Evaluation of optical sensor technologies to optimize winter wheat (*Triticum aestivum L.)* management

by

ASHLEY ABAGAIL LORENCE

B.S., Kansas State University, 2015

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Agronomy
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2017

Approved by:

Major Professor
Dr. Antonio Ray Asebedo

Copyright

Abstract

Sensor technology has become more important in precision agriculture, by real time sensing for site specific management to monitor crops during the season especially nitrogen (N). In Kansas N available in the soils can vary year to year or over a course of a year. The objective of this study was to compare current available passive (PS) and active optical sensor technologies (AOS) performance in regards to sky conditions effects and derive the NDVI (normalized difference vegetation index) relationship to wheat yield, as well as evaluate KSU optical sensor-based N recommendations against KSU soil test N recommendation system and sUAS (small unmanned aircraft systems) based recommendation algorithms with the PS and AOS platforms. Each year (2015-2016 & 2016-2017) five field trails across Kansas were conducted during the winter wheat crop year in cooperation with county ag agents, farmers, and KSU Agronomy Experiment Fields. Treatments consisted of N response curve, 1st and 2nd generation KSU N recommendation algorithms, sUAS based recommendation algorithms, and KSU soil test based N recommendations applied in the spring using N rates ranging from 0 to 140 kg ha^{-1}. Results indicate the Holland Scientific Rapid Scan and MicaSense RedEdge NDVI data was strongly correlated and generated strong relationships with grain yield at 0.60 and 0.57 R^2 respectively. DJI X3 lacks an NIR band producing uncalibrated false NDVI and no relationship to grain yield at 0.03 R^2. Calibrated NDVI from both sensors are effective for assessing yield potential and could be utilized for developing N recommendation algorithms. However, sensor based treatments preformed equal to higher yields compared the KSU soil test recommendations, as well as reduced the amount of fertilizer applied compared to the soil test recommendation. The intensive management algorithm was the most effective in determining appropriate N recommendations across locations. This allows farmers to take advantage of

potential N mineralization that can occur in the spring. Further research is needed considering on setting the NUE (nitrogen use efficiency) in KSU N rec. algorithms for effects of management practice, weather, and grain protein for continued refinement.

Table of Contents

List of Figures

List of Tables

Acknowledgements

I would like to thank and acknowledge those who have assisted me in my whole college career and pushing me to further myself and education. I would like to thank my family, especially my parents and my boyfriend, Jarrod Blackburn, for supporting me and pushing me to get my Master's. Also, I would also like to thank Cristie (Edwards) Preston for taking me on as and undergrad worker who then turned into a great mentor and friend who pushed me to pursue a higher education. Another person I would like to thank is my major professor Dr. Antonio Ray Asebedo for his support and mentoring throughout my Master's career. Additionally, I would like to thank my committee members, Dorivar Ruiz Diaz and Romulo Lollato for their assistance in the success of my research. Furthermore, I would like to thank those who provided field support, and data analysis help that includes fellow graduate students Huan Wang, Andrew Newsum, Dana Mayer, Tyler Gardner, and student worker Scott Cain. Finally, I would like to thank Kansas State University (KSU) county extension agents, producers, and KSU research station for their cooperation for assisting in maintenance of the research studies.

Dedication

I would like to dedicate my work to my parents (Dwayne & Sheila Lorence) and my grandparents (Doyle & Wanda Lorence and Barbra Schlatter) who has passed away. They have helped mold me to the person I am today. Instilling me to have a strong work ethic, passion, drive, to challenging myself, and never give up. Without my parents push me to do things I didn’t like, I wouldn’t be here today. To my grandparents who have passed away, they would be proud of how far I have come in my education career. I would like to dedicate my thesis work to each one of them as I am the first in the family to get my Master’s degree.

Chapter 1 - Factors Involved in Remote Sensing Affecting Nitrogen (N) Management: A Literature Review

Remote Sensing

Where would remote sensing be without the work of William Allen, David Gates, Harold Gausman, and Joseph Woolley who have their roots in using the visible and near-infrared portions of the electromagnetic spectrum for relating morphological characteristics of crops to optical properties (Gates et al., 1965, Allen et al., 1969, Gausman et al., 1969a, Woolley, 1971; Allen et al., 1973; Gausman 1973, 1974; Gausman et al., 1971, 1974; Gausman, 1977). With the ground work that has been laid out, sensor technology can measure spectral reflectance giving the opportunity to quantify agronomic parameters. During the last 100 years, the application of remote sensing to agronomic problems created new methods for improved management of crops (Hatfield et al., 2008).

Remote sensing has two primary types, passive and active. Passive remote sensing relies on sun's energy being either reflected or absorbed wavelengths. In return can only be operated from ground base equipment, aircrafts or satellites. Since sunlight is a limiting factor sky conditions, such as, clouds, and changing solar zenith angle are the most influential since they are very variable. Active sensors on the other hand, contains its own light source, thus does not require sunlight to be present and can operate under cloudy sky conditions or at night, resulting in more feasible and applicable sensors to measure agronomic parameters. Among these two types of sensing they measure a number of wavelengths in the visible and near-infrared spectrum. Measurement of these wavelengths can enable calculations of different vegetation indices (VI).

Active Optical Sensors

Active optical sensors (AOS) as defined by Holland et al. (2012) “are specialized instruments that irradiate a target with radiation and measure that which is scattered back to the sensor’s integral photo-detector”. Visible wavelength leaf reflectance is relatively low due to high chlorophyll absorption (Curran, 1989) leaning to a strong linear relationship between leaf chlorophyll and leaf N content (Lamb et al., 2002). Along with visible reflectance having a strong relationship with leaf chlorophyll, near-infrared indices can quantify high plant biomass (Mistle et al., 2004; Heege et al., 2008; Reusch et al., 2010).

When both the visible and near-infrared wavelengths are emitted and radiation returned from the sensed area, a calculation of VI can be made for specific characteristics of interest. Normalized Difference Vegetation Index (NDVI) is among the most common vegetation index to be calculated in agriculture (Rouse et al., 1973; Fitzgerald 2010) and is computed as (NIR – Red) / (NIR +Red) (Red 650-690 nm and NIR 760-900nm). NDVI measurements can be reliable for indirectly predicting nitrogen (N) uptake, biomass, and crop yield (Stone et al., 1996; Solie et al., 1996; Tucker et al., 1980; Pinter et al., 1982). On the other hand, NDVI is prone to strongly saturate out when leaf area index (LAI) exceeds 2-3 (Aparicio et al., 2000; Mistele et al., 2004; Heege et al., 2008). With the changes throughout the growing season saturation with NDVI can be more affected by the changes in LAI (Daughtry et al.,2000; Eitel et al., 2008,2009) resulting in limiting effectiveness for evaluation of N in crops.

Use of AOS allows for quick measurements regarding the plants’ characteristics throughout the growing season. Many sensors have been designed and tested to provide beneficial information to provided assistance in crop management systems, a few on the market being Trimble GreenSeeker, Holland Scientific Rapid Scan, and MicaSense RedEdge. These sensors can measure the crop health or vigor to provide inputs in N fertilizer recommendations. Optical sensor-based approach is promising for practical applications due to its nondestructive and timely measuring characteristics (Li et al., 2009).

Nitrogen

With current times, today much knowledge has been acquired about how N was discovered, what it is, where it was found, and the list of know's go on. As humans evolve into the ever changing environment, N becomes a crucial component for survival. It is among one of the largest quantities of the essential elements needed for plant and animal growth. However, research is needed to further understand the radical changes that can occur with nitrogen.

N is one of the three primary macronutrients essential for plant growth followed by phosphorus (P) and potassium (K). Nitrogen can be found in available and unavailable forms. In the mobile form it is present as nitrate, but present as ammonium form it can be retained and stored in the soil. Within agriculture the focus leans towards looking at the soil level in regions with limited precipitation. At the soil level plants can exploit to extract essential nutrients for growth, particular utilizing N depending on where the fertilizer was placed and its key transformation form present. Many interactions occur in soils, such as, microbial populations thriving mingling with the plants and soil, and transformations of N in either available or unavailable forms. Knowledge about the nitrogen cycle about the vital components as follows: volatilization, denitrification, leaching, immobilization and mineralization are crucial to keep in mind when increasing maximum production potential, input efficiency and the environmental risk with N management (Griffith and Murphy, 1991).

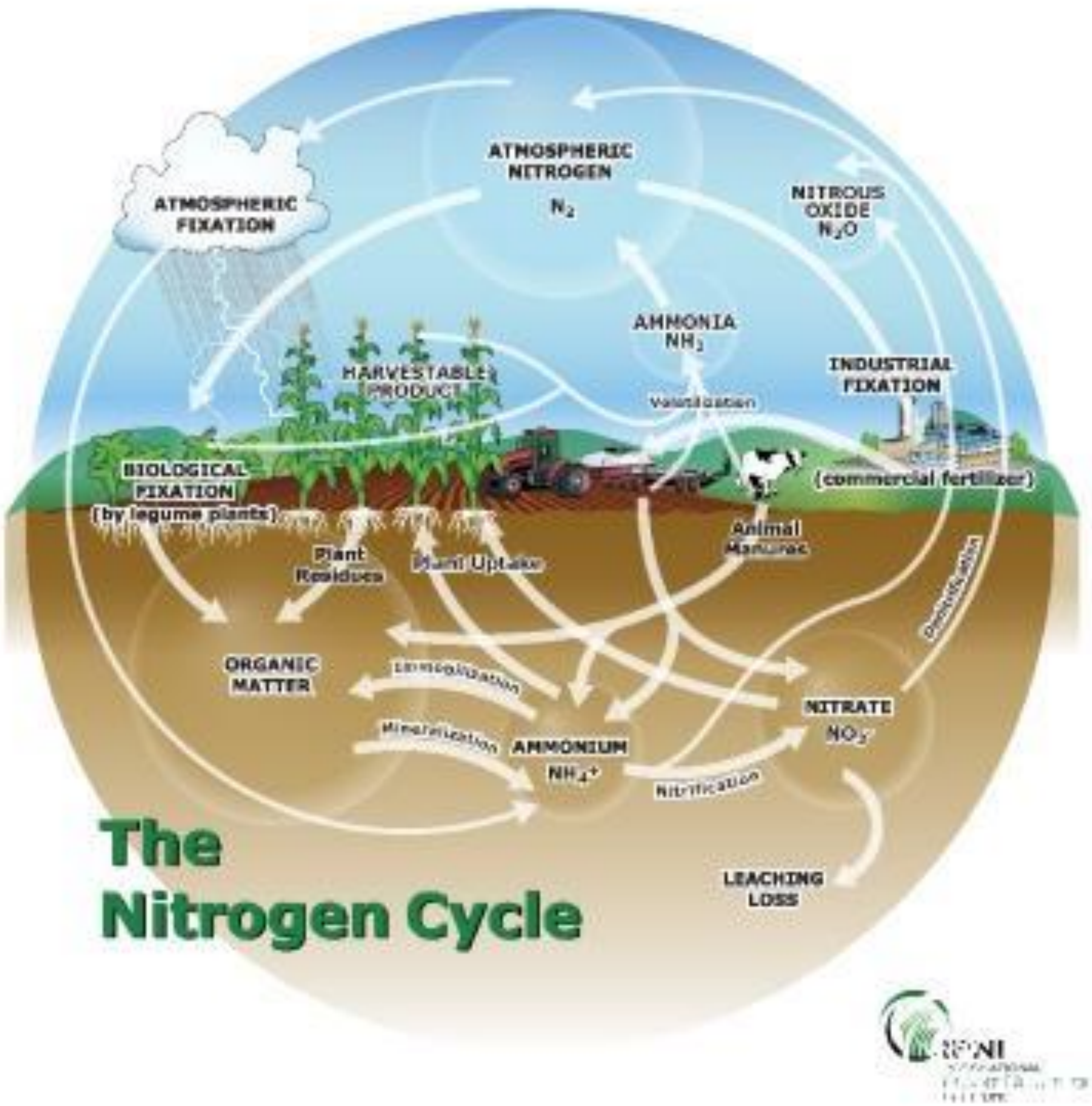


Figure 1-1 The Nitrogen Cycle, (IPNI, 2013)

