.223  3.558  8.512

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 99.345532  10.672282   9.309 1.87e-11 ***
FlowOut     -0.008023   0.000952  -8.428 2.56e-10 ***
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.325 on 39 degrees of freedom
  (32 observations deleted due to missingness)
Multiple R-squared:  0.6456,    Adjusted R-squared:  0.6365
F-statistic: 71.03 on 1 and 39 DF,  p-value: 2.565e-10

> ITN.FO=lm(I.TN~FlowOut)
> summary(ITN.FO)

Call:
lm(formula = I.TN ~ FlowOut)

Residuals:
    Min      1Q  Median      3Q     Max
-133.22  -69.24  -22.95   27.05  570.00

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -612.64926  273.04022  -2.244   0.0298 *
FlowOut        0.06699    0.02601   2.576   0.0133 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 136.7 on 45 degrees of freedom
  (26 observations deleted due to missingness)
Multiple R-squared:  0.1285,    Adjusted R-squared:  0.1091
F-statistic: 6.636 on 1 and 45 DF,  p-value: 0.01335

> ITP.FO=lm(I.TP~FlowOut)
> summary(ITP.FO)

Call:
lm(formula = I.TP ~ FlowOut)

Residuals:
    Min      1Q  Median      3Q     Max
-54.791 -32.482  -8.594  13.935 242.622

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -330.28447  118.71776  -2.782  0.00792 **
FlowOut        0.03345    0.01129   2.963  0.00489 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 58.68 on 44 degrees of freedom
  (27 observations deleted due to missingness)
Multiple R-squared:  0.1664,    Adjusted R-squared:  0.1474
F-statistic: 8.782 on 1 and 44 DF,  p-value: 0.004895

> ITP.FO=lm(I.COD~FlowOut)
> ICOd.FO=lm(I.COD~FlowOut)
> ICOD.FO=lm(I.COD~FlowOut)
> summary(ICOD.FO)

Call:
lm(formula = I.COD ~ FlowOut)

Residuals:
    Min      1Q  Median      3Q     Max
-343.21 -125.17  -43.05  108.67  453.05

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1147.76108  341.25183   3.363  0.00152 **
FlowOut       -0.08148    0.03215  -2.534  0.01458 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 195.2 on 48 degrees of freedom
  (23 observations deleted due to missingness)
Multiple R-squared:  0.118,     Adjusted R-squared:  0.09966
F-statistic: 6.424 on 1 and 48 DF,  p-value: 0.01458

> ITOC.FO=lm(I.TOC~FlowOut)
> summary(ITOC.FO)

Call:
lm(formula = I.TOC ~ FlowOut)

Residuals:
    Min      1Q  Median      3Q     Max
-25.488 -13.093  -4.895   9.148  29.545

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 352.869778  41.808785   8.440 7.42e-10 ***
FlowOut      -0.028963   0.003806  -7.611 7.65e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 15.92 on 34 degrees of freedom
  (37 observations deleted due to missingness)
Multiple R-squared:  0.6301,    Adjusted R-squared:  0.6192
F-statistic: 57.92 on 1 and 34 DF,  p-value: 7.645e-09

> OTN.FO=lm(O.TN~FlowOut)
> summary(OTN.FO)

Call:
lm(formula = O.TN ~ FlowOut)

Residuals:
   Min     1Q  Median     3Q    Max
-155.54  -45.92  -13.03   65.30  154.89

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.522e+03  1.407e+02  -17.93   <2e-16 ***
FlowOut      2.900e-01  1.344e-02   21.58   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 90.87 on 63 degrees of freedom
  (8 observations deleted due to missingness)
Multiple R-squared:  0.8808,    Adjusted R-squared:  0.8789
F-statistic: 465.7 on 1 and 63 DF,  p-value: < 2.2e-16

> OTP.FO=lm(O.TP~FlowOut)
> summary(OTP.FO)

Call:
lm(formula = O.TP ~ FlowOut)

Residuals:
   Min     1Q  Median     3Q    Max
-79.128 -24.885  -4.525  42.300  69.680

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.086e+03  6.831e+01  -15.90   <2e-16 ***
FlowOut      1.236e-01  6.524e-03   18.95   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 44.12 on 63 degrees of freedom
```

```
  (8 observations deleted due to missingness)
Multiple R-squared:  0.8507,    Adjusted R-squared:  0.8483
F-statistic: 358.9 on 1 and 63 DF,  p-value: < 2.2e-16

> OCOD.FO=lm(O.COD~FlowOut)
Error in eval(expr, envir, enclos) : object 'O.COD' not found
> OTOC.FO=lm(O.TOC~FlowOut)
> summary(OTOC.FO)

Call:
lm(formula = O.TOC ~ FlowOut)

Residuals:
    Min      1Q  Median      3Q     Max
-20.272  -9.692  -0.652  11.783  19.869

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 241.939628  28.483741   8.494 5.59e-11 ***
FlowOut      -0.020130   0.002548  -7.899 4.17e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.21 on 46 degrees of freedom
  (25 observations deleted due to missingness)
Multiple R-squared:  0.5756,    Adjusted R-squared:  0.5664
F-statistic:  62.4 on 1 and 46 DF,  p-value: 4.166e-10

> OC3.OTN=lm(O.C3~O.TN)
> summary(OC3.OTN)

Call:
lm(formula = O.C3 ~ O.TN)

Residuals:
     Min       1Q   Median       3Q      Max
-0.97689 -0.30225  0.04476  0.25288  1.18305

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.7294429  0.1138534   23.97  < 2e-16 ***
O.TN        -0.0020818  0.0002008  -10.37 3.02e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4196 on 63 degrees of freedom
```

```
  (8 observations deleted due to missingness)
Multiple R-squared:  0.6304,    Adjusted R-squared:  0.6246
F-statistic: 107.5 on 1 and 63 DF,  p-value: 3.019e-15

> OC3.OFI=lm(O.C3~O.FI)
> summary(OC3.OFI)

Call:
lm(formula = O.C3 ~ O.FI)

Residuals:
    Min      1Q  Median      3Q     Max
-0.80356 -0.32591  0.03986  0.25431  1.66191

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -8.1858     1.1100  -7.375 2.58e-10 ***
O.FI          5.2948     0.5979   8.855 4.87e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4635 on 70 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.5284,    Adjusted R-squared:  0.5216
F-statistic: 78.42 on 1 and 70 DF,  p-value: 4.869e-13

> OFI.OTN=lm(O.FI~O.TN)
> summary(OFI.OTN)

Call:
lm(formula = O.FI ~ O.TN)

Residuals:
     Min       1Q    Median       3Q      Max
-0.107307 -0.039633 -0.007206  0.039061  0.155532

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.010e+00  1.408e-02  142.80   <2e-16 ***
O.TN        -2.967e-04  2.483e-05  -11.95   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05188 on 63 degrees of freedom
  (8 observations deleted due to missingness)
Multiple R-squared:  0.6939,    Adjusted R-squared:  0.689
```

```
F-statistic: 142.8 on 1 and 63 DF,  p-value: < 2.2e-16

> OC.OTN=lm(O.C~O.TN)
> summary(OC.OTN)

Call:
lm(formula = O.C ~ O.TN)

Residuals:
    Min      1Q  Median      3Q     Max
-1.09131 -0.38066  0.04176  0.33500  1.16648

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.1513903  0.1246521   25.28   <2e-16 ***
O.TN        -0.0024886  0.0002199  -11.32   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4594 on 63 degrees of freedom
  (8 observations deleted due to missingness)
Multiple R-squared:  0.6704,    Adjusted R-squared:  0.6651
F-statistic: 128.1 on 1 and 63 DF,  p-value: < 2.2e-16

> OM.OTN=lm(O.M~O.TN)
> summary(OM.OTN)

Call:
lm(formula = O.M ~ O.TN)

Residuals:
    Min      1Q  Median      3Q     Max
-0.94150 -0.21432  0.09698  0.21545  1.39120

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.8906039  0.1180661  24.483  < 2e-16 ***
O.TN        -0.0019574  0.0002083  -9.399 1.33e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4351 on 63 degrees of freedom
  (8 observations deleted due to missingness)
Multiple R-squared:  0.5837,    Adjusted R-squared:  0.5771
F-statistic: 88.35 on 1 and 63 DF,  p-value: 1.326e-13
```

Appendix D - MatLab Code

```
%-- 5/20/2015 11:38 AM --%
%-- 5/20/2015 1:12 PM --%
a = 1
b = 2
c = a + b
DOMFluor
load PARAFACexample.mat
OriginalData
PlotEEMby1(1:5,OriginalData,'R.U.')
PlotEEMby5(1:5.OriginalData,'R.U.')
PlotEEMby5(1:5,OriginalData,'R.U.')
PlotEEMby4(1:5,OriginalData,'R.U.')
PlotEEMby4FixZ(1,OriginalData,'R.U.')
PlotEEMby4FixZ(1:1,OriginalData,'R.U.')
help PlotEEMby1
help load
whos
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'No')
help EEMCut
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'Yes')
[CutData]=EEMCut(OriginalData,2,2,NaN,NaN,'No')
[CutData]=EEMCut(OriginalData,2,2,1,1,'No')
[CutData]=EEMCut(OriginalData,20,20,20,20,'No')
[CutData]=EEMCut(OriginalData,20,20,NaN,Nan,'')
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
help OutlierTest
[Test1]=OutlierTest(CutData,4,2,6,'No','No')
help PlotLoadings
PlotLoadings(Test1,2)
help PlotLeverage
PlotLeverage(Test1,2)
PlotLL(Test1,2)
PlotLoadings(Test1,2)
PlotLoadings(Test1,3)
PlotLoadings(Test1,4)
PlotLoadings(Test1,3)
PlotLoadings(Test1,2)
PlotLoadings(Test1,5)
PlotLoadings(Test1,6)
PlotLoadings(Test1,7)
PlotLoadings(Test1,2)
[Test2]=OutlierTest(CutData,4,2,6,'Yes','No')
PlotLoadings(Test1,4)
```

```
PlotLoadings(Test2,4)
PlotLL(Test1,4)
PlotLL(Test2,4)
PlotEEMby4(1,CutData,'R.U.')
help RemoveOutliers
[Test3]=RemoveOutliers(Test1,[5 30],,)
[Test3]=RemoveOutliers(Test1,[5 30],[],[])
[Test3]=OutlierTest(Test3,1,1,7,'No','No')
PlotLL(Test3,4)
PlotLL(Test3,3)
PlotLL(Test3,5)
PlotLL(Test3,2)
PlotLL(Test3,3)
PlotLL(Test3,6)
PlotLL(Test3,7)
PlotLL(Test3,3)
[Test3]=OutlierTest(Test3,1,1,7,'Yes','No')
PlotLL(Test3,3)
PlotEEMby1(18:22,Test3,'R.U.')
help EvalModel
EvalModel(Test3,4)
EvalModel(Test3,43)
EvalModel(Test3,4)
EvalModel(Test3,5)
EvalModel(Test2,4)
help Compare2Models
help CompareSpecSSE
Compare2Models(Test3,4,5)
Compare2Models(Test3,4,5,'No')
Compare2Models(Test3,4,5)
Compare2Models(Test3,5,6)
Compare2Models(Test3,3,4)
PlotLoadings(Test3,4)
PlotLoadings(Test3,5)
PlotLoadings(Test3,6)
PlotLoadings(Test3,7)
CompareSpecSSE(Test3,3,4,5)
CompareSpecSSE(Test3,4,5,6)
CompareSpecSSE(Test3,5,6,7)
help SlpitData
help SplitData
[AnalysisData]=SplitData(Test3)
[AnalysisData]=SplitHelfAnalysis(AnalysisData,(3:7),'MyData.mat')
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:7),'MyData.mat')
help SplitHalfValidation
SplitHalfValidation(AnalysisData,'1-2',3)
```

```
SplitHalfValidation(AnalysisData,'1-2',2)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'1-2',7)
help RandInitAnal
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
PlotLL(AnalysisData,4)
EvalModel(AnalysisData,4)
SplitHalfValidatin(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',4)
EvalModel(AnalysisData,4)
help TCC
TCC(AnalysisData.Model4,NalaysisData.Slpit(1).Fac_4)
TCC(AnalysisData.Model4,AnalysisData.Slpit(1).Fac_4)
TCC(AnalysisData.Model4,AnalysisData.Split(1).Fac_4)
%-- 11/10/2015 4:20 PM --%
load('C:\Users\jdscott\Desktop\Kansas River File Copies\2015_10_27\20151025104950.mat')
load('C:\Users\jdscott\Desktop\Kansas River File Copies\2015_10_27\20151025113032.mat')
BottomTrack
plot(Depth, Mean_Vel)
plot(Summary.Depth,Summary.Mean_Vel)
variance Summay.Depth
cov(Summary.Depth)
std(Summary.Depth)
mean(Summary.Depth)
load('C:\Users\jdscott\Desktop\Kansas River File
Copies\2015_10_27\MATLab\20151025104950.mat')
load('C:\Users\jdscott\Desktop\Kansas River File
Copies\2015_10_27\MATLab\20151025113032.mat')
load('C:\Users\jdscott\Desktop\Kansas River File
Copies\2015_10_27\MATLab\20151025113534.mat')
load('C:\Users\jdscott\Desktop\Kansas River File
Copies\2015_10_27\MATLab\20151025121812.mat')
load('C:\Users\jdscott\Desktop\Kansas River File
Copies\2015_10_27\MATLab\20151025122321.mat')
load('C:\Users\jdscott\Desktop\Kansas River File
Copies\2015_10_27\MATLab\20151025124325.mat')
load('C:\Users\jdscott\Desktop\Kansas River File
Copies\2015_10_27\MATLab\20151025124907.mat')
```

load('C:\Users\jdscott\Desktop\Kansas River File Copies\2015_10_27\MATLab\20151025132752.mat')
load('C:\Users\jdscott\Desktop\Kansas River File Copies\2015_10_27\MATLab\20151025133225.mat')
load('C:\Users\jdscott\Desktop\Kansas River File Copies\2015_10_27\MATLab\20151025104950.mat')
%-- 11/11/2015 10:31 AM --%
load('20151025104950.mat')
exist(20151025104950.mat)
clear all
load('20151025104950.mat')
load('20151025113032.mat')
load('20151025104950.mat')
loadfixnames(20151025104950 [,names] [,verbose])
S = loadfixnames(20151025104950 [,names] [,verbose])
S = loadfixnames(20151025104950 ,names] [,verbose])
S = loadfixnames(20151025104950 [,names] [,verbose])
S = loadfixnames(20151025104950 ,names ,verbose)
loadfixnames(20151025104950 [,names] [,verbose])
loadfixnames(20151025104950 ,Summary.Depth ,0)
load('20151025113032.mat')
std(Summary.Depth)
mean(Summary.Depth)
load('20151025113534.mat')
std(Summary.Depth)
mean(Summary.Depth)
load('20151025121812.mat')
std(Summary.Depth)
mean(Summary.Depth)
Summary.Depth
load('20151025113032.mat')
Summary.Depth
%-- 11/11/2015 2:14 PM --%
load('20151025122321.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151025124325.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151025124907.mat')
std(Summary.Depth)
mean(Summary.Depth)
load('20151025132752.mat')
std(Summary.Depth)
mean(Summary.Depth)
load('20151025133225.mat')

```
std(Summary.Depth)
mean(Summary.Depth)
load('20151007104009.mat')
std(Summary.Depth)
mean(Summary.Depth)
std(Summary.Depth)
load('20151007105037.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151007110913.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020093319.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020094625.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020102726.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020103344.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020103825.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020110902.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020112650.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020113109.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020123038.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020123501.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020130826.mat')
mean(Summary.Depth)
std(Summary.Depth)
load('20151020131426.mat')
```

```
mean(Summary.Depth)
std(Summary.Depth)
load('20151007104009.mat')
load('20151007105037.mat')
load('20151007110913.mat')
load('20151020093319.mat')
load('20151020094625.mat')
load('20151020102726.mat')
load('20151020103344.mat')
load('20151020103825.mat')
load('20151020110902.mat')
load('20151020112650.mat')
load('20151020113109.mat')
load('20151020123038.mat')
load('20151020123501.mat')
load('20151020130826.mat')
load('20151020131426.mat')
load('20151025104950.mat')
load('20151025113032.mat')
load('20151025113534.mat')
load('20151025121812.mat')
load('20151025122321.mat')
load('20151025124325.mat')
load('20151025124907.mat')
load('20151025132752.mat')
load('20151025133225.mat')
%-- 11/12/2015 8:35 AM --%
load('20151025113032.mat')
load('20151025113534.mat')
load('20151025121812.mat')
load('20151025122321.mat')
load('20151025113032.mat')
mean Summary.Mean_Vel
load('20151025113534.mat')
mean Summary.Mean_Vel
load('20151025122321.mat')
mean Summary.Mean_Vel
mean (Summary.Mean_Vel)
load('20151025113032.mat')
mean (Summary.Mean_Vel)
load('20151025113032.mat', 'Processing')
plot(Summary.Mean_Vel,'DisplayName','Summary.Mean_Vel')
%-- 11/12/2015 2:02 PM --%
load('20151025113032.mat')
load('20151025113534.mat')
load('20151025121812.mat')
```

load('20151025122321.mat')
load('20151025124325.mat')
load('20151025124907.mat')
load('20151025132752.mat')
load('20151025133225.mat')
%-- 11/13/2015 10:06 AM --%
load('20151007104009.mat')
load('20151007105037.mat')
load('20151007110913.mat')
load('20151007105037.mat')
load('20151020093319.mat')
load('20151020094625.mat')
load('20151020102726.mat')
load('20151020103344.mat')
load('20151020110902.mat')
load('20151020103825.mat')
load('20151020110902.mat')
load('20151020112650.mat')
load('20151020113109.mat')
load('20151020123038.mat')
load('20151020123501.mat')
load('20151020130826.mat')
load('20151020131426.mat')
load('20151007105037.mat')
load('20151007110913.mat')
load('20151007105037.mat')
load('20151020093319.mat')
load('20151020094625.mat')
load('20151020102726.mat')
load('20151020103344.mat')
load('20151020103825.mat')
load('20151020110902.mat')
load('20151020112650.mat')
load('20151020113109.mat')
load('20151020123038.mat')
load('20151020123501.mat')
load('20151020130826.mat')
load('20151020131426.mat')
%-- 4/20/2016 2:27 PM --%
%-- 8/29/2016 10:18 AM --%
ProcessData ('C:\Users\jdscott\Documents\MBR\Data Analysis\PF model 2')
1
0
1
close all
%-- 8/29/2016 10:30 AM --%

ProcessData ('C:\Users\jdscott\Documents\MBR\Data Analysis\Raw Data')
1
0
1
ProcessData ('C:\Users\jdscott\Documents\MBR\Data Analysis\Raw Data\P160817')
1
0
1
ProcessData ('C:\Users\jdscott\Documents\MBR\Data Analysis\Raw Data\P160817\int0pt5')
1
Raw Data
Abs Spectra Graphs>> Graphs
ABS Spectra Graphs>> Graphs
ProcessData ('C:\Users\jdscott\Documents\MBR\Data Analysis\Raw Data')
1
0
1
close all
ProcessData ('C:\Users\jdscott\Documents\MBR\Data Analysis\Raw Data')
1
0
1
%-- 8/29/2016 10:52 AM --%
ProcessData ('C:\Users\jdscott\Documents\MBR\Data Analysis\Raw Data')
1
0
1
close all
%-- 8/29/2016 12:43 PM --%
ProcessData ('C:\Users\jdscott\Documents\MBR\Data Analysis\Raw Data\P160817\int0pt5')
1
clo
cl
close all
clear
ProcessData ('C:\Users\jdscott\Documents\MBR\Data Analysis\Raw Data\P160817\int0pt5')
1
%-- 8/29/2016 12:56 PM --%
ProcessData('C:\Users\jdscott\Documents\MBR\Data Analysis\Raw Data\P160817\int0pt5')
1
%-- 8/29/2016 12:58 PM --%
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160817\int0pt5')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160817\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160817\int0pt5\')

```
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160817\int0pt5\')
1
close all
%-- 8/29/2016 1:07 PM --%
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160817\int0pt5\')
1
%-- 8/29/2016 1:11 PM --%
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160817\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160817\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160817\int0pt25\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160819\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160822\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160823\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160825\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160826\int0pt5\')
1
11
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160826\int0pt5\')
close all
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160826\int0pt5\')
%-- 8/29/2016 1:28 PM --%
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\P160826\int0pt5\')
1
cloase all
close all
%-- 8/29/2016 1:34 PM --%
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\PF\')
%-- 8/29/2016 1:48 PM --%
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\PF\')
%-- 8/29/2016 4:21 PM --%
i
clc
clear
```

```
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\P160817\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\P160817\int0pt25\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\P160819\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\P160822\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\P160823\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\P160825\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\P160826\int0pt5\')
1
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\PF\')
clear
close all
%-- 8/30/2016 9:45 AM --%
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\PF\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\PF\')
close all
%-- 8/30/2016 10:06 AM --%
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\PF model 2\Parafacfiles\PF\')
DOMFlour
DOMFluor
load pf.mat
OriginalData
PlotEEMby4FixZ(1,OriginalData,'R.U.')
help EEMCut
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'No')
help OutlierTest
[Test1]=OutlierTest(CutData,2,1,7,'No','No')
help PlotLoadings
PlotLoadings(Test1,2)
PlotLoadings(Test1,3)
PlotLoadings(Test1,4)
PlotLoadings(Test1,3)
PlotLoadings(Test1,5)
PlotLoadings(Test1,6)
PlotLoadings(Test1,7)
help PlotLeverage
```

```
PlotLeverage(Test1,2)
PlotLL(Test1,2)
PlotLL(Test1,3)
PlotLL(Test1,4)
PlotLL(Test1,5)
PlotLL(Test1,6)
PlotLL(Test1,7)
PlotLL(Test1,2)
PlotLL(Test1,4)
[Test2]=OutlierTest(CutData,2,1,7,'Yes','No')
PlotLL(Test2,2)
PlotLL(Test2,3)
PlotLL(Test2,4)
PlotLL(Test2,5)
PlotLL(Test2,6)
PlotLL(Test2,7)
PlotLL(Test2,6)
PlotLL(Test2,2)
PlotLL(Test2,3)
PlotLL(Test2,6)
PlotLL(Test2,4)
PlotLL(Test2,6)
PlotLL(Test2,4)
help EvalModel
EvalModel(Test2,4)
EvalModel(Test2,6)
EvalModel(Test2,2)
help Compare2Models
Compare2Models(Test2,2,3)
help CompareSpecSSE
CompareSpecSSE(Test2,3,4,5)
CompareSpecSSE(Test2,2,6,7)
CompareSpecSSE(Test2,2,3,4)
CompareSpecSSE(Test2,4,5,6)
CompareSpecSSE(Test2,5,6,7)
help SplitData
[AnalysisData]=SplitData(Test2)
help SplitHalfAnalysis
[AnalysisData]=SplitHalfAnalysis(AnalisisData,2:7,'MyPFData.mat')
[AnalysisData]=SplitHalfAnalysis(AnalysisData,2:7,'MyPFData.mat')
help SplitHalfValidation
SplitHalfValidation(AnalysisData,'1-2',2)
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
```

```
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',2)
help RandInitAnal
[AnalysisData]=RandInitAnal(AnalysisData,2,10)
PlotLL(AnalysisData,2)
SplitHalfValidation(AnalysisData,'1-2',2)
EvalModel(AnalysisData,2)
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
PlotLL(AnalysisData,3)
EvalModel(AnalysisData,3)
RandInitResult
help RandInitResult
[AnalysisData]=RandInitResult(AnalysisData,3,10)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
[AnalysisData]=RandInitResult(AnalysisData,4,10)
PlotLL(AnalysisData,4)
EvalModel(AnalysisData,4)
[AnalysisData]=RandInitResult(AnalysisData,4,10)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
PlotLL(AnalysisData,5)
EvalModel(AnalysisData,5)
[AnalysisData]=RandInitResult(AnalysisData,5,10)
[AnalysisData]=RandInitResult(AnalysisData,4,10)
[AnalysisData]=RandInitResult(AnalysisData,2,10)
[AnalysisData]=RandInitAnal(AnalysisData,2,10)
PlotLL(AnalysisData,2)
EvalModel(AnalysisData,2)
[AnalysisData]=RandInitResult(AnalysisData,2,10)
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
[AnalysisData]=RandInitResult(AnalysisData,3,10)
PlotLL(AnalysisData,3)
EvalModel(AnalysisData,3)
[AnalysisData]=RandInitResult(AnalysisData,3,10)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
PlotLL(AnalysisData,4)
EvalModel(AnalysisData,4)
[AnalysisData]=RandInitResult(AnalysisData,4,10)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
PlotLL(AnalysisData,5)
EvalModel(AnalysisData,5)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
```