4R Concept

An avid tool that is utilized for decreasing N loss, environmental risks, increasing nitrogen use efficiency is called the 4R's. Commonly known as the following: right product, right rate, right time, and right place (Roberts, 2007). With these components site-specific management of N is considered a primary investment in integration (Mulla and Schepers, 1997). The 4R concept can be used in any given crop and environment to obtain maximum yield potential and crop utilization, and has potential to reduce environmental impact. Properly understanding the 4R tool can be beneficial for producers and consultants for decision making in N management and crop N status. Site – specific management can optimize N for increasing grain yield and reduce environmental impact when choosing fertilizer sources, time of application, amount applied, and placement for the right cropping system.

Nitrogen Cycle

Many environmental factors affect the nitrogen cycle, such as environment, management practices, and physical properties of the soil (Figure 1-1). Volatilization occurs when N is transferred from ammonia gas and lost to the atmosphere. A problem with volatilization is surface applied urea applications not getting incorporated into the soil. The 4R concept of right placement and right source play a huge role in volatilization. If volatilization is increased, the loss of N needed for crop N uptake can result in yield reductions. Fertilizers associated with increased levels of volatilization are urea based, which are surface applied to soils. It has been reported that up to 40% of ammonia volatilization losses have been from urea applied products

(Fowler and Brydon, 1989). Incorporating urea products is the best placement and practice to reduce ammonia volatilization.

Denitrification is the loss of N in the conversion of NO_3 to N_2 gas and occurs in water logged soils where oxygen is limited. Without the present of nitrate, denitrification will not occur. The amount of oxygen present in soils is impacted by moisture content and soil texture. Oxygen levels decrease when moisture increases then denitrification occurs. Greatest potential for denitrification to occur in is fine textured waterlogged soils. Anaerobic bacteria are linked to the rates at which denitrification occurs.

Leaching can be defined as the movement of soluble material from one soil zone to another via water movement in the profile (Glossary of Soil Science Terms, 2013). NO_3 is the main form that is lost by leaching. Nitrate movement through the soil profile is affected by soil type and climate. Heavy rainfall events can increase the movement of nitrate throughout the soil profile into the groundwater. Leaching of NO_3 in mass quantities limit crop uptake in return reduce yields. Coarse textured soils have large pore size increasing infiltration and percolation rates compared to a fine textured soil, increasing potential for leaching (Mulla and Strock, 2008). Water movement through differently soil textures promote varies infiltration rates through the soil profile and moves NO_3 out of the root zone. Management is critical to minimize leaching, taking into account the N source and timing are key strategies. Timing of application during active crop uptake is vastly the most important management practice during the growing season.

Immobilization can be described as the process of inorganic nitrogen into organic forms conducted by organism or plants. The process that breaks down the organic material such as plant residue is mineralization into a form of inorganic N which is released in the soil for available plant uptake. The amount of organic matter can affect the rate of mineralization occurring in the soil. Soil conditions such as temperature, moisture, and aeration play a huge role. Predicting the amount of mineralization present in field can be complicated not knowing soil conditions. Crop residue can provide some amount of energy for microbes to complete their lifecycle. C:N ratio is a very important part of managing nitrogen as it affects how much N is moved to the available form (Brady and Weil, 2009) and can affect whether or not nitrogen is going to be mineralized or immobilized. With that the microbial activity factors that can affect the process of the conversion of nitrogen is soil temperature and moisture. High amounts of crop carbon residue increase N immobilization and removal from the available plant nutrient pool. In order for the carbon residue to break down and be utilized for the crop uptake microbial populations reproduce taking advantage of the energy pool provided. After completing their lifecycle, they decompose and mineralization occurs releasing inorganic N to the soil.

In situations where C:N ratios are greater than 25:1, the microbes need the additional N, resulting in immobilization. Understanding the process of immobilization of different crop residues is key for N management especially in no-till systems where high levels of residue potentially lead to increased immobilization. Placement is a crucial part to reduce immobilization it can be achieved by surface applications (knifing or banding) to minimize contact with the residue in no-till systems (Mengel, et al., 1982).

Nitrogen Use Efficiency

The need to increase nitrogen use efficiency is becoming more of interest, due to the fact producers are optimistic in crop yields and over apply for insurance to achieve desired yield goals. NUE can be defined as the measurement of crop biomass as a function of N available for the crop. N uptake efficiency (NUpE) and N utilization efficiency (NUtE) can be derived from

NUE. NUpE is the total N taken up by the plant divided by the N available including soil. NUtE is the total grain produced divided by total N in biomass and grain (Figure 1-2). The ability to evaluate N recovery from the soil and plants utilization in generating yield can be calculated by multiplying N uptake efficiency by N utilization efficiency for overall NUE.

Utilization of efficient fertilizer use is essential if not the most important when increasing NUE. It has been stated that 50% of applied N is recovered in harvested grain worldwide (Raun et al., 2001 and Hawkesford, 2010). Future consideration in management practices need to factor in appropriate agronomic management and cultivar selection. Using N in the most effective way is considerably the most sustainable in managing N. Typically in Kansas the NUE is valued around 50% in winter wheat when making N rate recommendations with 30% applied N being incorporated into soil organic matter (Olson and Swallow, 1985), resulting in less than 20% of actual N is lost from these systems.

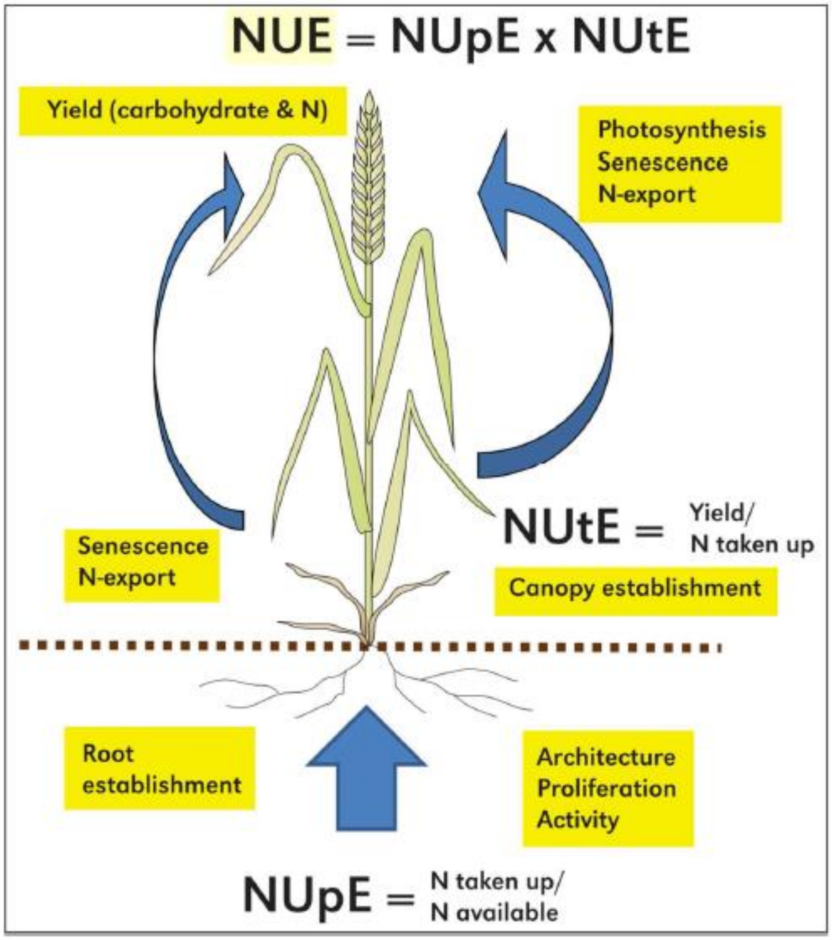


Figure 1-2. Nitrogen Use Efficiency (Hawksford, 2012).

Nitrogen Recommendation Algorithms

Continued work in optical sensor technology is ever evolving from year to year. Data collection in season on crop health can be utilized for creating solutions for N man. Algorithms are developed from the spectral data collected to generate agronomic interpretations. The first developed algorithm for in-season use in winter wheat for AOS was by Dr. William Raun and his collaborators (Raun et al., 2002). On the go AOS sensors using NDVI values have successfully predicted in-season yield potentials for critical growth stages in winter wheat (Raun et al., 2001).

Algorithm development can have issues where they become very robust and sensor specific, in return make it hard to apply to different slowing regions. Advancements in development have led to more robust generalized algorithms designed to be used throughout the growing season across various environmental conditions, extending life expectancy of the algorithm. Refinement of developed algorithms through data collection will be of importance due to changing conditions.

Sensor Technology

Different sensors have become commercially available to use in production agriculture through the year's. The problem is simplifying the utilization and cost for the producers to integrate into their cropping system. Without simplified ways to calibrate and collect the data need from the sensors, the usefulness to the producer is limited. On-the-go sensing that is mounted to equipment can be more feasible and sensible in the producer's mind.

Sensor technology began with the use of chlorophyll meters. The chlorophyll meter known more commonly by SPAD-502 meter (Konica Minolta, Tokyo, Japan) and Hydro N Tester (Yara International ASA, Oslo, Norway; HNT) can detect nitrogen availability through chlorophyll content in the plant leaves and canopy (Schlemmer et al., 2005). The higher the reading means that more red light is absorbed by the leaves, which means more chlorophyll is present. The chlorophyll meter can only detect the current N status of the plant, but cannot predict the future status as to indicate how much fertilizer would need to be applied for crop growth for achieving potential increased yields.