```
[AnalysisData]=RandInitAnal(AnalysisData,6,10)
PlotLL(AnalysisData,5)
EvalModel(AnalysisData,6)
PlotLL(AnalysisData,6)
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
EvalModel(AnalysisData,7)
PlotLL(AnalysisData,7)
[AnalysisData]=RandInitResult(AnalysisData,7,10)
[Test2]=OutlierTest(OriginalData,1,1,7,'Yes','No')
[Test2]=OutlierTest(CutData,1,1,7,'Yes','No')
[AnalysisData]=SplitData(Test2)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(2:7),'MyPFData.mat')
SplitHalfValidation(AnalysisData,'1-2',2)
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'3-4',2)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
[AnalysisData]=RandInitAnal(AnalysisData,2,10)
PlotLL(AnalysisData,2)
EvalModel(AnalysisData,2)
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
helpRandInitResult
help RandInitResult
[AnalysisData]=RandInitResult(3,10)
[AnalysisData]=RandInitResult(AnalysisData,3,10)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
[AnalysisData]=RandInitResult(AnalysisData,4,10)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',5)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
help CompareSpecSSE
CompareSpecSSE(CutData,2,3,4)
CompareSpecSSE(Test2,2,3,4)
CompareSpecSSE(Test2,3,4,5)
CompareSpecSSE(Test2,2,3,4,)
CompareSpecSSE(Test2,2,3,4)
CompareSpecSSE(Test2,3,4,5)
```

```
CompareSpecSSE(Test2,3,4,7)
SplitHalfValidation(AnalysisData,'1-2',7)
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
help ComponentEEM
ComponentEEM(AnalysisData,7)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
ComponentEEM(AnalysisData,4)
help Modelout
[FMax,B,C]=ModelOut(AnalysisData,7,C:\Users\jdscott\Desktop\Data Analysis\PF model
2\Parafacfiles\7 Component Model\MyParafacResults.xls')
[FMax,B,C]=ModelOut(AnalysisData,7,'C:\Users\jdscott\Desktop\Data Analysis\PF model
2\Parafacfiles\7 Component Model\MyParafacResults.xls')
[FMax,B,C]=ModelOut(AnalysisData,4,'C:\Users\jdscott\Desktop\Data Analysis\PF model
2\Parafacfiles\4 Component Model\MyParafacResults.xls')
MyPFData
%-- 9/8/2016 2:12 PM --%
load pf.mat
load MyPFData.mat
PlotEEMby4FixZ
PlotEEMby4FixZ(1,OriginalData,'R.U.')
clc
dsaklh
PlotEEMby4FixZ(1,OriginalData,'R.U.')
%-- 9/9/2016 4:09 PM --%
%-- 9/12/2016 10:13 AM --%
PlotEEMby4FixZ(1,OriginalData,'R.U.')
load pf.mat
load MyPFDate.mat
load MyPFData.mat
PlotEEMby4FixZ(1,OriginalData,'R.U.')
clc
close all
%-- 9/12/2016 3:40 PM --%
ProcessData ('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\')
1
ProcessData ('C:\Users\jdscott\Desktop\Data Analysis\Raw Data\160912\')
1
dataprep4pf ('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles3\')
1
loadpfdata ('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles3\PF\')
load pf.mat
PlotEEMby4Fixz(1,OriginalData,'R.U.')
PlotEEMby4FixZ(1,OriginalData,'R.U.')
help EEMCut
[CutData]=EEMCut(OriginalData,20,20,Nan,Nan,'')
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
```

```
close all
%-- 9/12/2016 4:08 PM --%
ProcessData ('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\160819\')
1
ProcessData ('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\160912\')
1
%-- 9/12/2016 4:12 PM --%
ProcessData ('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\160912\')
1
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles\PF\')
%-- 9/13/2016 10:12 AM --%
load pf.mat
[CutData]=EEMCut(OriginalData,20,20NaN,NaN,'')
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
help OutlierTest
[Test1]=OutlierTest(CutData,2,1,8,'Yes','No')
PlotLL(Test1,4)
PlotLL(Test1,5)
PlotLL(Test1,6)
PlotLL(Test1,7)
PlotLL(Test1,8)
PlotLL(Test1,3)
PlotLL(Test1,6)
PlotLL(Test1,4)
PlotLL(Test1,5)
PlotLL(Test1,6)
PlotLL(Test1,7)
PlotLL(Test1,8)
PlotLL(Test1,4)
PlotEEMby4(1,CutData,'R.U.')
PlotLL(Test1,5)
help RemoveOutliers
PlotLL(Test1,4)
[NoOutliers]=RemoveOutliers(CutData,[68 80 163 183],[],[])
[Test2]=OutlierTest(CutData,2,1,7,'Yes','No')
PlotLL(Test1,4)
PlotLL(Test1,5)
PlotLL(Test1,6)
PlotLL(Test1,7)
PlotLL(Test1,8)
PlotEEMby4(78:82,CutData,'R.U.')
[Test2]=OutlierTest(NoOutliers,2,1,7,'Yes','No')
PlotLL(Test2,4)
PlotEEMby1(187,CutData,'R.U.')
```

```
PlotEEMby1(166,CutData,'R.U.')
PlotLL(Test2,5)
PlotLL(Test2,6)
PlotLL(Test2,7)
PlotLL(Test2,4)
[Test2]=OutlierTest(CutData,2,1,7,'Yes','No')
[Test2]=OutlierTest(NoOutliers,1,1,7,'Yes','No')
PlotLL(Test2,4)
hep EvalModel
help EvalModel
EvalModel(Test2,4)
EvalModel(Test2,5)
EvalModel(Test2,7)
EvalModel(Test1,4)
EvalModel(Test1,7)
Compare2Models(Test3,2,3)
Compare2Models(Test2,2,3)
[Test2]=OutlierTest(NoOutliers,1,1,9,'Yes','No')
EvalModel(Test2,8)
Compare2Models(Test2,7,8)
CompareSpecSSE(Test2,3,4,5)
CompareSpecSSE(Test2,4,5,6)
CompareSpecSSE(Test2,5,6,7)
CompareSpecSSE(Test2,6,7,8)
CompareSpecSSE(Test2,4,5,6)
[AnalysisData]=SplitData(Test2)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:8),'MyPFData.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',8)
SplitHalfValidation(AnalysisData,'1-2',9)
SplitHalfValidation(AnalysisData,'3-4',8)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',8)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'3-4',4)
help RandInitAnal
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
```

```
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
[AnalysisData]=RandInitAnal(AnalysisData,8,10)
PlotLL(AnalysisData,8)
PlotLL(AnalysisData,7)
PlotLL(AnalysisData,4)
PlotEEMby1(15,AnalysisData,'R.U.')
PlotEEMby1(16,AnalysisData,'R.U.')
ComponentEEM(AnalysisData,8)
ComponentEEM(AnalysisData,4)
ComponentEEM(AnalysisData,7)
ComponentEEM(AnalysisData,8)
PlotEEMby1(16,AnalysisData,'R.U.')
EvalModel(AnalysisData,7)
PlotEEMby1(2,AnalysisData,'R.U.')
PlotLL(AnalysisData,7)
help MOdelOut
[FMax,B,C]=ModelOut(AnalysisData,8,'C:\Users\jdscott\Desktop\Data Analysis\PF model
3\ParafacFiles\8 Component\8CResults\')
[FMax,B,C]=ModelOut(AnalysisData,8,'C:\Users\jdscott\Desktop\8CResults\')
[FMax,B,C]=ModelOut(AnalysisData,8,'C:\Users\jdscott\Desktop\Data Analysis\PF model
3\ParafacFiles\8 Component\8CResults.xls')
%-- 9/13/2016 2:59 PM --%
load pf.mat
load MyPFData.mat
%-- 9/13/2016 3:02 PM --%
load pf.mat
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[AnalysisData]=SplitData(CutData)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:8),'MyPFData.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',8)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',8)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
PlotLL(AnalysisData,5)
```

```
ComponentEEM(AnalysisData,5)
EvalModel(AnalysisData,5)
[Test1]=RemoveOutliers(CutData,[68 80 163 183],[],[])
[AnalysisData]=SplitData(Test1)
[Test1]=OutlierTest(Test1,2,1,8,'Yes','Yes')
PlotLL(Test1,4
PlotLL(Test1,4)
PlotLL(Test1,5)
PlotLL(Test1,6)
EvalModel(Test1,4
EvalModel(Test1,4)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:8),'MyPFData.mat')
%-- 9/13/2016 3:52 PM --%
SplitHalfValidation(AnalysisData,'1-2',3)
load pf.mat
load MyPFData.mat
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',8)
SplitHalfValidation(AnalysisData,'3-4',8)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',3)
ComponentEEM(AnalysisData,7)
ComponentEEM(AnalysisData,4)
help ComponentEEM
AnalysisData
SplitHalfValidation(AnalysisData,'3-4',7)
ComponentEEM(AnalysisData,7)
ComponentEEM(AnalysisData,3)
ComponentEEM(AnalysisData,4)
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
ComponentEEM(AnalysisData,7)
EvalModel(AnalysisData,7)
PlotLL(AnalysisData,7)
[FMax,B,C]=ModelOut(AnalysisData,7,'C:\Users\jdscott\Desktop\Data Analysis\PF model
3\ParafacFiles\8 Component\MyPFResults.xls')
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
PlotLL(AnalysisData,5)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
CompareSpecSSE(AnalysisData,4,5,7)
```

```
[FMax5,B,C]=ModelOut(AnalysisData,5,'C:\Users\jdscott\Desktop\Data Analysis\PF model
3\ParafacFiles\5 Component\MyPFResults.xls')
ComponentEEM(AnalysisData,5)
ComponentEEM(AnalysisData,4)
[FMax5,B,C]=ModelOut(AnalysisData,5,'C:\Users\jdscott\Desktop\Data Analysis\PF model
3\ParafacFiles\4 Component\MyPFResults.xls')
EvalModel(AnalysisData,4)
CompareSpecSSE(AnalysisData,4,5,7)
EvalModel(AnalysisData,5)
EvalModel(AnalysisData,7)
ComponentEEM(AnalysisData,7)
CompareSpecSSE(AnalysisData,4,5,7)
EvalModel(AnalysisData,5)
ComponentEEM(AnalysisData,5)
ComponentEEM(AnalysisData,7)
EvalModel(AnalysisData,7)
EXIT
%-- 9/23/2016 11:40 AM --%
load pf.mat
load MyPFData.mat
ComponentEEM(AnalysisData,7)
EvalModel(AnalysisData,7)
load temp.mat
ComponentEEM(AnalysisData,7)
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
ComponentEEM(AnalysisData,7)
EvalModel(AnalysisData,7)
close all
%-- 9/23/2016 2:20 PM --%
load pf.mat
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[Test1]=RemoveOutliers(CutData,[68 80 163 183],[],[])
[AnalysisData]=SplitData(Test1)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:8),'MyPFData.mat')
SplitHalfValidation(AnalysisDate,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',8)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
```

```
SplitHalfValidation(AnalysisData,'3-4',8)
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
PlotLL(AnalysisData,3)
RandInitResult(AnalysisData,3,10)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
PlotLL(AnalysisData,4)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
PlotLL(AnalysisData,7)
CompareSpecSSE(AnalysisData,4,5,7)
ComponentEEM(AnalysisData,7)
EvalModel(AnalysisData,7)
EvalModel(AnalysisData,5)
ComponentEEM(AnalysisData,5)
[FMax,B,C]=ModelOut(AnalysisData,7,'C:\Users\jdscott\Desktop\Data Analysis\PF model
3\ParafacFiles\Total PF Model\7CResults.xls')
[FMax,B,C]=ModelOut(AnalysisData,5,'C:\Users\jdscott\Desktop\Data Analysis\PF model
3\ParafacFiles\Total PF Model\5C\5CResults.xls')
[FMax,B,C]=ModelOut(AnalysisData,4,'C:\Users\jdscott\Desktop\Data Analysis\PF model
3\ParafacFiles\Total PF Model\4C\4CResults.xls')
close all
ComponentEEM(AnalysisData,7)
EvalModel(AnalysisData,7)
cloase all
close all
ComponentSurf(AnalysisData,7)
close all
ComponentEEM(AnalysisData,7)
EvalModel(AnalysisData,7)
close all
help parafac
help MeanError
MeanError(AnalysisData(4,5,7)
MeanError(AnalysisData4,5,7)
MeanError(AnalysisData,4,5,7)
help MMR
help calcore
help Nwayparafac
help Itest
load('C:\Users\jdscott\Desktop\Data Analysis\MATLAB and Articles
1\ModifiedDOMFluor\nway\howto1.mat')
MeanError(AnalysisData,4,5,7)
help DOMFluor
%-- 9/28/2016 3:13 PM --%
load('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles\PF\MyPFData.mat')
MeanError(AnalysisData,4,5,7)
```

```
AnalysisData
ComponentSurf(AnalysisData,7)
load('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles\PF\pf.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles\PF\temp.mat')
ComponentSurf(AnalysisData,7)
help ModelIn
help help
load('temp.mat')
ComponentSurf(AnalysisData,7)
load('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles\PF\temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles\PF\pf.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\PF model 3\ParafacFiles\PF\MyPFData.mat')
ComponentSurf(AnalysisData,7)
AnalysisData
ComponentSurf(AnalysisData,7)
help ModelOut
help readineems
help modelout
%-- 9/30/2016 3:23 PM --%
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Breakthrough\day 1\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Breakthrough\day 1\')
1
clear
clc
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Breakthrough\day 1\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Breakthrough\day 2\')
1
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Breakthrough\day 3\')
1
dataperp4pf('C:\Users\jdscott\Desktop\Data Analysis\Final Model\')
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\Final Model\')
1
loadpfdata(C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\')
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\')
load pf.mat
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[Test1]=OutlierTest(CutData,2,1,8,'Yes','No')
PlotLL(Test1,2
PlotLL(Test1,2)
PlotLL(Test1,3)
PlotLL(Test1,4)
PlotLL(Test1,5)
PlotLL(Test1,6)
PlotLL(Test1,7)
```

```
PlotLL(Test1,8)
PlotEEMby4(78,CutData,'R.U.')
close all
[Test2]=RemoveOutliers(CutData,[78 79 80],[],[])
[Test2]=OutlierTest(Test2,1,1,8,'Yes','No')
PlotLL(Test1,7)
PlotLL(Test2,7)
[Test2]=RemoveOutliers(CutData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
25 26 27 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56
57 58 59 60 61 62],[],[])
PlotEEMby4(1,Test2,'R.U.')
[Test3]=RemoveOutliers(Test2,[71 82 164 184],[],[])
PlotLL(Test3,3)
[Test4]=OutlierTest(Test3,1,1,8,'Yes'.'No')
[Test4]=OutlierTest(Test3,1,1,8,'Yes','No')
PlotLL(Test4,3)
PlotLL(Test4,4)
PlotLL(Test4,5)
PlotLL(Test4,6)
PlotLL(Test4,7)
PlotLL(Test4,8)
close all
EvelModel(Test4,2)
EvalModel(Test4,2)
lc
clc
close all
EvalModel(Test4,5)
close all
[AnalysisData]=SplitData(Test4)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:8),'MyData.mat')
SplitHalfvalidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',8)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',8)
close all
[AnalysisData4]=RandInitAnal(AnalysisData,4,10)
```

```
[AnalysisData5]=RandInitAnal(AnalysisData,5,10)
[AnalysisData6]=RandInitAnal(AnalysisData,6,10)
[AnalysisData7]=RandInitAnal(AnalysisData,7,10)
%-- 10/3/2016 9:16 AM --%
load('pf.mat')
load('MyData.mat')
load('temp.mat')
RandInitResult(AnalysisData,4,10)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',8)
SplitHalfValidation(AnalysisData,'3-4',8)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',3)
cloase all
close all
RandInitResult(AnalysisData4,4,10)
[AnalysisData=RandInitAnal(Analysisdata,4,10)
[AnalysisData]=RandInitAnal(Analysisdata,4,10)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
ComponentEEM(AnalysisData,4)
EvalModel(AnalysisData,4)
close all
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
ComponentEEM(AnalysisData,5)
EvalModel(AnalysisData,5)
close all
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
ComponentEEM(AnalysisData,7)
EvalModel(AnalysisData,7)
close all
[AnalysisData]=RandInitAnal(AnalysisData,8,10)
ComponentEEM(AnalysisData,8)
EvalModel(AnalysisData,8)
close all
help describecomp
describecomp(AnalysisData,8)
help ModelOut
%-- 10/3/2016 10:36 AM --%
```

```
load('pf.mat')
load('MyData.mat')
load('temp.mat')
[AnalysisData]=RandInitAnal(AnalysisData,8,10)
ComponentEEM(AnalysisData,8)
close all
describecomp(AnalysisData,8)
help ModelOut
[FMax,B,C]=ModelOut(AnalysisData,8,'C:\Users\jdscott\Desktop\Data Analysis\Final Model\8
Component\8CDOMFluorOutPut.xls')
help ModelOut
[FMax,B,C,FMaxFull,Proj]=ModelOut(AnalysisData,8,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\8 Component\8CdrEEMModelOut.xls',CutData)
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[FMax,B,C,FMaxFull,Proj]=ModelOut(AnalysisData,8,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\8 Component\8CdrEEMModelOut.xls',CutData)
[FMax,B,C,FMaxFull]=ModelOut(AnalysisData,8,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\8 Component\8CdrEEMModelOut.xls',CutData)
[FMax,B,C,FMaxFull]=ModelOut(AnalysisData,8,'8CdrEEMModelOut.xls',CutData)
modelout
[FMax,B,C,FMaxFull]=ModelOut(AnalysisData,8,'8CdrEEMModelOut.xls',CutData)
help ModelOut
[FMax,B,C,FMaxFull]=ModelOut(AnalysisData,8,'8CdrEEMModelOut.xls',CutData)
[FMax,B,C,FMaxFull]=ModelOut(AnalysisData,8,'8CdrEEMModelOut.xls')
[FMax,B,C,FMaxFull]=modelout(AnalysisData,8,'8CdrEEMModelOut.xls',CutData)
1
ComponentEEM(AnalysisData,8)
ComponentSurf(AnalysisData,8)
EvalModel(AnalysisData,8)
close all
EvalModel(AnalysisData,8)
help MMR
help meanerror
MeanError(AnalysisData,5,7,8)
MeanError(AnalysisData,4,7,8)
MeanError(AnalysisData,,,8)
MeanError(AnalysisData,[],[],8)
close all
%-- 10/3/2016 11:56 AM --%
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\Effluent Model\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\Effluent Model\PF\')
load('pf.mat')
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[Test1]=OutlierTest(CutData,2,1,7,'No','No')
PlotLL(Test1,3)
```

```
PlotLL(Test1,4)
PlotLL(Test1,5)
PlotLL(Test1,6)
PlotLL(Test1,7)
PlotLL(Test1,8)
close all
[Test1]=RemoveOutliers(CutData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55
56 57 58 59 60 61 62 80 127],[],[])
[Test2]=OutlierTest(Test1,1,1,8,'Yes','No')
PlotLL(Test2,8)
PlotLL(Test2,3)
close all
PlotEEMby4(45,Test2,'R.U.')
PlotEEMby4(1,Test2,'R.U.')
close all
[Test3]=RemoveOutliers(Test2,[53 54 55],[],[])
[AnalysisData]=SplitData(Test3)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:8),'MyData.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',8)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',8)
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
PlotLL(AnalysisData,3)
ComponentEEM(AnalysisData,3)
close all
EvalModel(AnalysisData,3)
close all
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
PlotLL(AnalysisData,4)
ComponentEEM(AnalysisData,3)
ComponentEEM(AnalysisData,4)
EvalModel(AnalysisData,4)
ComponentEEM(AnalysisData,4)
[FMax,B,C]=ModelOut(AnalysisData,8,'C:\Users\jdscott\Desktop\Data Analysis\Final Model\8
Component\8CDOMFluorOutPut.xls')
```

```
[FMax,B,C]=ModelOut(AnalysisData,4,'C:\Users\jdscott\Desktop\Data Analysis\Effluent
Model\PF\4C\C4DOMFluor.xls')
[FMax,B,C,FMaxFull]=modelout(AnalysisData,4,C:\Users\jdscott\Desktop\Data
Analysis\Effluent Model\PF\4C\4CdrEEM.xls',CutData)
[FMax,B,C,FMaxFull]=modelout(AnalysisData,4,'C:\Users\jdscott\Desktop\Data
Analysis\Effluent Model\PF\4C\4CdrEEM.xls',CutData)
1
describecomp(AnalysisData,4)
MeanError(AnalysisData,3,4,5)
MeanError(AnalysisData,3,4,)
MeanError(AnalysisData,3,4,[])
MeanError(AnalysisData,3,4,'NaN')
ComponentSurf(AnalysisData,4)
close all
%-- 10/3/2016 4:34 PM --%
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\Effluent Model\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\Effluent Model\PF\')
load('pf.mat')
[CutData]=EEMCut(OriginalData,20,20,'NaN','NaN','')
[Test1]=RemoveOutliers(CutData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55
56 57 58 59 60 61 62],[],[])
[Testi1]-OutlierTest(Test1,2,1,7,'Yes','No')
[Test1]=OutlierTest(Test1,2,1,7,'Yes','No')
PlotEEMby4(1,Test1,'R.U.')
[Test1]=OutlierTest(Test1,2,1,7,'Yes','No')
PlotLL(3,4,5)
PlotLL(Test1,4)
PlotEEMby4(54,Test1,'R.U.')
[AnalysisData]=SplitData(Test1)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:7),'MyData.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
ComponentEEM(AnalysisData,4)
RandInitAnal(AnalysisData,4,10)
ComponentEEM(AnalysisData,4)
SplitHalfValidation(AnalysisData,'1-2',4)
```

```
close all
RandInitAnal(AnalysisData,4,10)
PlotLL(AnalysisData,4)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
PlotLL(AnalysisData,4)
RandInitResult(AnalysisData,4,1)
RandInitResult(AnalysisData,4,2)
RandInitResult(AnalysisData,4,3)
RandInitResult(AnalysisData,4,4)
RandInitResult(AnalysisData,4,5)
RandInitResult(AnalysisData,4,6)
RandInitResult(AnalysisData,4,7)
RandInitResult(AnalysisData,4,8)
RandInitResult(AnalysisData,4,9)
RandInitResult(AnalysisData,4,10)
[FMax,B,C]=ModelOut(AnalysisData,4,'C:\Users\jdscott\Desktop\Data Analysis\Effluent
Model\PF\4C\C4DOMFluor.xls')
[FMax,B,C]=ModelOut(AnalysisData,4,'C:\Users\jdscott\Desktop\Data Analysis\Effluent
Model\4Component Model\C4DOMFluor.xls')
[FMax,B,C,FMaxFull]=modelout(AnalysisData,4,'C:\Users\jdscott\Desktop\Data
Analysis\Effluent Model\4Component Model\4CdrEEM.xls',CutData)
[CutData]=EEMCut(OriginalData,20,20,'NaN','NaN','')
%-- 10/4/2016 9:15 AM --%
load('pf.mat')
[CutData]=EEMCut(OriginalData,20,20,'NaN','NaN','')
%-- 10/4/2016 9:25 AM --%
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\Effluent Model\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\Effluent Model\PF\')
load pf.mat
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[Test1]=RemoveOutliers(CutData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55
56 57 58 59 60 61 62],[],[])
[AnalysisData]=SplitData(Test1)
close all
PlotEEMby4(1,Test1)
PlotEEMby4(1,Test1,'R.U.')
[Test2]=RemoveOutliers(Test1,[54],,)
[Test2]=RemoveOutliers(Test1,[54],[],[])
PlotEEmby4(1,Test2,'R.U.')
PlotEEMby4(1,Test2,'R.U.')
[AnalysisData]=SplitData(Test2)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:7),'MyData.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
```