Optical sensor such as Trimble Greenseeker and Holland Scientific Crop Circle/Rapid Scan have been popular in the concept of on the go sensing. Both sensors utilize their specific

Red and Near Infrared bands to calculate NDVI. A difference between these two sensor's that deal with sensitivity is the footprint size between the sensor and target. With the Holland Scientific sensors, the size of the footprint can be adjusted by increasing the distance, which can strongly affect the measurement performance if it decreases the more intense the reflected light is greater than at a greater distance (Samborski et al., 2009). The footprint of Greenseeker on the other hand, does not change between sensor and the target. It was designed using mask approach to maintain the footprint of 600 by 1 cm (Samborski et al., 2009). Such optical sensors are designed so that if intensity of the light diminishes from center outward, positioning of the sensor in nadir view over the crop canopy before driving/walking using the sensor (Schepers, 2008).

There are advantages of using sensor technology for nitrogen recommendations over traditional soil test recommendation. Soil test recommendations rely on the use of profile nitrate test, in result are not commonly done due to that fact they are difficult to sample. Sensors can be used in place of soil testing to allow for estimating N availability from the soil based on response index (RI) (Mengel and Asebedo, 2013). When considering soil test, soil sampling should occur prior to planting. Often times soil tests taken prior to planting will not accurately consider N loss mechanisms, such as leaching, denitrification, and mineralization. Sensors have an upper hand to provide more current status on spring N availability for crop nutrient management recommendations. Management plans with the use of sensors can help with potential second N application before head is visible. The second application can help determine the rate of mineralization occurring from residue and soil organic matter, to determine if the second application is necessary to supply the crop for development. Sensor technology can provide current data of N availability, which is important in areas that greater potential of high N loss.

Summary

The use of N in agronomic decisions have led to increased crop production and limited resources. Understanding the N cycle is extremely important as N is key for crop production. As humans continue to exist N fertilization impacts are a major concern. Without proper care and attention, the arable land will have traumatic effects for successfully producing valuable crops.

Through development of sensor technology improving NUE exist as a solution to the problem. Evaluating the crop N status and providing N recommendations for the individual crops helps to determine how much N is need to continue crop development throughout the growing season.

References

Allen, W.A., H.W. Gausman, A.J. Richardson, and J.R. Thomas. (1969). Interaction of isotropic light with a compact plant leaf. *J. Opt. Soc. Am*. 59;1376-1379.

Aparicio, N., D. Villegas, J. Casadesus, J.L. Araus, C. Royo. (2000). Spectral vegetation indices as nondestructive tools for determining durum wheat yield. *Agronomy* J. 92:83-91.

Brady, N.C., & Weil, R.R. (2009). *Elements of the Nature and Properties of Soils* (Third Edition ed.). Pearson.

Curran, P.J. (1989). Remotes sensing of foliar chemistry. *Remote Sens. Environ*. 30:271-278. http://doi.org/10.1016/0034-4257(89)90069-2.

Daughtry, C.S.T., C.L. Walthall, M.S. Kim, E. Brown de Colstoun, and J.E. McMurtrey III. (2000). Estimating corn leaf chlorophyll concentration for leaf and canopy reflectance. *Remote Sens. Enviro*. 74:229-239. http://doi:10.1016/S0034-42579(00)00113-9.

Eitel, J.U.H, D.S. Long, P.E. Gessler, E.R. Hunt, Jr. and D.J. Brown. (2009). Sensitivity of ground-based remote sensing estimates of wheat chlorophyll content to variation in soil reflectance. *Soil Sci. Soc. Am. J.* 73:1715-1723. http://doi.org/10.2136/sssaj2008.0288.

Eitel, J.U.H., D.S. Long, P.E. Gessler, and E.R. Hunt, Jr. (2008). Combined spectral index to improve ground-based estimates of nitrogen status in dryland wheat. *Agronomy J*. 100:1694-1702. http://doi.10.2134/agronj2007.0362.

Fitzgerald, G.J. (2010). Characterizing vegetation indices derived from active and passive sensors. *International Journal of Remote sensing*, 31(16), 4335-4348. http://doi.org/10.1080/01431160903258217.

Fowler, D.B., and J. Brydon. (1989). No-till winter wheat production on the Canadian prairies: Placement of urea and ammonium nitrate fertilizers. *Agronomy J*. 81:518-524.

Gates, D.M., H.J. Keegan, J.C. Schleter, and V.R. Weidner. (1965). Spectral properties of plants. *Appl. Opt*. 4:11-20.

Gausman, H.W. (1973). Reflectance, transmittance, and absorptance of light by subcellular particles of spinach (*Spinacia oleracea* L.) leaves. *Agron. J*. 65:551-553.

Gausman, H.W. (1974). Leaf reflectance of near-infrared. *Photogrammetric Eng. Remote Sens*. 40:183-191.

Gausman, H.W. (1977). Reflectance of leaf components. *Remote Sens. Environ*. 6:1-9.

Gausman, H.W., W.A. Alled, R. Cardenas, (1969a). Reflectance of cotton leaves and their structure. *Remote Sens. Environ*. 1:19-22.

Gausman, H.W., W.A. Allen, and D.E. Escobar. (1974). Refractive-index of plant-cell walls. *Appl. Opt*. 13:109-111.

Gausman, H.W., W.A., Allen, R. Cardenas, and A.J. Richardson. (1971). Effects of leaf nodal position on absorption and scattering coefficients and infinite reflectance of cotton leaves, *Gossypium hirsutum* L. *Agronomy J*. 63:87-91.

Glossary of Soil Science Terms. (2013). Retrieved August 18, 2016 from Soil Science Society of America: http://www.soils.org/publications/soils-glossary#

Griffith, W.K., & Murphy, L.S. (1991). The development of crop production systems using best management practices.

Hatfield, J.L., Gitelson, a.a., Schepers, J.S., & Walthall, C.L. (2008). Application of spectral remote sensing for agronomic decisions. *Agronomy J*. 100:117-131. http://doi.org/10.2134/agronj2006.0370c.

Hawkesford, B.M.J. (2010). The diversity of nitrogen use efficiency for wheat varieties and the potential for crop improvement. *Better Crops with Plant Food, 96*(3), 10-12.

Heege, H.J., Reusch, S., Thiessen, E., (2008). Prospects and results for optical systems for site-specific on-the-go control of nitrogen-top-dressing in Germany. *Prec. Agri*. 9:115-131.

Holland, K.H., D.W. Lamb, and J.S. Schepers. (2012). Radiometry of proximal active optical sensors (AOS) for agricultural sensing. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote sensing, 5(6),* 1793-1802. http://doi.org/10.1109JSTARS.2012.2198049.

International Plant Nutrition Institute. *Generalized Nutrient Cycles.* (2013). Retrieved August 18, 2016, from http://www.ipni.net/article/IPNI-3326.

Lamb, D.W., M. Steyn-Ross, P. Scharre, M.M. Hanna, W. Silverster, and A. Steyn-Ross. (2002). Estimating leaf nitrogen concentration in ryegrass (*Lolium spp.)* pasture using the chlorophyll red-edge; theoretical modelling and experimental observations. *Int. J. Remote Sens*. 23:3619-3648.

Li, F., Y. Miao, F. Zhang, Z. Cui, R. Li, x. Chen, H. Zhang, J. Schroder, W.R. Raun, L. Jia. (2009). In-season optical sensing improves nitrogen-use efficiency for winter wheat. *Soil Sci. Soc. Am. J*. 43(5), 1566. http://doi.org/10.2136/sssaj2008.0150.

Mengel, D.B., A.R. Asebedo. (2013). Using the K-State intensive management, multiple application sensor based N rate calculator for winter wheat. Accessed 1 May 2017. www.agronomy.k-state.edu/services/soiltesting/documents/fertilizer_and_referencs.

Mengel, D.B., D.W. Nelson, & D.M. Huber. (1982). Placement of N fertilizers for no-till and conventional till corn. *Agronomy J.* 74:515-518.

Mistele, B., Guster, R., Schmidhlater, U., (2004). Validation of field-scaled spectral measurements of national Conference on Precision Agriculture and other Precision Resources Management. Minneapolis, Minnesota, USA, 99. 1187-1195.

Mulla, D.J., & Strock, J.S. (2008). Nitrogen transport processes in soil. *Nitrogen in Agricultural Soil*, 361-400.

Mulla, D.J., and J.S. Schepers. (1997). Key processes and properties for site-specific soil and crop managemtn. P. 1-18. *In* F.J. Pierce and E.J. Sadler (ed.0 The site specific management for agricultural systems. ASA, CSSA, and SSSA, Madison, WI.

Olson, R.V. and C.W. Swallow. (1984). Fate of labeled nitrogen fertilizer applied to winter wheat for five years. *Soil Sci. Soc. Am. J.* 48:583-586.

Pinter, P.J., Jr., R.D. Jackson, S.B. Idso, and R.J. Reginato (1981). Multidate spectral reflectance as predictors of yield in water stressed wheat and barley. *Int. J. Remote Sens*. 2:43-48.

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, E.V. Lukina, W.E. Thomason, J.S. Schepers. (2001). In-season prediction of potential grain yield in winter wheat using canopy reflectance. *Agronomy J.* 93:131-138.

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, M.L., Mullen, R.W., Freeman, K.W., Lukina, E.V. (2002). Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. *Agronomy J. 94*(4), 815-820. http://doi.org/10.2134/agronj2002.8150.

Reusch, S., J. Jasper, A. Link. (2010) Estimating crop biomass and nitrogen uptake using CropSpec TM, a newly developed active crop-canopy reflectance sensor. In: 10th International Conference on Precision Agriculture, Denver, Colorado.

Rice, C.W., & Smith, M.S. (1984). Short-term immobilization of fertilizer nitrogen at the surface of no-till and plowed soils. *Soil Science Society of Americal Journal*, 48:295-297.

Roberts, T.L. (2007). Right products, right rate, right time and right place…the foundation of best management practices for fertilizer. *Fertilizer Best Management Practices* (1), 29-32.

Rouse, J.W., R.H. Haas, J.A. Schell, and D.W. Deering. (1973). Monitoring vegetation systems in the Great Plains with ERTS, *Third ERTS, Third Symposium*, NASA Sp-351 I, 309-317.

Samborksi, S.M., N. Tremblay, and E. Fallon. (2009) Strategies to make use of plant sensors-based diagnostic information for nitrogen recommendations. *Agronomy J.* 101 (4), 800-816.

Schepers, J.S. 2008. Active sensor tidbits. Available at http://www.isafarmnet.com/08OFNConfPresent/Nitrogen/Nitrogen_Sensor_Handout.pdf [revised 26 Jan. 2008; cited 1 May 2017] Iowa Soybean Association, Urbandale.