```
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
close all
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
RandInitResult(AnalysisData,4,1)
RandInitResult(AnalysisData,4,2)
RandInitResult(AnalysisData,4,3)
RandInitResult(AnalysisData,4,4)
RandInitResult(AnalysisData,4,5)
RandInitResult(AnalysisData,4,6)
RandInitResult(AnalysisData,4,7)
RandInitResult(AnalysisData,4,8)
RandInitResult(AnalysisData,4,9)
RandInitResult(AnalysisData,4,10)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
RandInitResult(AnalysisData,5,10)
RandInitResult(AnalysisData,5,9)
RandInitResult(AnalysisData,5,8)
EvalModel(AnalysisData,5)
ComponentEEM(AnalysisData,5)
ComponentEEM(AnalysisData,4)
EvalModel(AnalysisData,5)
PlotLL(AnalysisData,5)
EvalModel(AnalysisData,5)
CompareSpecSSE(AnalysisData,3,4,5)
EvalModel(AnalysisData,4)
close all
EvalModel(AnalysisData,5)
[Test3]=RemoveOutliers(Test2,[4],[],[])
[AnalysisData]=SplitData(Test3)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:7),'MyData.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
```

```
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
ComponentEEM(AnalysisData,7)
close all
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
ComponentEEM(AnalysisData,7)
ComponentEEM(AnalysisData,4)
[AnalysisData]=SplitData(Test2)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:7),'MyData.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',3)
close all
ComponentEEM(AnalysisData,4)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
ComponentEEM(AnalysisData,4)
ComponentEEM(AnalysisData,5)
close all
Compare2Models(AnalysisData,4,5)
[FMax,B,C]=ModelOut(AnalysisData,4,'C:\Users\jdscott\Desktop\Data Analysis\Effluent
Model\4C\4CDOMFluor.xls')
[FMax,B,C]=ModelOut(AnalysisData,5,'C:\Users\jdscott\Desktop\Data Analysis\Effluent
Model\5C\5CDOMFluor.xls')
ComponentEEM(AnalysisData,5)
ComponentSurf(AnalysisData,4)
ComponentEEM(AnalysisData,4)
[FMax,B,C,FMaxFull]=modelout(AnalysisData,4,'C:\Users\jdscott\Desktop\Data
Analysis\Effluent Model\4C\4CdrEEM.xls',CutData)
1
describecomp(AnalysisData,4)
%-- 10/4/2016 2:17 PM --%
ProcessData('C:\Users\jdscott\Desktop\Data Analysis\Breakthrough\day 1\')
1
%-- 10/4/2016 2:29 PM --%
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\Final Model\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\')
load('pf.mat')
```

```
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[Test1]=RemoveOutliers(CutData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
25 26 27 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56
57 58 59 60 61 62],[],[])
[Test2]=OutlierTest(Test1,2,1,7,'Yes','No')
[Test2]=OutlierTest(Test1,2,1,9,'Yes','No')
PlotLL(Test2,3)
PlotLL(Test2,4)
PlotLL(Test2,5)
PlotLL(Test2,6)
PlotLL(Test2,7)
PlotLL(Test2,8)
PlotLL(Test2,9)
close all
PlotEEMby4(1,Test2,'R.U.')
[AnalysisData]=SplitData(Test1)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:9),'MyData.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',8)
SplitHalfValidation(AnalysisData,'1-2',9)
SplitHalfValidation(AnalysisData,'3-4',9)
SplitHalfValidation(AnalysisData,'3-4',8)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',3)
close all
PlotLL(AnalysisData,7)
[AnalysisData]=RandInitAnal(AnalysisData,7,10)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
PlotLL(AnalysisData,7)
EvalModel(AnalysisData,7)
ComponentEEM(AnalysisData,7)
close all
EvalModel(AnalysisData,4)
[FMax,B,C]=ModelOut(AnalysisData,7,'C:\Users\jdscott\Desktop\Data Analysis\Final
Model\7C\7CDOMFluor.xls')
ComponentEEM(AnalysisData,7)
ComponentSurf(AnalysisData,7)
MeanError(AnalysisData,3,4,7)
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
```

```
MeanError(AnalysisData,3,4,7)
[FMax,B,C,FMaxFull]=modelout(AnalysisData,7,'C:\Users\jdscott\Desktop\Data Analysis\Final Model\7C\7CdrEEM.xls',CutData)
1
describecomp(AnalysisData,7)
close all
%-- 10/4/2016 3:51 PM --%
dataprep4pf('C:\Users\jdscott\Desktop\Data Analysis\Effluent Model\')
1
loadpfdata('C:\Users\jdscott\Desktop\Data Analysis\Effluent Model\PF\')
load('pf.mat')
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[Test1]=RemoveOutliers(CutData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62],[],[])
PlotEEMby4(1,Test1,'R.U.')
[AnalysisData]=SplitData(Test1)
[AnalysisData]=SplitHalfAnalysis(AnalysisData,(3:7),'MyData.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
[AnalysisData]=RandInitAnal(AnalysisData,4,10)
RandInitResult(AnalysisData,4,1)
RandInitResult(AnalysisData,4,2)
RandInitResult(AnalysisData,4,3)
RandInitResult(AnalysisData,4,4)
RandInitResult(AnalysisData,4,5)
RandInitResult(AnalysisData,4,6)
RandInitResult(AnalysisData,4,7)
RandInitResult(AnalysisData,4,8)
RandInitResult(AnalysisData,4,9)
RandInitResult(AnalysisData,4,10)
EvalModel(AnalysisData,4)
ComponentEEM(AnalysisData,4)
ComponentSurf(AnalysisData,4)
MeanError(AnalysisData,3,4,5)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
MeanError(AnalysisData,3,4,5)
[AnalysisData]=RandInitAnal(AnalysisData,3,10)
```

```
MeanError(AnalysisData,3,4,5)
[FMax,B,C]=ModelOut(AnalysisData,4,'C:\Users\jdscott\Desktop\Data Analysis\Effluent
Model\4C\4CDOMFluor.xls')
[FMax,B,C,FMaxFull]=modelout(AnalysisData,4,'C:\Users\jdscott\Desktop\Data
Analysis\Effluent Model\4C\4CdrEEM.xls',CutData)
1
describecomp(AnalysisData,4)
CompareSpecSSE(AnalysisData,3,4,5)
help randinitanal
[CorrCon4]=randinitanal(AnalysisData,4,10,'existing')
[CorrCon4]=randinitanal(AnalysisData,4,10,'nonnegativity'))
[CorrCon4]=randinitanal(AnalysisData,4,10,'nonnegativity')
[CorrCon3]=randinitanal(AnalysisData,3,10,'nonnegativity')
EvalModel(AnalysisData,4)
close all
%-- 10/5/2016 3:53 PM --%
load('pf.mat')
load('MyData.mat')
load('temp.mat')
[corcon3]=randinitanal(AnalysisData,3,10,'nonnegativity')
[corcon3]=randinitanal(AnalysisData,4,10,'nonnegativity')
[corcon3]=randinitanal(AnalysisData,7,10,'nonnegativity')
plotLL(AnalysisData,7)
PlotLL(AnalysisData,7)
PlotLL(corcon3,7)
EvalModel(corcon3,7)
[Test2]=OutlierTest(AnalysisData,2,1,9,'Yes','No')
PlotLL(Test2,7)
PlotLL(Test2,6)
PlotLL(Test2,5)
PlotLL(Test2,8)
PlotLL(Test24)
close all
[Test2]=RemoveOutliers(AnalysisData,[17 18 19 81],[],[])
[Test2]=OutlierTest(Test2,2,1,9,'Yes','No')
PlotLL(Test2,7)
[Test2]=SplitData(Test2)
[Test2]=SplitHalfAnalysis(Test2,(3:9),'MyData2.mat')
SplitHalfValidation(Test2,'1-2',3)
SplitHalfValidation(Test2,'1-2',4)
SplitHalfValidation(Test2,'1-2',5)
SplitHalfValidation(Test2,'1-2',6)
SplitHalfValidation(Test2,'1-2',7)
SplitHalfValidation(Test2,'1-2',8)
SplitHalfValidation(Test2,'3-4',3)
SplitHalfValidation(Test2,'3-4',4)
```

```
SplitHalfValidation(Test2,'3-4',5)
SplitHalfValidation(Test2,'3-4',6)
SplitHalfValidation(Test2,'3-4',7)
SplitHalfValidation(Test2,'3-4',8)
close all
[Test2]=randinitanal(Test2,3,10,'nonnegativity')
[Test2]=randinitanal(Test2,4,10,'nonnegativity')
[Test2]=randinitanal(Test2,5,10,'nonnegativity')
[Test2]=randinitanal(Test2,7,10,'nonnegativity')
CompareSpecSSE(Test2,7,5,4)
[Test2]=randinitanal(Test2,7,10,'existing')
help randinitresult
randinitresult(Test2,7,10)
RandInitResult(Test2,7,10)
[Test2]=randinitanal(Test2,7,10,'existing')
[Test2]=randinitanal(Test2,7,10,'nonnegativity')
ComponentEEM(Test2,7)
ComponentEEM(Test2,5)
EvalModel(Test2,5)
EvalModel(Test2,7)
EvalModel(Test2,4)
EvalModel(Test2,3)
close all
ComponentEEM(Test2,7)
ComponentEEM(Test2,5)
[Test3]=OutlierTest(Test2,2,1,8,'Yes','No')
PlotLL(Test3)
PlotLL(Test3,3)
PlotLL(Test3,4)
PlotLL(Test3,5)
PlotLL(Test3,6)
PlotLL(Test3,7)
PlotLL(Test3,8)
PlotEEMby4(1,Test3)
PlotEEMby4(1,Test3,'R.U.')
PlotEEMby4(1,Test1,'R.U.')
PlotEEMby4(1,AnalysisData,'R.U.')
PlotLL(Test3,7)
PlotLL(Test3,8)
PlotLL(Test3,6)
PlotLL(Test3,5)
PlotLL(Test3,4)
PlotLL(Test3,3)
PlotEEMby4(1,Test3,'R.U.')
PlotEEMby4(175,Test3,'R.U.')
PlotEEMby4(154,Test3,'R.U.')
```

```
[Test3]=RemoveOutliers(Test3,[187 159 179],[],[])
[Test3]=OutlierTest(Test3,2,1,8,'Yes','No')
close all
PlotLL(Test3,3)
PlotLL(Test3,4)
PlotLL(Test3,5)
PlotLL(Test3,6)
PlotLL(Test3,7)
PlotLL(Test3,8)
PlotEEMby4(30,Test3)
PlotEEMby4(30,Test3,'R.U.'))
PlotEEMby4(30,Test3,'R.U.')
PlotEEMby4(104,Test3,'R.U.')
PlotEEMby4(140,Test3,'R.U.')
[Test3]=RemoveOutliers(Test3,[184 159 164],[],[])
[Test4]=SplitData(Test3)
[Test4]=SplitHalfAnalysis(Test4,(3:8),'MyData3.mat')
SplitHalfValidation(Test4,'1-2',3)
SplitHalfValidation(Test4,'1-2',4)
SplitHalfValidation(Test4,'1-2',5)
SplitHalfValidation(Test4,'1-2',6)
SplitHalfValidation(Test4,'1-2',7)
SplitHalfValidation(Test4,'1-2',8)
SplitHalfValidation(Test4,'3-4',3)
SplitHalfValidation(Test4,'3-4',4)
SplitHalfValidation(Test4,'3-4',5)
SplitHalfValidation(Test4,'3-4',6)
SplitHalfValidation(Test4,'3-4',7)
SplitHalfValidation(Test4,'3-4',8)
close all
[Test4]=randinitanal(Test4,3,10,'nonnegativity')
[Test4]=randinitanal(Test4,4,10,'nonnegativity')
[Test4]=randinitanal(Test4,6,10,'nonnegativity')
[Test4]=randinitanal(Test4,7,10,'nonnegativity')
ComponentEEM(Test3,7)
ComponentEEM(Test4,7)
close all
ComponentEEM(Test4,6)
close all
ComponentEEM(Test4,7)
close all
EvalModel(Test4)
EvalModel(Test4,7)
MeanError(Test4,3,6,7)
EvalModel(Test4,7)
PlotLL(Test4,7)
```