Schlemmer, M.R., D.D. Francis, J.F. Shanahan, and J.S. Schepers. (2005). Remotely measuring chlorophyll content in corn leaves with differing nitrogen levels and relative water content. *Agronomy J.* 97:106-112.

Solie, J.B., W.R. Raun, R.W. Whitney, M.L. Stone, and J.D. Ringer. (1996). Optical sensor based field element size and sensing strategy for nitrogen application. Trasn. ASAE 39:1983-1992.

Stone, M.L., J.B. Solie, W.R. Raun, R.W. Whitney, S.L. Taylor, and J.D. Ringer. (1996). Use of spectral radiance for correcting in-season fertilizer nitrogen deficiencies in winter wheat. Trans. ASAE 39:1623-1631.

Tucker, C.J., J.H. Elgin, Jr., and J.E. McMurtry III. (1980). Relationship of spectral data to grain yield variation. *Photogrammetric Eng. Remote Sens*. 46:657-666.

Woolley, J.T. (1971). Reflectance and transmittance of light by leaves. *Plant Physiol*. 47:656-662.

Chapter 2 - Comparison of Active and Passive Optical Sensor Technologies to Increase Grain Yield and Nitrogen (N) Use Efficiency for In-Season Crop Monitoring in Winter Wheat (*Triticum aestivum L.*)

Abstract

Nitrogen (N) in Kansas soils can vary dramatically over the course of a year, and from year to year. Optical sensors have the potential to assess the N status of winter wheat in these cropping systems and optimize N recommendations. Sensor technology has become more readily available for applications in precision agriculture. Real-time sensing has become more of interest for site-specific management for crop monitoring, fertilizer, pesticide, and irrigation applications, especially for in-season nitrogen (N) applications. Two objectives for this study: 1) Compare the DJI X3 RGB camera and MicaSense RedEdge Multispectral Imager (Passive Optical Sensors) against the Holland RapidScan (Active Optical Sensor) for calibration reliability and producing stable relationships between NDVI and Grain Yield. 2) Compare Grain Yield performance and N rates of KSU optical sensor-based N recommendation algorithms against the KSU soil test based N recommendation system. Each year (2015-2016 & 2016-2017) five field trials across Kansas were conducted during the crop year in cooperation with county ag agents, farmers, and KSU Agronomy Experiment Fields. Treatments consisted of an N response curve, 1st (Feekes 4 single topdress, no reference strip) and 2nd (Feekes 4-9 multiple application, reference strip needed) generation KSU sensor-based N recommendation algorithms, sUAS based recommendation algorithms, and KSU soil test based N recommendations applied in the spring using applied N rates ranging from 0 to 140 kg ha^{-1}. The 1st generation KSU N recommendation algorithms

utilized N reference strip to determine N sufficiency, while 2nd generation KSU algorithms base N recommendations on potential biomass response of the crop and do not require a N reference. Three optical sensors were utilized in this study: 1) Holland Scientific Rapid Scan active optical sensor, 2) MicaSense RedEdge Multispectral Camera, 3) DJI X3 RGB Camera. Optical sensor data was collected under full sun and overcast sky conditions. Results of the optical sensor comparison indicates that the MicaSense RedEdge provides reliable spectral data during overcast and sunny sky conditions and was able to produce strong relationships between NDVI and Grain Yield. The results from the field studies conducted had shown soil test and optical sensor based N recommendation systems can produce optimal grain yields at a reduced N rate under most conditions. Both methodologies provide N recommendations that would allow Kansas wheat producers to maintain or increase grain yield, reduce N inputs, and enhance profitability while reducing environmental impact.

Introduction

Today many technological advances have been made to aid producers in being more sustainable modern farming practices. Nitrogen (N) is a limiting factor in crop production that is heavily influenced by weather conditions (Jensen et al., 1990). As well as a driving force for yields as it is an essential nutrient for crop growth (Kim et al., 2000). Demand of N by crops can vary spatially across field locations due to spatial differences in varying soil conditions (LaRuffa et al., 2001). In some cases, N is over applied without considering crop requirements or potential environmental risk to achieve adequate grain yield. Excess N that is applied can excessively increase plant biomass, causing increase potential of lodging and leading to decreased yields (Stokes et al., 1998). As Flowers (et al., 2002, 2003b, 2004) suggested, remote sensing has the potential to improve nitrogen efficiency in winter wheat to provide the appropriate recommendation of N fertilizer needed.

Remote sensing (RS) applications can be used to assess N status through the visible spectrum and understanding the spectral response curves (Hatfield et al., 2008). Using RS is a non-contact measurement for reflected radiation or emitted from crop production fields (Mulla, 2012). With RS technologies, specific wavelengths can be targeted that are indicative of crop health (Thenkabail et al., 2002). Photosynthetically active radiation (PAR) (400-700nm) is strongly absorbed by chlorophyll and indicative of N status (400 to 700 nm) (Pinter et al., 2003). Plants can likewise reflect wavelengths in the near infrared (NIR 700-1300 nm) region of the spectrum due to leaf density and canopy structure (Mulla, 2012). Vegetation indices are often applied in RS to integrate multiple wavelengths to measure the crops health response. The most common vegetation index in agriculture is normalized difference vegetation index (NDVI) that utilizes the red (R) and NIR wavelengths, and can be an indicator of plant biomass and grain yield (Wanjura and Hatfield, 1987). NDVI is capable of separating plant and soil signals and tend to have saturation effects due to increasing plant biomass. These saturation effects occur when leaf area index (LAI) exceeds 2.5-3 (Aparicio et al., 2000; Mistele et al., 2004; Heege et al., 2008).

Passive optical sensors such as satellites and cameras have been employed for crop monitoring for many decades. Passive sensors rely on the ambient light to measure the reflected light from the canopy in the visible and NIR spectrum (Mulla, 2012). When using PS, sky conditions must be considered. Clouds can result in variable illumination across the sky that can affect the quality of light being absorbed and reflected from the plant (Fitzgerald, 2010). Time of day (solar zenith angle) is important to considered in collecting imagery as solar zenith angle

(10:00 am to 4:00 pm) can change during the day and best time to collect data is within 2 hours of solar noon (12:00 pm) (Fitzgerald, 2010). The difficulty of using PS is the need to calibrate these sensors to account for the effects of cloud cover and sun zenith angle. Passive sensors and their potential difficulties with calibration induces limitations for RS applications in precision agriculture.

In more recent years, proximal remote sensing applications utilizing active optical sensors (AOS) have been used for the main purpose of real-time specific management for assessing crop status (Schepers et al., 1992). Active optical sensors emit their own light from pulse modulated light emitting diodes to measure the reflected light from the canopy (Mulla, 2012). As a result, AOS can be used in any sky conditions or at any time including night. The first sensing tool was Minolta soil plant analysis (SPAD) measuring leaf chlorophyll content for N applications (Schepers et al., 1992). As years progressed Stone et al. (1996) began work on measuring Red and NIR bands on winter wheat with AOS for in-season on-the-go sensing. Active optical sensor platforms can be mounted on farming equipment, such as tractors, spreaders, and sprayers. Work done by Stone et al. 1996 transitioned to on the go sensor readings to vary N fertilizer applications using algorithms for the N applications. Two main AOS have been used throughout literature which are GreenSeeker (Trimble Navigation Limited, Sunnyvale, California, USA) and Rapid Scan (Holland Scientific, Inc., Lincoln, NE, USA) for collecting NDVI throughout the growing season for wheat (*Triticum aestivum L.*) and corn (*Maize*).

Sensor-based nutrient management has been a slow adoption, but has been consistent with the delayed adoption of other agriculture technologies (Fugle and Kascak, 2015). Different vegetation indices have been created to relate leaf or canopy reflectance (Hatfield et al., 2004).

One thing that stays consist in predicting biomass and potential yield, is the use of normalized difference vegetation index (NDVI) in algorithms. The first algorithm developed for in-season for winter wheat was by Raun et al., (2002), which stated that N fertilization in-season relies on the use of ground based optical sensors to sense the crop and trigger N applications per the crop's yield potential response (Raun et al., 2002). Applying N after tillering tends to increase yield, but under certain weather conditions, such as dry conditions, the uptake of N can be impaired (Grant and Flaten, 1998). Although previous work done by Flowers (2001, 2003) shows that canopy reflectance can be used to accurately predict winter wheat tiller density for Feekes 4 N applications. An intensive approach of split applying N fertilizer can maximize vegetative growth at booting and increase grain protein content (Spratt, 1974). The challenge for producers to start adapting to use minimal input for maximum return is largely due to unpredictable weather conditions (Tremblay et al., 2007a).

Recent advances in calibration methods for multispectral cameras mounted to small unmanned aerial vehicles (UAVs) has resulted in a resurgence in the use of PS for assessing crop health. Two objectives were established for this study: 1) Compare the DJI X3 RGB camera and MicaSense RedEdge Multispectral Imager (Passive Optical Sensors) against the Holland RapidScan (Active Optical Sensor) for calibration reliability and producing stable relationships between NDVI and Grain Yield. 2) Compare Grain Yield performance and nitrogen rates of KSU optical sensor-based N recommendation algorithms against the KSU soil test based N recommendation system.

Material & Methods

This study was conducted during two winter wheat growing seasons, 2015-2016 and 2016-2017 in cooperation with Kansas Extension Agents, Kansas producers, and KSU Agronomy Experiment Fields. The locations of the sites were for 2015-2016 were Athol, Clifton, Valley Center, and Victoria (Table 2.1). The site locations for 2016-2017 were Belleville, Manhattan (Ashland Bottoms and North Farm), Salina, and Solomon (Table 2.2). Sites were located across Kansas to capture variability in soil, local weather, and potential grain yield and productivity.

Small plots (3x12 meters and 2x3 meters) were arranged at each location in a randomized complete block design with four replications with 0.91 m alley way for maneuvering equipment between treatments. Structure for the treatments (N time x N split) are summarized in Table 2.1 applied across site locations. N response curve was established with single rates of 0, 28, 56, 84, 112, 140 kg N ha^{-1} applied in the fall or winter period to establish a grain yield response to different N rates applied at each location. Split applications were applied after NDVI readings were taken to determine the rate of application needed at Feekes 4/5, 7, or 9. All treatments were applied by hand broadcasting granular urea (46-0-0).