```
[Test4]=RemoveOutliers(Test4,[104],[],[])
[Test4]=SplitData(Test4)
[Test4]=SplitHalfAnalysis(Test4,(3:8),'MyData3.mat')
SplitHalfValidation(Test4,'1-2',3)
SplitHalfValidation(Test4,'1-2',4)
SplitHalfValidation(Test4,'1-2',5)
SplitHalfValidation(Test4,'1-2',6)
SplitHalfValidation(Test4,'1-2',7)
SplitHalfValidation(Test4,'1-2',8)
SplitHalfValidation(Test4,'3-4',3)
SplitHalfValidation(Test4,'3-4',4)
SplitHalfValidation(Test4,'3-4',5)
SplitHalfValidation(Test4,'3-4',6)
SplitHalfValidation(Test4,'3-4',7)
SplitHalfValidation(Test4,'3-4',8)
[Test4]=randinitanal(Test4,3,10,'nonnegativity')
close all
[Test4]=randinitanal(Test4,5,10,'nonnegativity')
ComponentEEM(Test4,5)
EvalModel(Test4,5)
PlotLL(Test4,7)
PlotLL(Test4,5)
PlotLL(Test4,3)
[Test5]=RemoveOutliers(Test4,[32 43 54 110],[],[])
[Test5]=SplitData(Test5)
[Test5]=SplitHalfAnalysis(Test5,(3:8),'MyData4.mat')
SplitHalfValidation(Test5,'1-2',3)
SplitHalfValidation(Test5,'1-2',4)
SplitHalfValidation(Test5,'1-2',5)
SplitHalfValidation(Test5,'1-2',6)
SplitHalfValidation(Test5,'1-2',7)
SplitHalfValidation(Test5,'1-2',8)
SplitHalfValidation(Test5,'3-4',3)
SplitHalfValidation(Test5,'3-4',4)
SplitHalfValidation(Test5,'3-4',5)
SplitHalfValidation(Test5,'3-4',6)
SplitHalfValidation(Test5,'3-4',7)
SplitHalfValidation(Test5,'3-4',8)
PlotLL(Test5,7
PlotLL(Test5,7)
[Test5]=randinitanal(Test5,3,10,'nonnegativity')
[Test5]=randinitanal(Test5,4,10,'nonnegativity')
[Test5]=randinitanal(Test5,5,10,'nonnegativity')
[Test5]=randinitanal(Test5,6,10,'nonnegativity')
[Test5]=randinitanal(Test5,7,10,'nonnegativity')
PlotLL(Test5,7)
```

```
ComponentEEM(Test5,7)
EvelModel(Test5,7)
EvalModel(Test5,7)
close all
EvalModel(Test5,7)
PlotEEMby4(1,AnalysisData,'R.U.')
[Test1]=OutlierTest(Test1,2,1,8,'Yes','No')
[Test1]=OutlierTest(AnalysisData,2,1,8,'Yes','No')
PlotLL(Test1,3)
PlotLL(Test1,4)
PlotLL(Test1,5)
PlotLL(Test1,6)
PlotLL(Test1,7)
PlotLL(Test1,8)
[Test2]=RemoveOutliers(Test1[70 115 4 41 106],[],[])
[Test2]=RemoveOutliers(Test1,[70 115 4 41 106],[],[])
[Test2]=OutlierTest(Test2,2,1,8,'Yes','No')
PlotLL(Test2,3)
PlotLL(Test2,4)
PlotLL(Test2,5)
PlotLL(Test2,6)
PlotLL(Test2,7)
PlotLL(Test2,8)
PlotEEMby4(100,Test2,'R.U.')
close all
[Test2]=RemoveOutliers(Test1,[70 115],[],[])
[AnalysisData2]=SplitData(Test2)
[AnalysisData2]=SplitHalfAnalysis(Test2,(3:8),'AllSamples.mat')
[AnalysisData2]=SplitHalfAnalysis(AnalysisData2,(3:8),'AllSamples.mat')
SplitHalfValidation(AnalysisData2,'1-2',3)
SplitHalfValidation(AnalysisData2,'1-2',4)
SplitHalfValidation(AnalysisData2,'1-2',5)
SplitHalfValidation(AnalysisData2,'1-2',6)
SplitHalfValidation(AnalysisData2,'1-2',7)
SplitHalfValidation(AnalysisData2,'1-2',8)
SplitHalfValidation(AnalysisData2,'3-4',3)
SplitHalfValidation(AnalysisData2,'3-4',6)
SplitHalfValidation(AnalysisData2,'3-4',8)
close all
[AnalysisData2]=randinitanal(AnalysisData2,3,10,'nonnegativity')
[AnalysisData2]=randinitanal(AnalysisData2,4,10,'nonnegativity')
[AnalysisData2]=randinitanal(AnalysisData2,5,10,'nonnegativity')
[AnalysisData2]=randinitanal(AnalysisData2,7,10,'nonnegativity')
close all
[AnalysisData3]=SplitData(Test3)
```

```
[Test3]=RmoveOutliers(Test1,[4 39 40 41 70 74 75 76 77 106 191 17 18 19 45 47 48 120 46 57
118 144 145 146 169 180 190 198 199 200 70 115 77 81 82 163 171 183],[],[])
[Test3]=RemoveOutliers(Test1,[4 39 40 41 70 74 75 76 77 106 191 17 18 19 45 47 48 120 46 57
118 144 145 146 169 180 190 198 199 200 70 115 77 81 82 163 171 183],[],[])
[AnalysisData3]=SplitData(Test3)
[AnalysisData3]=SplitHalfAnalysis(AnalysisData3,(3:8),'NoOutliers.mat')
SplitHalfValidation(AnalysisData3,3)
SplitHalfValidation(AnalysisData3,'1-2',3)
SplitHalfValidation(AnalysisData3,'1-2',4)
SplitHalfValidation(AnalysisData3,'1-2',5)
SplitHalfValidation(AnalysisData3,'1-2',6)
SplitHalfValidation(AnalysisData3,'1-2',7)
SplitHalfValidation(AnalysisData3,'1-2',8)
close all
[AnalysisData3]=randinitanal(AnalysisData3,3,10,'nonnegativity')
[AnalysisData3]=randinitanal(AnalysisData3,4,10,'nonnegativity')
[AnalysisData3]=randinitanal(AnalysisData3,5,10,'nonnegativity')
[AnalysisData3]=randinitanal(AnalysisData3,6,10,'nonnegativity')
ComponentEEM(AnalysisData3,6
ComponentEEM(AnalysisData3,6)
ComponentEEM(AnalysisData2,7)
EvalModel(AnalysisData3,6)
EvalModel(AnalysisData2,7)
[Test3]=RemoveOutliers(Test3,[31],[],[])
PlotLL(AnalysisData3,7)
PlotLL(AnalysisData3,6)
[AnalysisData3]=SplitData(Test3)
[AnalysisData3]=SplitHalfAnalysis(AnalysisData3,(3:8),'NoOutliers.mat')
SplitHalfValidation(AnalysisData3,3)
SplitHalfValidation(AnalysisData3,'1-2',3)
SplitHalfValidation(AnalysisData3,'1-2',4)
SplitHalfValidation(AnalysisData3,'1-2',5)
SplitHalfValidation(AnalysisData3,'1-2',6)
SplitHalfValidation(AnalysisData3,'1-2',7)
SplitHalfValidation(AnalysisData3,'1-2',8)
SplitHalfValidation(AnalysisData3,'3-4',3)
SplitHalfValidation(AnalysisData3,'3-4',4)
SplitHalfValidation(AnalysisData3,'3-4',5)
SplitHalfValidation(AnalysisData3,'3-4',6)
SplitHalfValidation(AnalysisData3,'3-4',7)
SplitHalfValidation(AnalysisData3,'3-4',8)
[AnalysisData3]=randinitanal(AnalysisData3,7,10,'nonnegativity')
[AnalysisData3]=randinitanal(AnalysisData3,6,10,'nonnegativity')
[AnalysisData3]=randinitanal(AnalysisData3,5,10,'nonnegativity')
[AnalysisData3]=randinitanal(AnalysisData3,4,10,'nonnegativity')
[AnalysisData3]=randinitanal(AnalysisData3,3,10,'nonnegativity')
```

```
ComponentEEM(AnalysisData3,6)
ComponentEEM(AnalysisData2,7)
ComponentEEM(AnalysisData3,5)
EvalModel(AnalysisData3,5)
[Test4]=RemoveOutliers(Test1,[70 115 4 39 40 41 74 75 76 77 106 191],[],[])
[AnalysisData4]=SplitData(Test4)
[AnalysisData4]=SplitHalfAnalysis(AnalysisData4,(3:8),'No250peak.mat')
SplitHalfValidation(AnalysisData4,'1-2',3)
SplitHalfValidation(AnalysisData4,'1-2',4)
SplitHalfValidation(AnalysisData4,'1-2',5)
SplitHalfValidation(AnalysisData4,'1-2',6)
SplitHalfValidation(AnalysisData4,'1-2',7)
SplitHalfValidation(AnalysisData4,'1-2',8)
SplitHalfValidation(AnalysisData4,'3-4',3)
SplitHalfValidation(AnalysisData4,'3-4',4)
SplitHalfValidation(AnalysisData4,'3-4',5)
SplitHalfValidation(AnalysisData4,'3-4',6)
SplitHalfValidation(AnalysisData4,'3-4',7)
SplitHalfValidation(AnalysisData4,'3-4',8)
PlotLL(AnalysisData4,4)
[AnalysisData4]=randinitanal(AnalysisData4,3,10,'nonnegativity')
[AnalysisData4]=randinitanal(AnalysisData4,4,10,'nonnegativity')
ComponentEEM(AnalysisData4,4)
EvalModel(analysisData4,4)
EvalModel(AnalysisData4,4)
[Test5]=RemoveOutliers(Test1,[70 115 4 39 40 41 70 74 75 76 77 106 191 81 82 163 171
183],[],[])
[AnalysisData5]=SplitData(Test5)
[AnalysisData5]=SplitHalfAnalysis(AnalysisData5,(3:8),'ProPeaks.mat')
SplitHalfValidation(AnalysisData5,'1-2',3)
SplitHalfValidation(AnalysisData5,'1-2',4)
SplitHalfValidation(AnalysisData5,'1-2',5)
SplitHalfValidation(AnalysisData5,'1-2',6)
SplitHalfValidation(AnalysisData5,'1-2',7)
SplitHalfValidation(AnalysisData5,'1-2',8)
SplitHalfValidation(AnalysisData5,'3-4',3)
SplitHalfValidation(AnalysisData5,'3-4',4)
SplitHalfValidation(AnalysisData5,'3-4',5)
SplitHalfValidation(AnalysisData5,'3-4',6)
SplitHalfValidation(AnalysisData5,'3-4',7)
SplitHalfValidation(AnalysisData5,'3-4',8)
[AnalysisData5]=randinitanal(AnalysisData5,4,10,'nonnegativity')
[AnalysisData5]=randinitanal(AnalysisData5,6,10,'nonnegativity')
ComponentEEM(AnalysisData5,6)
EvalModel(AnalysisData5,6)
close all
```