Table 2.1 Timing, Rate, and Average Total N Applied to Winter Wheat Across 2016 & 2017 Locations

Treatment	1	2	3	4	5	6	7	8	9	10	11
Timing	Control	N Response Curve				N Reference Strip	Soil Test N Rec.	AOS ⸸ FKS 4 ‡ N Rec.	AOS FKS 4 & 7 N Rec.	sUAS § FKS 4 N Rec	sUAS FKS 4 & 7 N Rec.
	kg N ha^{-1}										
Fall/Winter	0	28	56	84	112	140	68	0	0	0	0
Feekes 4	0	0	0	0	0	0	0	45	26	46	33
Feekes 7-9	0	0	0	0	0	0	0	0	10	0	11
Total N Applied	0	28	56	84	112	140	68	45	36	46	44

⸸ AOS = Active Optical Sensor
‡ FKS = Feekes
§ sUAS = Small Unmanned Aircraft System

Cultural Practices

Tables 2.2, 2.3, 2.4, and 2.5 include key information that were used in establishing this study. All locations were soil sampled by pre-and post-harvest to assess other nutrients besides N. The winter wheat variety's that were used by the producer cooperative fields were their choice for the season and planted by their common methods. Most common method for planting winter wheat is by drill in Kansas. Locations varied in using preplant or starter fertilizer, which the producer used their most common practice in their field management. Producers made applications of herbicide in the early spring if needed as well as fungicides that were applied at flag leaf appearance.

Table 2.2. Site Information and Management Across 2016.

Year	2015-2016				
Location	Athol	Clifton	Valley Center	Victoria	Sabetha
Latitude	39.778177	39.554647	38.778177	37.874093	39.912247
Longitude	-98.903024	-97.236159	-98.201224	-97.244777	-95.877619
Soil Type	Holdrege Silt Loam	Crete Silty Clay Loam	Silty Clay Loam	Harney	Wymore Silty Clay Loam
Previous Crop	Summer Fallow	Soybeans	Corn	Wheat	Corn
Tillage Management	Conventional	No-Till	Minimal Till	No-Till	Minimal Till

Table 2.3. Site Information and Management Across 2017.

Year	2016-2017				
Location	Ashland Bottoms	Belleville	North Farm	Salina	Solomon
Latitude	39.145455	38.815047	39.213926	38.740521	38.870981
Longitude	-96.635152	-97.673848	-96.593277	-97.612077	-97.432551
Soil Type	Belvue Silt Loam	Reading Silt Loam	Silty Clay Loam	Roxbury Silt Loam	McCook Silt Loam
Previous Crop	Soybeans	Fallow	Soybeans	Wheat	Wheat
Tillage Management	Conventional	Minimal-Till	Conventional	Conventional	Conventional

Table 2.4. Key Dates and Cultural Practices Utilized at Sites in 2016.

Year	2015 – 2016				
Location	Athol	Clifton	Valley Center	Victoria	Sabetha
Variety	Everest	WB Grainfield	Everest	TAM 111	SY-Wolf
Seeding Rate (kg ha^{-1})	87	112	118	90	136
Planting Date	10/5/15	10/13/15	10/8/15	9/30/15	10/2/15
Winter/Fall Applications	3/5/16	3/15/16	2/25/16	3/14/16	3/3/16
Feekes 4 Treatment	3/19/16	3/18/16	2/25/16	3/18/16	3/16/16
Feekes 7- 9Treatment	4/19/16	4/16/16	4/15/16	4/16/19	N/A
Harvest Date	7/1/16	6/29/16	6/13/16	7/7/16	6/27/16

N/A = Not applicable

Table 2.5. Key Dates and Cultural Practices Utilized at Sites in 2017.

Year	2016-2017				
Location	Ashland Bottoms	Belleville	North Farm	Salina	Solomon
Variety	1863	Everest	1863	Everest	WB 4458
Seeding Rate (kg ha^{-1})	84	100	100	99	73
Planting Date	11/1/16	10/3/16	11/4/16	9/26/16	9/22/16
Winter/Fall Applications	11/15/16	11/16/15	11/15/16	11/1/16	11/1/16
Spring Applications	3/18/17	3/10/17	3/18/17	3/14/17	3/15/17
Feekes 4 Treatment	3/18/17	3/10/17	3/18/17	3/14/17	3/15/17
Feekes 7-9 Treatment	4/20/17	4/14/17	4/20/17	4/10/17	4/10/17
Harvest Date	6/16/17	6/28/17	6/20/17	6/14/17	6/21/17

Sampling Methods

Soil Sampling and Analysis

Soil samples were taken in the fall at the beginning of the growing season with a hand soil probe to a total depth of 60 cm at each site location. Across locations study area a composite soil sample of 6-8 cores were taken at both 0-15 and 0-60 cm depths. The samples for 0-15 cm were analyzed for soil pH, organic matter by loss of ignition, Mehlich-3 phosphorus, potassium, nitrate, ammonium nitrate, and zinc. The 0-60cm samples were analyzed for nitrate, ammonium nitrate, chloride, and sulfate. Coinciding with winter wheat harvest (through June and July) 0-15 and 0-60 cm soil samples were taken after harvesting was complete. Due to weather conditions during this time 0-60 cm depth soil samples were taken only if soil moisture allowed the soil probe to reach such depth. Summary of the pre-and post-harvest soil samples data is presented in Tables 2.6 and 2.7. Kansas State University (KSU) Soil Testing Laboratory analyzed all the soil samples. Nitrate analysis was used in KSU soil test recommendation calculation for this study's treatments. Locations did not receive any additional fertilizer supplementations other than N (urea).

Table 2.6. Soil Nutrient Analysis Across 2016 Locations.

Location	Athol		Clifton		Sabetha		Valley Center		Victoria	
	---------- Harvest ----------									
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
pH	5.6	2.9	6.0	6.3	6.3	6.5	6.5	6.5	6.2	6.2
0-15 % OM	2.8	2.9	2.8	3.2	4.0	4.3	2.8	3.1	2.3	2.4
0-15 P (ppm)	47.9	48.8	9.7	8.8	33.3	22.2	20.1	18.7	23.2	25.3
0-15 K (ppm)	607.5	530.8	287.5	266.8	442.5	313.8	330.8	208.7	485.0	407.2
0-15 NH_4-N (ppm)	15.5	8.9	10.7	7.0	12.6	8.7	7.8	10.4	5.4	8.9
0-15 $N0_3$-N (ppm)	17.6	9.9	2.1	9.4	19.2	2.8	1.8	2.6	6.8	3.5
0-60 NH_4-N (ppm)	8.0	9.3	5.9	9.3	9.9	N/A	5.6	7.2	5.0	9.0
0-60 NO_3-N(ppm)	9.0	6.8	2.6	5.4	2.6	N/A	0.9	2.8	3.6	3.1
0-60 Cl^- (ppm)	5.8	6.5	3.1	5.6	4.8	N/A	3.8	5.4	4.9	2.0
0-60 $S0_4$-S (ppm)	3.6	3.9	2.8	4.5	20.4	N/A	6.9	5.4	11.6	3.0

N/A = Soil conditions to dry and compacted, no more than 0-15 reliable.

Table 2.7. Soil Nutrient Analysis Across 2017 Locations.

Location	Ashland Bottoms		Belleville		North Farm		Salina		Solomon	
	--- Harvest									
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
pH	6.23	6.23	5.35	5.14	6.20	5.89	6.66	6.73	7.96	8.24
0-15 % OM	31.00	1.11	2.02	3.18	2.73	3.07	3.64	4.05	2.01	2.42
0-15 P (ppm)	50.48	38.88	55.53	71.50	50.48	16.40	26.91	20.58	22.49	26.03
0-15 K (ppm)	162.00	161.75	502.50	424.50	162.00	200.00	395.00	379.00	400.00	411.00
0-15 NH_4-N (ppm)	6.50	4.36	2.85	6.50	6.50	6.05	7.48	7.32	3.33	21.58
0-15 $N0_3$-N (ppm)	4.07	2.54	12.66	4.62	4.07	2.14	42.88	2.92	46.71	6.93
0-60 NH_4-N (ppm)	3.65	4.99	4.41	N/A	7.53	N/A	5.52	9.98	3.74	15.29
0-60 NO_3-N(ppm)	1.60	1.14	9.29	N/A	2.68	N/A	26.33	3.44	31.68	3.61
0-60 Cl^- (ppm)	4.25	3.36	4.95	N/A	6.20	N/A	5.78	2.97	8.80	4.68
0-60 $S0_4$-S (ppm)	1.38	1.13	3.89	N/A	4.78	N/A	3.28	4.10	2.56	3.07

N/A = Soil conditions to dry and compacted, no more than 0-15 reliable.

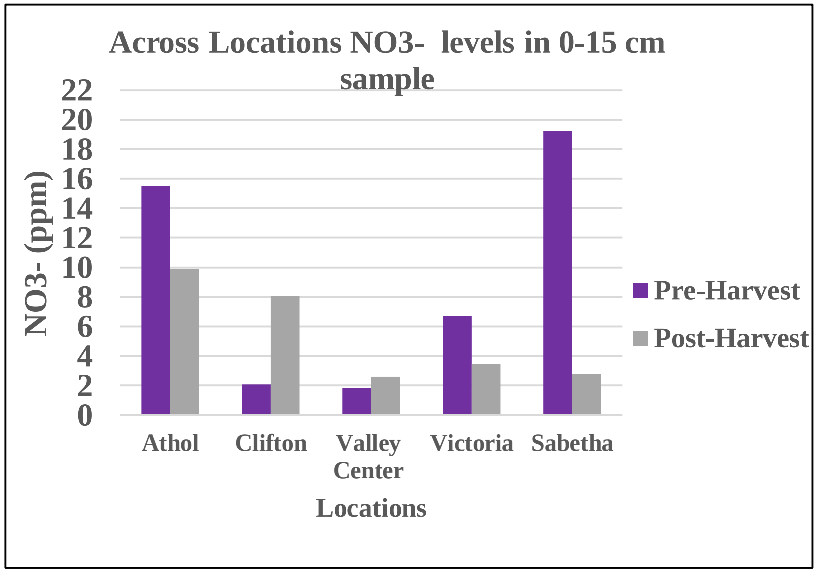


Figure 2-1. 2016 Pre-and-Post Harvest NO_3^- Present in 0-15 cm Sample.