```
ComponentEEM(AnalysisData5,6)
EvalModel(AnalysisData5,6)
ComponentSurd(AnalysisData5,6)
ComponentSurf(AnalysisData5,6)
[AnalysisData5]=randinitanal(AnalysisData5,5,10,'nonnegativity')
[AnalysisData5]=randinitanal(AnalysisData5,6,10,'nonnegativity')
ComponentEEM(AnalysisData5,6)
help randinitanal
[AnalysisData5]=randinitanal(AnalysisData5,6,10,'nonnegativity',1e-8)
ComponentEEM(AnalysisData5,6)
CompareSpecSSE(AnalysisData5,4,5,6)
describecomp(AnalysisData5,6)
ComponentSurf(AnalysisData5,6)
[FMax,B,C]=ModelOut(AnalysisData5,6,'C6DOMFlour.xls')
[FMax,B,C,FMaxFull=modelout(AnalysisData5,6,'C:\Users\jdscott\Desktop\Data Analysis\Final
Model\C6 final\C6drEEM.xls',Test1)
[FMax,B,C,FMaxFull]=modelout(AnalysisData5,6,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\C6 final\C6drEEM.xls',Test1)
1
[FMax,B,C,FMaxFull]=modelout(AnalysisData,4,'C:\Users\jdscott\Desktop\Data
Analysis\Effluent Model\4C\4CdrEEM.xls',CutData)
1e-8
[FMax,B,C,FMaxFull]=modelout(AnalysisData5,6,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\C6 final\C6drEEM.xls',Test1)
1
1e-8
help randinitresults
help randinitresult
randinitresult(AnalysisData5,4,10)
RandInitResult(AnalysisData5,4,10)
PlotLL(AnalysisData5,6)
EvalModel(AnalysisData5,6)
[Test6]=RemoveOutliers(Test5,[16 17 18],[],[])
[Test6]=OutlierTest(Test6,1,1,7,'Yes','No')
PlotLL(Test6,6)
PlotLL(Test6,7)
PlotLL(Test6,5)
PlotLL(Test6,4)
PlotLL(Test6,3)
[AnalysisData6]=randinitanal(Test6,6,10,'nonnegativity')
ComponentEEM(AnalysisData6,6)
ComponentEEM(AnalysisData6,5)
[AnalysisData6]=SplitData(Test6)
[AnalysisData6]=SplitHalfAnalysis(Analysisdata6,(3:7),'six.mat')
[AnalysisData6]=SplitHalfAnalysis(AnalysisData6,(3:7),'six.mat')
SplitHalfValidation(AnalysisData6,'1-2',3)
```

```
SplitHalfValidation(AnalysisData6,'1-2',4)
SplitHalfValidation(AnalysisData6,'1-2',5)
SplitHalfValidation(AnalysisData6,'1-2',6)
SplitHalfValidation(AnalysisData6,'1-2',7)
SplitHalfValidation(AnalysisData6,'3-4',6)
SplitHalfValidation(AnalysisData6,'3-4',7)
PlotLL(AnalysisData6,6)
ComponentEEM(AnalysisData6,6)
ComponentEEM(AnalysisData6,5)
ComponentEEM(AnalysisData6,4)
ComponentEEM(AnalysisData6,3)
ComponentEEM(AnalysisData6,7)
[AnalysisData6]=randinitanal(AnalysisData6,5,10,'nonnegativity')
ComponentEEM(AnalysisData6,5)
EvalModel(AnalysisData6,5)
PlotLL(AnalysisData6,5)
PlotLL(AnalysisData6,6)
[AnalysisData5]=randinitanal(AnalysisData5,4,10,'nonnegativity')
EvalModel(AnalysisData5,4)
EvalModel(AnalysisData5,6)
[Test6]=RemoveOutliers(Test1,[70 115 4 39 40 41 74 75 76 77 106 191 17 18 19 45 47 48
120],[],[]
[Test6]=RemoveOutliers(Test1,[70 115 4 39 40 41 74 75 76 77 106 191 17 18 19 45 47 48
120],[],[])
[AnalysisData6]=SplitData(Test6)
[AnalysisData6]=SplitHalfAnalysis(AnalysisData6,(3:7),'six.mat')
SplitHalfValidation(AnalysisData6,'1-2',3)
SplitHalfValidation(AnalysisData6,'1-2',4)
SplitHalfValidation(AnalysisData6,'1-2',5)
SplitHalfValidation(AnalysisData6,'1-2',6)
SplitHalfValidation(AnalysisData6,'1-2',7)
SplitHalfValidation(AnalysisData6,'3-4',3)
SplitHalfValidation(AnalysisData6,'3-4',4)
SplitHalfValidation(AnalysisData6,'3-4',5)
SplitHalfValidation(AnalysisData6,'3-4',6)
SplitHalfValidation(AnalysisData6,'3-4',7)
close all
ComponentEEM(AnalysisData6,4)
PlotLL(AnalysisData6,4)
[AnalysisData6]=randinitanal(AnalysisData6,4,10,'nonnegativity')
ComponentEEM(AnalysisData6,4)
PloLL(AnalysisData6,4)
PlotLL(AnalysisData6,4)
close all
EvalModel(AnalysisData6,4)
EvalModel(AnalysisData5,6)
```

```
ComponentEEM(AnalysisData5,4)
[Fmax,B,C]=ModelOut(AnalysisData5,6,'C6DOMFluor.xls')
[FMax,B,C,FMaxFull]=modelout(AnalysisData5,6,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\C6 final\C6drEEM.xls',CutData)
[FMax,B,C,FMaxFull]=modelout(AnalysisData5,6,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\C6 final\C6drEEM.xls',Test1)
1
1e-8
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'No')
[FMax,B,C,FMaxFull]=modelout(AnalysisData5,6,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\C6 final\C6drEEM.xls',CutData)
[CutData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[FMax,B,C,FMaxFull]=modelout(AnalysisData5,6,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\C6 final\C6drEEM.xls',CutData)
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\pf.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\pf.mat', 'OriginalData')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\AllSamples.mat')
%-- 10/10/2016 11:52 AM --%
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\pf.mat')
OriginalData
[AllData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[NoBreak]=RemoveOutliers(AllData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
24 25 26 27 29 30 31 32 33 34 35 36 37 38 39 40 411 42 43 44 45 46 47 48 49 50 51 52 53 54 55
56 57 58 59 60 61 62],[],[])
[NoBreak]=RemoveOutliers(AllData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
24 25 26 27 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55
56 57 58 59 60 61 62],[],[])
PlotEEMby4(1,NoBreak,'R.U.')
[NotInstBright250]=RemoveOutliers(NoBreak,[4 30 40 41 70 74 75 76 77 106 191 115 81 82
163 171 183],[],[])
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\ProPeaks.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\MyData.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\AllSamples.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\MyData.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\MyData2.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\MyData3.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\MyData4.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\No250peak.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\NoOutliers.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\ProPeaks.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\six.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\pf.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\temp.mat')
load('temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\C6 final\temp.mat')
```

```
[FMax,B,C,FMaxFull]=modelout(AnalysisData5,6,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\C6 final\C6drEEM.xls',CutData)
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\7C2\temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\MATLAB and Articles 1\temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\MATLAB and Articles
1\ModifiedDOMFluor\temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\drEEM\temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\drEEM\nway\temp.mat')
%-- 10/10/2016 12:07 PM --%
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\pf.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\temp.mat', 'Factors')
%-- 10/10/2016 12:09 PM --%
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\pf.mat')
OriginalData
[AllData]=EEMCut(OriginalData,20,20,NaN,NaN,'')
[NoB]=RemoveOutliers(AllData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
25 26 27 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56
57 58 59 60 61 62],[],[])
PlotEEMby4(1,NoB,'R.U.')
[NoInstBright250]=RemoveOutliers(NoB,[4 39 40 41 70 74 75 76 77 106 191 115 81 82 163
171 183],[],[])
[AnalysisData1]=SplitData(AllData)
[AnalysisData1]=SplitHalfAnalysis(AllData,(3:8),'AllData.mat')
[AnalysisData1]=SplitHalfAnalysis(AnalysisData1,(3:8),'AllData.mat')
[AnalysisData2]=SplitData(NoInstBright250)
[AnalysisData2]=SplitHalfAnalysis(AnalysisData2,(3:8),'NoInstBright250.mat')
SplitHalfValidation(AnalysisData2,'1-2',3)
SplitHalfValidation(AnalysisData2,'1-2',4)
SplitHalfValidation(AnalysisData2,'1-2',5)
SplitHalfValidation(AnalysisData2,'1-2',6)
SplitHalfValidation(AnalysisData2,'1-2',7)
SplitHalfValidation(AnalysisData2,'1-2',8)
SplitHalfValidation(AnalysisData2,'3-4',3)
SplitHalfValidation(AnalysisData2,'3-4',4)
SplitHalfValidation(AnalysisData2,'3-4',5)
SplitHalfValidation(AnalysisData2,'3-4',6)
SplitHalfValidation(AnalysisData2,'3-4',7)
SplitHalfValidation(AnalysisData2,'3-4',)
SplitHalfValidation(AnalysisData2,'3-4',8)
close al
close all
PlotEEMby4(1,NoInstBright250,'R.U.')
EvalModel(AnalysisData2,8)
[AnalysisData2]=randinitanal(AnalysisData2,4,10,'nonnegativity')
%-- 10/10/2016 1:26 PM --%
```

```
ComponentEEM(AnalysisData2,4)
close all
EvalModel(AnalysisData2,4)
[AnalysisData2]=randinitanal(AnalysisData2,5,10,'nonnegativity')
ComponentEEM(AnalysisData2,5)
EvalModel(AnalysisData2,5)
PlotLL(AnalysisData2,5)
EvalModel(AnalysisData2,5)
PlotLL(AnalysisData2,5)
[FMax,B,C,FMaxFull]=modelout(AnalysisData2,5,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\Lord Please\C5drEEM.xls',AllData)
1
[AnalysisData2]=randinitanal(AnalysisData2,8,10,'nonnegativity')
ComponentEEM(AnalysisData2,8)
EvalModel(AnalysisData2,8)
PlotLL(AnalysisData2,5)
describecomp(AnalysisData2,5)
MeanError(AnalysisData2,4,5,8)
ComponentSurf(AnalysisData2,5)
CompareSpecSSE(AnalysisData,4,5,8)
CompareSpecSSE(AnalysisData2,4,5,8)
[FMax,B,C]=ModelOut(AnalysisData2,5,'C:\Users\jdscott\Desktop\Data Analysis\Final
Model\Lord Please\C5DOMFluor.xls')
%-- 10/11/2016 7:54 PM --%
[AnalysisData2]=randinitanal(AnalysisData2,4,10,'nonnegativity')
PlotLL(AnalysisData1,5)
PlotLL(AllData,5)
[AnalysisData1]=SplitHalfAnalysis(AnalysisData1,(3:8),'AllData.mat')
PlotLL(AnalysisData1,5)
[holderdata]=OutlierTest(AnalysisData,1,1,7,Yes,No)
[holderdata]=OutlierTest(AnalysisData1,1,1,7,Yes,No)
[holderdata]=OutlierTest(AnalysisData1,1,1,7,'Yes','No')
PlotLL(holderdata,5)
PlotLL(holderdata,6)
PlotLL(holderdata,7)
PlotLL(holderdata,8)
PlotLL(holderdata,4)
PlotLL(holderdata,3)
close all
PlotLL(holderdata,5)
[holderdata]=RemoveOutliers(AnalysisData1,[ 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
21 22 23 24 25 26 27 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52
53 54 55 56 57 58 59 60 61 62],[],[])
[holderdata]=OutlierTest(holderdata,1,1,7,'Yes','No')
PlotLL(holderdata,5)
PlotLL(holderdata,6)
```

```
PlotLL(holderdata,7)
close all
EvalModel(AnalysisData2,5)
[holderdata]=RemoveOutliers(AnalysisData2,[16 17 18],[],[])
EvalModel(AnalysisData2,5)
[holderdata]=OutlierTest(holderdata,1,1,7,'Yes','No')
PlotLL(holderdata,6)
PlotLL(holderdata,7)
[holderdata]=SplitData(holderdata)
[holderdata]=SplitHalfAnalysis(holderdata,(3:7),'check.mat')
SplitHalfValidation(holderdata,'1-2',3)
SplitHalfValidation(holderdata,'1-2',4)
SplitHalfValidation(holderdata,'1-2',5)
SplitHalfValidation(holderdata,'1-2',6)
SplitHalfValidation(holderdata,'1-2',7)
SplitHalfValidation(holderdata,'1-2',8)
SplitHalfValidation(holderdata,'3-4',3)
SplitHalfValidation(holderdata,'3-4',4)
SplitHalfValidation(holderdata,'3-4',5)
SplitHalfValidation(holderdata,'3-4',6)
SplitHalfValidation(holderdata,'3-4',7)
[holderdata]=randinitanal(holderdata,5,10,'nonnegativity')
EvalModel(holderdata,5)
[holderdata]=randinitanal(holderdata,5,10,'nonnegativity')
ComponentEEM(holderdata,5)
EvalModel(holderdata,5)
close all
[moresplits]=splitds(NoInstBright250,[],4,'alternating',{[1 2],[3 4],[1 3],[2 4],[1 4],[2 3]})
[moresplits]=splitanalysis(moresplits,6:7,'nonnegativity')
splitvalidation(moresplits,6,[1 2;3 4;5 6],{'AB','CD','AC','BD','AD','BC'})
splitvalidation(moresplits,7,[1 2;3 4;5 6],{'AB','CD','AC','BD','AD','BC'})
[moresplits]=splitanalysis(moresplits,6:7,'nonnegativity')
splitvalidation(moresplits,6,[1 2;3 4;5 6],{'AB','CD','AC','BD','AD','BC'})
splitvalidation(moresplits,7,[1 2;3 4;5 6],{'AB','CD','AC','BD','AD','BC'})
close all
[Final]=RemoveOutliers(NoB,[4 39 40 41 70 74 75 76 77 106 191 115 81 82 163 171 183 17 18
19 45 47 48 120],[],[])
[AnalysisData3]=SplitData(Final)
[AnalysisData3]=SplitHalfAnalysis(Final,(3:8),'Final.mat')
[AnalysisData3]=SplitHalfAnalysis(AnalysisData3,(3:8),'Final.mat')
SplitHalfValidation(AnalysisData3,'1-2',3)
SplitHalfValidation(AnalysisData3,'1-2',4)
SplitHalfValidation(AnalysisData3,'1-2',5)
SplitHalfValidation(AnalysisData3,'1-2',)
SplitHalfValidation(AnalysisData3,'1-2',6)
SplitHalfValidation(AnalysisData3,'1-2',7)
```