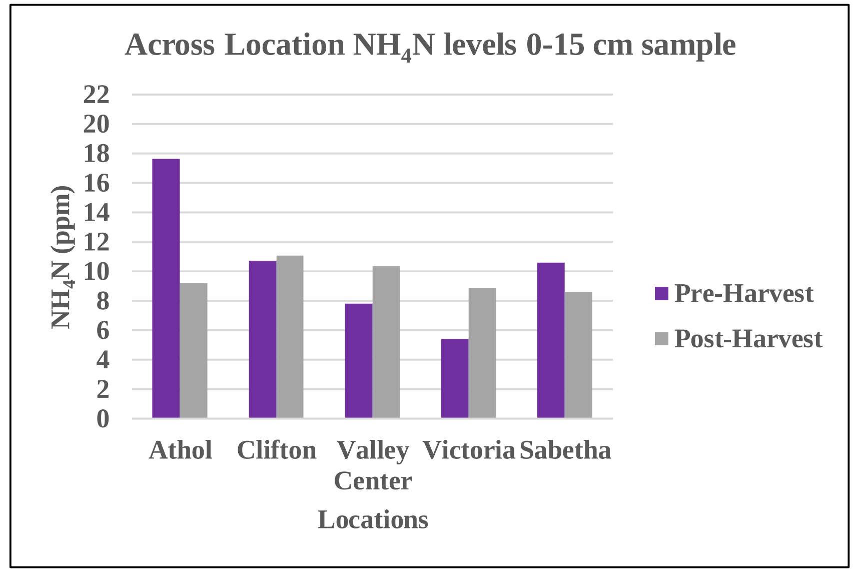


Figure 2-2 2016 Pre-and-Post Harvest NH_4N Present in 0-15 cm Sample.

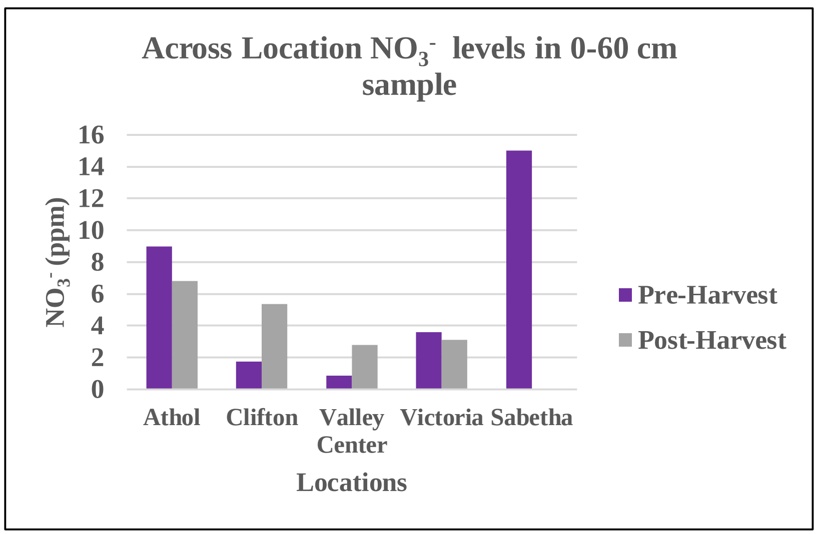


Figure 2-3 2016 Pre-and Post-Harvest $N0_3^-$ Present in 0-60 cm Sample.

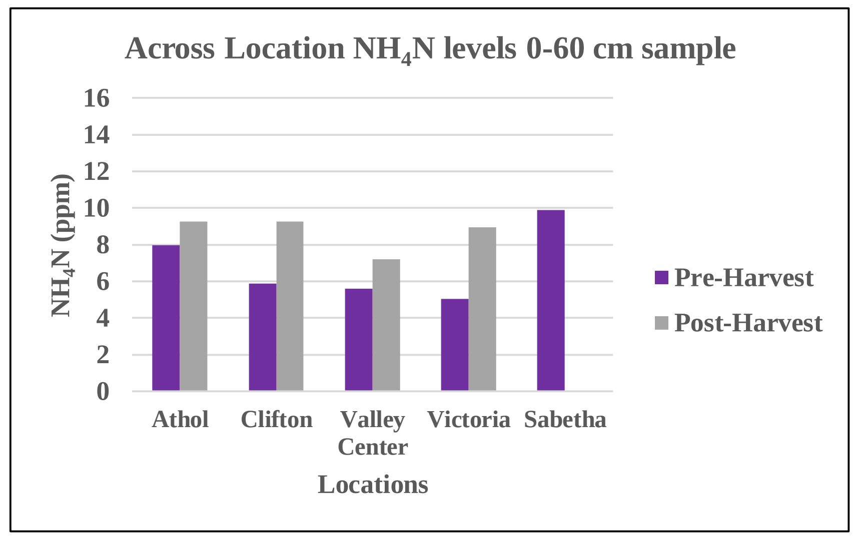


Figure 2-4 2016 Pre-and Post-Harvest NH_4N Present in 0-15 cm Sample.

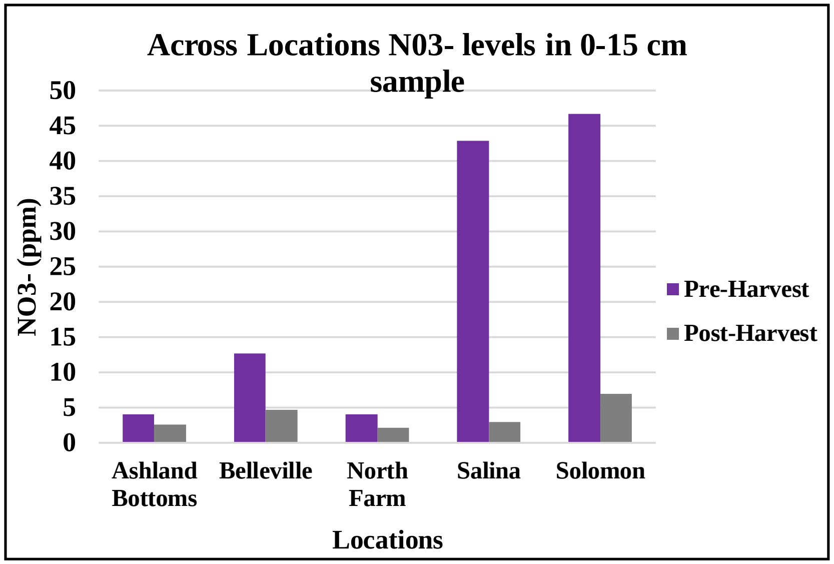


Figure 2-5. 2016 Pre-and-Post Harvest NO_3^- Present in 0-15 cm Sample.

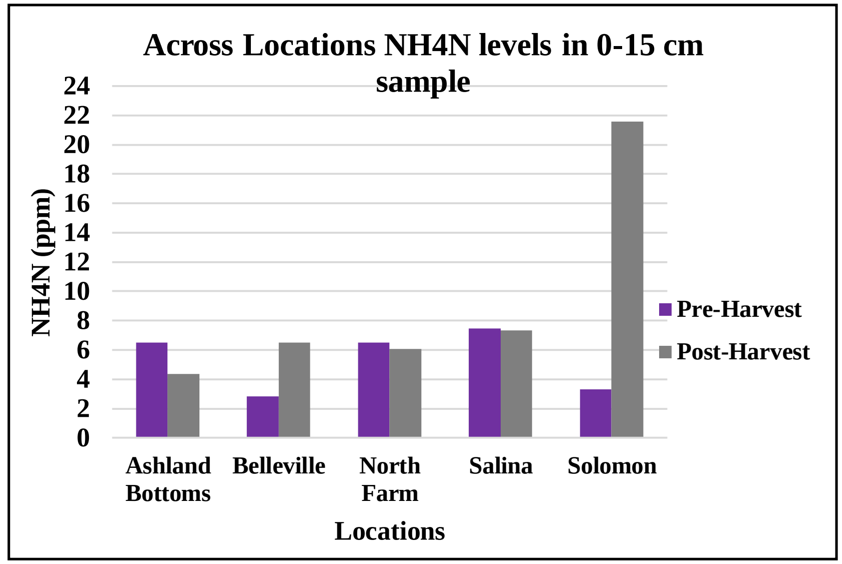


Figure 2-6 2016 Pre-and-Post Harvest NH_4N Present in 0-15 cm Sample.

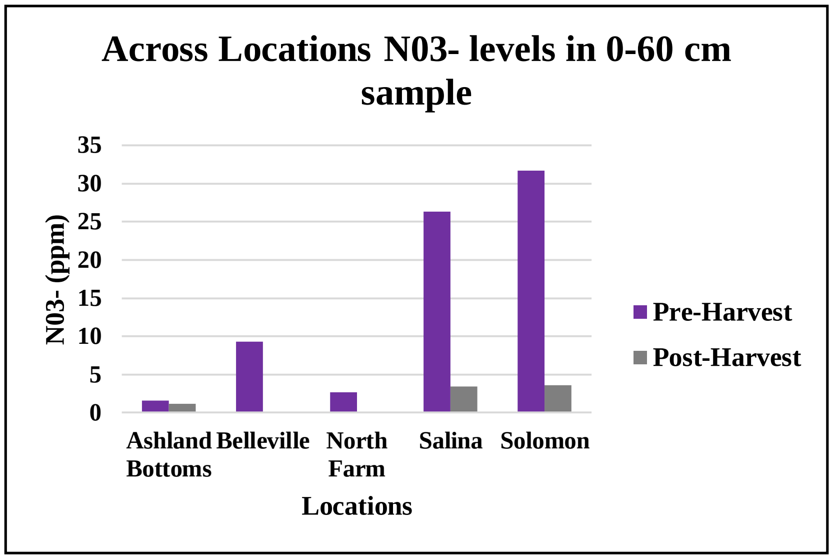


Figure 2-7. 2016 Pre-and-Post Harvest NO_3^- Present in 0-60 cm Sample.

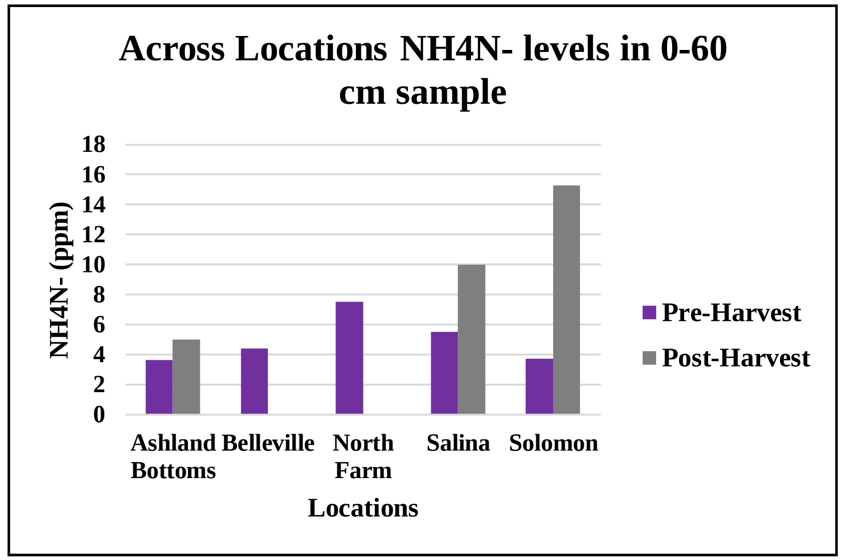


Figure 2-8. 2016 Pre-and Post-Harvest NH_4N Present in 0-60 cm Sample.