```
SplitHalfValidation(AnalysisData3,'1-2',8)
SplitHalfValidation(AnalysisData3,'3-4',3)
SplitHalfValidation(AnalysisData3,'3-4',4)
SplitHalfValidation(AnalysisData3,'3-4',5)
SplitHalfValidation(AnalysisData3,'3-4',6)
SplitHalfValidation(AnalysisData3,'3-4',7)
SplitHalfValidation(AnalysisData3,'3-4',8)
[AnalysisData3]=randinitanal(AnalysisData3,6,10,'nonnegativity')
ComponentEEM(AnalysisData3,6)
close all
EvalModel(AnalysisData2,4)
EvalModel(AnalysisData2,5)
ComponentEEM(AnalysisData2,4)
[Fmax4,B4,C4]=modelout(AnalysisData2,4,'4componentdomfluor.xls')
help Loadings
help loadings
help plotloadings
PlotLoadings(AnalysisData2,5)
PlotLoadings(AnalysisData2,8)
ComponentEEM(AnalysisData2,8)
MeanError(AnalysisData2,4,5,8)
cloase all
close all
ComponentEEM(AnalysisData2,8)
close all
EvalModel(AnalysisData2,8)
PlotLL(AnalysisData2,8)
PlotLL(AnalysisData2,5)
close all
ComponentEEM(AnalysisData2,8)
Component##M(AnalysisData3,6)
ComponentEEM(AnalysisData3,6)
[AnalysisData3]=randinitanal(AnalysisData3,5,10,'nonnegativity')
ComponentEEM(AnalysisData3,5)
describecomp(AnalysisData3,5)
close all
ComponentEEM(AnalysisData3,5)
close all
[AnalysisData3]=randinitanal(AnalysisData3,4,10,'nonnegativity')
help randinitanal
[AnalysisData3]=randinitanal(AnalysisData3,5,10,'existing')
randinitanal(AnalysisData3,5,10,'existing')
[AnalysisData3]=randinitanal(AnalysisData3,3,10,'existing')
[AnalysisData3]=randinitanal(AnalysisData3,3,10,'nonnegativity')
[AnalysisData3]=randinitanal(AnalysisData3,5,10,'nonnegativity')
ComponentEEM(AnalysisData3,5)
```

```
describecomp(AnalysisData3,5)
[AnalysisData3]=randinitanal(AnalysisData3,6,10,'nonnegativity')
CompareSpecSSE(AnalysisData3,4,5,6)
ComponentEEM(AnalysisData3,4)
close all
MeanError(AnalysisData3,4,5,6)
help specloadings
help loadings
help lptloadings
help plotloadings
PlotLoadings(AnalysisData3,5)
[FMax,B,C,FMaxFull]=modelout(AnalysisData3,5,'C:\Users\jdscott\Desktop\Data
Analysis\Final Model\Lord Please\C5drEEM.xls',AllData)
1
[FMax,B,C]=ModelOut(AnalysisData3,5,'C:\Users\jdscott\Desktop\Data Analysis\Final
Model\Lord Please\C5DOMFluor.xls')
PlotEEMby4(1,NoB,'R.U.')
PlotEEMby1(158,NoB,'R.U.')
PlotEEMby1(58,NoB,'R.U.')
%-- 10/13/2016 2:52 PM --%
load('pf.mat')
load('MyData.mat')
load('temp.mat')
SplitHalfValidation(AnalysisData,'1-2',3)
SplitHalfValidation(AnalysisData,'1-2',4)
SplitHalfValidation(AnalysisData,'1-2',5)
SplitHalfValidation(AnalysisData,'1-2',6)
SplitHalfValidation(AnalysisData,'1-2',7)
SplitHalfValidation(AnalysisData,'1-2',8)
SplitHalfValidation(AnalysisData,'3-4',5)
SplitHalfValidation(AnalysisData,'3-4',4)
SplitHalfValidation(AnalysisData,'3-4',3)
SplitHalfValidation(AnalysisData,'3-4',6)
SplitHalfValidation(AnalysisData,'3-4',7)
SplitHalfValidation(AnalysisData,'3-4',8)
randinitresult(AnalysisData,4,10)
RandInitResult(AnalysisData,4,10)
[AnalysisData]=RandInitAnal(AnalysisData,5,10)
ComponentEEM(AnalysisData,5)
[AnalysisData]=randinitanal(AnalysisData,5,10,'nonnegativity')
[AnalysisData]=randinitanal(AnalysisData,3,10,'nonnegativity')
[AnalysisData]=randinitanal(AnalysisData,4,10,'nonnegativity')
describecomp(AnalysisData,4)
[Fmax,B,C]=ModelOut(AnalysisData,4,'4CDOMFluor.xls')
[AllData]=EEMCut(OriginalData,20,20,'','','No')
[AllData]=EEMCut(OriginalData,20,20,NaN,NaN,'No')
```

```
[NoB]=RemoveOutliers(AllData,2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55
56 57 58 59 60 61 62,[],[])
[NoB]=RemoveOutliers(AllData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55
56 57 58 59 60 61 62,[],[])
[NoB]=RemoveOutliers(AllData,[2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55
56 57 58 59 60 61 62],[],[])
PlotEEMby4(1,NoB,'R.U.')
[Modelset]=RemoveOutliers(NoB,[3 41],[],[])
PlotLL(ModelSet,4)
[Modelset]=SplitHalfAnalysis(Modelset,(3:7),'effluent.mat')
[Modelset]=SplitData(Modelset]
[Modelset]=SplitData(Modelset)
[Modelset]=SplitHalfAnalysis(Modelset,(3:7),'effluent.mat')
SplitHalfValidation(Modelset,'1-2',3)
SplitHalfValidation(Modelset,'1-2',4)
SplitHalfValidation(Modelset,'1-2',5)
SplitHalfValidation(Modelset,'1-2',6)
SplitHalfValidation(Modelset,'1-2',7)
SplitHalfValidation(Modelset,'1-2',8)
SplitHalfValidation(Modelset,'3-4',3)
SplitHalfValidation(Modelset,'3-4',6)
SplitHalfValidation(Modelset,'3-4',7)
[Modelset]=randinitanal(modelset,3,10,'nonnegativity')
[Modelset]=randinitanal(Modelset,3,10,'nonnegativity')
[Modelset]=randinitanal(Modelset,4,10,'nonnegativity')
[Modelset]=randinitanal(Modelset,5,10,'nonnegativity')
CompareSpecSSE(Modelset,3,4,5)
EvalModel(Modelset,5)
EvalModel(Modelset,4)
ComponentEEM(Modelset,5)
ComponentEEM(Modelset,4)
close all
ComponentEEM(Modelset,4)
ComponentEEM(Modelset,5)
ComponentSurf(Modelset,5)
ComponentSurf(Modelset,4)
describecomp(Modelset,4)
MeanError(Modelset,3,4,5)
[Fmax,B,C]=ModelOut(Modelset,4,'4CDOMFluor.xls')
[Fmax,B,C,FmaxFull]=modelout(Modelset,4,'4CdrEEM.xls',AllData)
1
modelout(Modelset,5,'5CdrEEM.xls',AllData)
1
```

```
%-- 10/17/2016 11:04 AM --%
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT Files\matlab.mat')
%-- 10/20/2016 11:13 AM --%
ProcessData('C:\Users\jdscott\Desktop\c5 run\160912\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160715\int1\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160715\intpt05\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160719\intpt5\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160719\intpt25\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160721\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160722\intpt5\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160722\intpt25\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160725\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160728\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160817\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160817\int0pt25\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160819\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160822\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160823\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160825\int0pt5\')
1
ProcessData('C:\Users\jdscott\Desktop\c5 run\P160826\int0pt5\')
1
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT Files\matlab.mat')
ComponentEEM(AnalysisData2,5)
ComponentSurf(AnalysisData2,5)
load('effluent.mat')
close
%-- 10/21/2016 4:24 PM --%
load('effluent.mat')
load('temp.mat')
load('c4workspace.mat')
```

```
ComponentEEM(AnalysisData,4)
ComponentSurf(AnalysisData,4)
ecit
%-- 10/21/2016 4:49 PM --%
load('Final.mat')
load('matlab.mat')
ComponentEEM(AnalysisData2,5)
clear all
load('effluent.mat')
ComponentEEMAnalysisData,4)
ComponentEEM(AnalysisData,4)
load('temp.mat')
ComponentEEM(AnalysisData,4)
load('c4workspace.mat')
ComponentEEM(AnalysisData,4)
%-- 10/25/2016 11:59 PM --%
%-- 10/31/2016 4:27 PM --%
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\pf.mat')
PlotEEMby1(57,OriginalData,'R.U.')
PlotEEMby1(58,OriginalData,'R.U.')
PlotEEMby1(59,OriginalData,'R.U.')
PlotEEMby1(60,OriginalData,'R.U.')
PlotEEMby1(61,OriginalData,'R.U.')
PlotEEMby1(62,OriginalData,'R.U.')
PlotEEMby1(63,OriginalData,'R.U.')
PlotEEMby1(64,OriginalData,'R.U.')
PlotEEMby1(65,OriginalData,'R.U.')
PlotEEMby1(66,OriginalData,'R.U.')
PlotEEMby1(67,OriginalData,'R.U.')
PlotEEMby1(68,OriginalData,'R.U.')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\NoOutliers.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\MyData2.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\PF\NoOutliers.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT Files\Final.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT Files\AllData
(2).mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT Files\Final.mat')
ComponentEEM(AnalysisData,5)
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT Files\matlab.mat')
ComponentEEM(AnalysisData,5)
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT Files\AllData
(2).mat')
ComponentEEM(AnalysisData,5)
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT Files\AllData.mat')
ComponentEEM(AnalysisData,5)
```

```
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT Files\temp.mat')
load('C:\Users\jdscott\Desktop\Data Analysis\Final Model\Lord Please\MAT
Files\workspace.mat')
ComponentEEM(AnalysisData1,5)
ComponentEEM(AnalysisData2,5)
%-- 11/4/2016 4:24 PM --%
load('pf.mat')
load('MyData.mat')
load('temp.mat')
load('c4workspace.mat')
load('temp.mat')
ComponentEEM(AnalysisData, 4)
close all
clear
%-- 11/6/2016 4:28 PM --%
load('AllData.mat')
load('AllData (2).mat')
load('Final.mat')
PlotEEMby4(1,AnalysisData,'R.U.')
PlotEEMby4(70,AnalysisData,'R.U.')
PlotEEMby4(90,AnalysisData,'R.U.')
PlotEEMby1(91,AnalysisData,'R.U.')
%-- 11/9/2016 3:28 PM --%
load('AllData.mat')
load('Final.mat')
load('matlab.mat')
load('Final.mat')
MMR(AnalysisData2,4)
PlotEEMby1(2,AnalysisData2,'R.U.')
%-- 11/17/2016 12:01 PM --%
ProcessData('C:\Users\jdscott\Desktop\Sophie PARAFAC\int 1pt0\')
1
close all
%-- 12/15/2016 5:27 PM --%
```