Table 2.8. Precipitation Accumulation During the 2016 Growing Season.

	Monthly Precipitation										
Location	September	October	November	December	January	February	March	April	May	June	July
	mm										
Athol	11.68	23.37	57.40	69.85	20.57	9.14	6.35	76.45	155.96	83.82	74.93
Clifton	71.37	14.48	76.71	124.97	17.78	16.51	20.07	88.65	205.23	22.86	74.17
Sabetha	51.31	14.48	7.03	60.96	10.41	10.92	28.19	167.89	123.19	20.57	70.36
Valley Center	41.66	24.13	93.98	89.66	9.40	12.45	33.53	95.76	159.26	72.64	100.84
Victoria	9.65	42.67	38.10	29.46	9.14	5.33	10.92	176.28	69.09	80.01	78.99

Table 2.9. Precipitation Accumulation During the 2017 Growing Season.

	Monthly Precipitation									
Location	September	October	November	December	January	February	March	April	May	June
	mm									
Ashland Bottoms	156.97	55.12	10.92	40.13	34.29	11.68	100.58	114.81	91.69	74.42
Belleville	0	40.13	22.10	25.15	35.81	3.81	50.80	38.86	224.79	22.10
North Farm	108.20	70.36	7.62	21.08	24.89	11.94	106.93	126.75	96.77	71.63
Salina	50.29	47.75	13.46	16.76	36.83	4.32	102.87	116.59	118.36	93.22
Solomon	50.29	47.75	13.46	16.76	36.83	4.32	102.87	116.59	118.36	93.22

Precipitation Data

Precipitation data was collected for each site during the crop year at the closest location available on the KSU Mesonet website. Precipitation data was collected prior to planting through grain harvest tabulated on a daily sum status in Table 2.8 and 2.9.

Analysis for sensor comparison of the three sensors only 2017 site years were used. The 2016 data for sensor comparisons was not used due to DLS was not available for use in collecting imagery.

Optical Sensor Data Collection

This study utilized three optical sensors, the first sensor is the Holland Scientific Rapid Scan (Holland Scientific, Lincoln, NE, USA) (ground platform) (Figure 2-9). The Holland Scientific Rapid Scan is a handheld active optical sensor (AOS) using a walking speed of approximately one meter per second at approximate height of one meter above the canopy (Figure 2-9). Wavelength channels set for this AOS are red (670 nm), red edge (730 nm), and near infrared (780 nm). On the DJI Matrice 100 (aerial platform) two sensors where mounted to the craft, MicaSense RedEdge multispectral camera (MicaSense Inc, 2015) capturing aerial imagery utilizing the blue (475 nm),

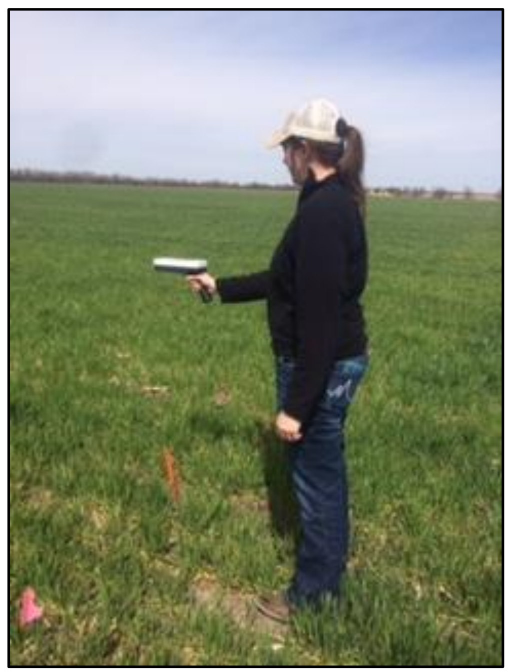


Figure 2-9. In-Season Use of the Active Optical Sensor (Rapid Scan).

green (560 nm), red (668 nm), red edge (717 nm) and near infrared (841 nm) and the DJI X3 camera capturing 12 mega pixel Red Green Blue (RGB) imagery (Figure 2-10).

In order to calibrate the MicaSense RedEdge to percent reflectance, the MicaSense reflectance panel was used before each flight and after each fight. Placed flat on the ground and ensured no shadow was on the panel receiving direct sunlight to calibrate the imagery collected (MicaSense Inc, 2015). The aerial platform was perpendicular to the reflectance panel (Figure 2-11) when calibration pictures were taken (MicaSense Inc, 2015). During 2017, the MicaSense downwelling light sensor (DLS) was acquired and mounted on top of the aerial platform. The DLS uses a 5-band incident light sensor to measure the ambient light during the flight for each of the 5 bands utilized by the MicaSense RedEdge. Information collected from the DLS is used for correcting lighting changes during flight in regards to the changing light from cloud cover over the sun (MicaSense Inc, 2015). DJI X3 RGB camera does not have a standardized calibration method and therefore was uncalibrated and image brightness values were utilized.

Figure 2-10. DJI Matrice 100 Platform Equipped with DJI X3 and MicaSense RedEdge. Photograph credit: Antonio Ray Asebedo.

Figure 2-11. MicaSense RedEdge calibration reflectance panel. Photograph credit: Antonio Ray Asebedo.

The aerial platform and ground platform optical sensor data was collected on the same day and approximate time. Aerial platform was flown at an approximate height and speed of 40 meters above ground level (AGL), 3-4 meters per second with front and sidelap of 85%. Imagery was collected with sky conditions of full sun or complete overcast between hours 10:00 am to 4:00 pm. Collection dates targeted key yield determining growth stages for sensor data collected is listed in Table 2.10.

MicaSense imagery was processed internally through Atlas (MicaSense Inc. Atlas, 2015) and the DJI X3 was processed through Agisoft Photscan (Agisoft, 2017). Spectral data from each optical sensor was analyzed in ArcMap (ArcGIS, 2016). For each site extraction of data, a field boundary shapefile was created based off the ground control points (GCP's) at each location. Fishnets were created based of the harvest area of the plots at each location (1.52x3.04 meters). For each sensor NDVI and NDRE means were calculated based of the sensors wavelengths per plot. To extract per plot NDVI and NDRE, zonal statistics by table extraction was used in the imagery collected.

Plant Samples/Harvest

All site locations were machined harvested with a plot combine with an area of 1.5 meters by 12 meters used for grain yield. Harvesting of the grain was placed into a sack, weighed, and a subsample was taken for analysis of grain moisture and test weight using a water basis meter (Dickey Jon 2100 GAC). Winter wheat grain yield was adjusted to 125 g kg^{-1} moisture. All grain samples and analyzed for N concentrations to the KSU Soil Testing Lab.

The following calculations were used in completing data analysis:

- **NUE Recovery** =

$$\frac{\text{Treatment Total Grain N Uptake (kg N ha}^{-1}\text{)} - \text{Control Total Grain N Uptake (kg N ha}^{-1}\text{)}}{\text{Total Top-dress N Applied (kg N ha}^{-1}\text{)}}$$

- **Grain Protein Content** = Grain N Content (g kg^{-1}) * 6.25

- **KSU Soil Testing N Rec for Winter Wheat** =

(Yield Goal (kg ha^{-1}) * 0.043 kg N kg^{-1} of Grain Yield – (Organic Matter (g kg^{-1})*1.12) - Soil Profile Nitrate (kg ha^{-1}) – manure credits – additional credits

- **Grain Protein Content** = Grain N Content (g kg^{-1}) * 6.25

- **Normalized Difference Vegetation Index (NDVI)** = (Rouse, 1937)

$$\frac{\text{NIR - Red}}{\text{NIR + Red}}$$

- **Normalized Difference Red Edge Index (NDRE)** = (Barnes et al., 2000)

$$\frac{\text{NIR - RE}}{\text{NIR + RE}}$$

- **False Normalized Difference Vegetation Index (False NDVI)** = (Fitzgerald, 2010)

$$\frac{\text{Green – Red}}{\text{Green + Red}}$$

Table 2.10. Shows the Key Determining Growth Stages Used for Collecting Data.

Growth Stage (Feekes)	Characteristics
Feekes 4	Leaf sheaths lengthen (spring greenup). Sheath begins to lengthen and starts to become erect. (Tillering)
Feekes 7	Second node of stem visible. (Stem Elongation)
Feekes 9	Flag leaf visible. Flag leaf is completely emerged from the whorl. (Stem Elongation)

Statistical Analysis

For representation of the dataset of the graphs and tables were created with EXCEL (Microsoft, 2016). Imaging processing for the MicaSense occurred internally with Atlas (MicaSense Inc, 2015) and the RGB imagery with Agisoft Photo (Agisoft, 2017). ArcMap (ArcGIS, 2016) was used for imagery extraction. Testing for data normality and regression analysis was conducted in R version 3.4 (R Core Team, 2017). Statistical analysis of the data using mixed effects models was conducted with SAS University Edition (SAS, 2016) utilizing the MIXED procedure.

Results and Discussion

Optical Sensor Comparison

The results from comparing the the MicaSense RedEdge (passive sensor) and the Holland Scientific Rapid Scan (active optical sensor) show a very good relationship with an R^2 of 0.82 under sunny sky conditions and R^2 0.82 under overcast sky conditions (Figure 2-12). Analysis of variance conducted comparing the slope of sunny and overcast conditions indicated that they are significantly different with a p-value less than 0.001. These results indicate that the calibration for the MicaSense RedEdge that utilizes a calibration reflectance panel and a downwelling light sensor is adequately compensating for changes in light conditions to provide reliable spectral data for assessing crop health throughout the growing season. However, figure 2-12 indicate that MicaSense RedEdge NDVI values are inflating under overcast conditions, which could lead to incorrect assessment of plant health if not accounted for. Hatfield et al. (2008) determined under overcast sky conditions, the reduction of sunlight available could be altering how much leaves are absorbing and reflecting and therefore affecting the reflectance values. Additional development to the MicaSense RedEdge calibration methods may be necessary to allow for a single calibration model to be used to address most sky conditions observed.

The comparison between the DJI X3 (RGB) False NDVI against the Holland Scientific Rapid Scan had a very poor relationship with an R^2 of 0.08 under overcast sky conditions and an R^2 of 0.43 under sunny sky conditions (Figure 2-12). This can be due to the fact DJI X3 (RGB) camera is not calibrated like the MicaSense RedEdge and Holland Scientific Rapid Scan. Therefore, the spectral data provided by the DJI X3 is heavily influenced by the sky conditions during imagery collection and is more likely to reflect changes in sky conditions and not plant health (Figure 2-12).

The analysis of NDVI with grain yield show that the MicaSense RedEdge and the Holland Scientific Rapid Scan produced a strong relationship with an R^2 of 0.66 and 0.62 (Figures 2-13 and 2-14). However, uncalibrated False NDVI generated by the DJI X3 had no relationship with grain yield with an R^2 of 0.0018. The poor relationship generated by the DJI X3 is likely due to the lack of a calibration reflectance panel for normalizing out sky conditions and the absence of a near-infrared (NIR) band for assessing plant biomass. The utilization of the Holland Scientific Rapid Scan provided stable spectral data for validating the reliability of imagery produced by the DJI X3 and MicaSense RedEdge for assessing crop health. These results are supported by previous work conducted by Fitzgerald (2010) in which he determined active optical sensor technology can be used to validate the reliability of spectral data produced by passive optical sensors under varying sky conditions.

Comparison between Soil Test and Optical Sensor based N recommendations by location within year

2016 Athol Field Analysis

No significance difference in grain yield was observed across all treatments (Table 2.11). Although grain yield ranged from 4.91 to 5.25 Mg ha^{-1}, high residual N in the soil profile provided enough N to support season long growth and achieve maximum grain yield (Table 2.6, Table 2.11). The lack of precipitation events during March till mid-April could have led to tiller abortion and potential to decrease yield (Table 2.8). Nitrogen recommendations generated by the optical sensor based N recommendation algorithms (treatments 8-11) applied nearly 70 kg less N per hectare when compared to the soil test based N recommendation system (treatment 7), without a statistical reduction in grain yield and protein (Table 2.11).

2016 Clifton Field Analysis

Grain yields produced at this site were ranged from 3.92 to 6.20 Mg ha $^{-1}$ with a significant grain yield response to applied N (Table 2.12). Precipitation events during the early part of the growing season were low (20-40 mm) till the latter half of the season, were greater

(40-100mm) rainfall amounts were observed (Table 2.8). Statistical differences in grain yield were observed between the soil test (treatment 7) and optical sensor (treatment 8-11). The soil test based N recommendation achieved grain yield of 5.72 Mg ha^{-1} which was statistically higher than single N application optical sensor treatments 8 and 10 at 5.02 and 5.03 Mg ha^{-1} (Table 2.8). However, the intensive N applications treatments 9 and 11 achieved statistically equal grain yield to the soil test treatment 8 while applying approximately 76 kg less N per hectare.

2016 Sabetha Field Analysis

At Sabetha in NE Kansas the crop was impacted by thin stands at green up. As the season progressed the stand increased in tillering that compensated for the patchy stand conditions. Despite the stand condition, grain yield ranged from 5.10 to 5.99 Mg ha^{-1} and no statistical differences were observed for grain yield across treatments (2.13). This was likely due to the very high residual N within the soil profile (Table 2.6). As a consequence, treatment 7, the KSU soil test recommendation provided a zero recommendation for N and achieved 5.77 Mg ha^{-1}. The optical sensor treatments 8-9 recommended less than 20 kg of N per hectare and did not observe a statistical increase in grain yield at 5.99 and 5.43 Mg ha^{-1} (Table 2.13).

2016 Valley Center Field Analysis

Adverse conditions occurred at Valley Center late in the season. A hail storm occurred prior to harvest at the study location and caused considerable damage to the plot area. Therefore, the results presented in Table 2.14 are highly confounded with hail damage and will not be assessed.

2016 Victoria Field Analysis

In this site-year, located in western KS, precipitation was minimal and drought conditions were observed (Table 2.8). Statistical differences were observed across treatments with grain yield ranging from 2.3 to 4.3 Mg ha^{-1} (Table 2.15). The soil test treatment 7 achieved a statistically higher grain yield and protein at 3.76 Mg ha^{-1} and 140 g kg^{-1} when compared to all of the optical sensor treatment 8-11 (Table 2.15). This reduction in performance by the optical sensor based treatments is likely due to precipitation events not incorporating optical based sensor treatments into the soil soon enough to impact tillering and head size formation (Table 2.4, 2.8)

2017 Ashland Bottoms Field Analysis

Early season drought conditions, heavy leaf rust pressure, and potential chloride deficiency were observed resulting in low grain yield ranges between 1.4 and 1.9 Mg ha^{-1} (Table 2.16). The results were confounded by these issues and therefore will not be assessed.

2017 Belleville Field Analysis

Overall grain yields were excellent with a range between 5.44 to 6.11 Mg ha $^{-1}$ with optical sensor treatment 10 at with the highest yield of 6.11 Mg ha^{-1} (Table 2.17). Limited statistical differences were observed across treatments for grain yield with treatment 6 at 140 kg N and optical sensor treatment 10 at 41 kg N applied making significantly higher grain yield over the 0 N applied treatment 1 (Table 2.17). Optical sensor based treatments 8 and 10 achieved statistically equal grain yield and protein when compared to the soil test treatment 7 and applied approximately 10 kg less N per hectare (Table 2.17).

2017 North Farm Field Analysis

Grain Yields produced at this site were excellent in response to applied N with a grain yield range between 3.25 to 5.80 Mg ha^{-1} (Table 2.18). Statistical significance in grain yield to treatments were observed (Table 2.18) with the highest yield being 5.80 Mg ha^{-1} being soil test treatment 7, while limited significance was observed between treatments 8-11 (Table 2.18). The soil test treatment 7 had a statistically higher grain yield when compared to optical sensor treatments 8,9,11. Optical Sensor treatment 10 achieved 5.01 Mg ha^{-1} grain yield which was statistically equal to soil test treatment 7 (Table 2.18). No statistical differences in grain protein was observed across soil test and optical sensor based treatments (Table 2.18)

2017 Salina Field Analysis

The Salina location had a high residual N level, with profile N of NO_3^- of 26.33 ppm and NH_4N of 42.88 ppm (Table 2.7) with grain yields of 4.12 to 4.70 Mg ha^{-1}. Treatments 10 & 11 (sUAS treatments) were not applied at this location due to being in close proximity to an airport. A statistical response was only observed over the zero N treatment 1 and no statistical response across treatments 2-9 (Table 2.19). Even though there was a better response on grain yield protein (Table 2.19). Treatment 6, high rate of N, 140 kg N ha^{-1}, achieved the statistically highest grain protein across treatments. The soil test and optical sensor treatments 7-9 recommend no N to be applied without a statistical reduction in grain yield. However, treatments 7-9 observed a statistical reduction in grain protein at approximately 121 g kg^{-1} when compared to treatment 6, 140 kg N ha^{-1} (Table 2.19).

2017 Solomon Field Analysis

This location was also a high N environment started the season with 85.46 ppm of residual (nitrate and ammonium) N in the soil profile (Table 2.7) and generated excessive early season growth. No statistical grain yield response to applied N was observed across the treatments (Table 2.20). Soil test and optical sensor treatments 7-11 did observe a 1 g kg^{-1} reduction in grain protein when compared to treatments 3-6 (Table 2.20). The soil test treatment 7 applied 30 to 64 kg less N per hectare when compared to the optical sensor treatments 8-10.

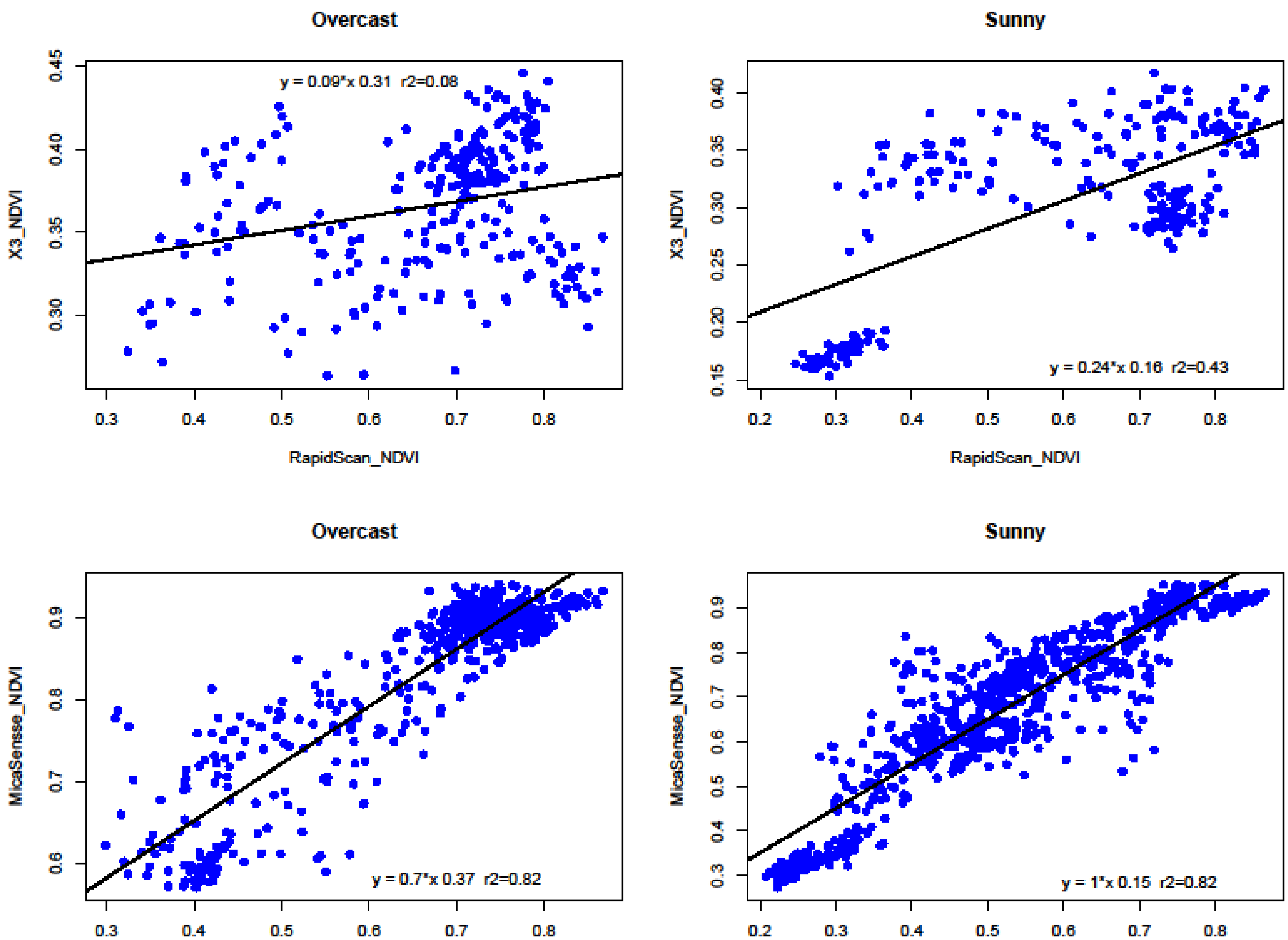


Figure 2-12. Comparison of RapidScan, MicaSense RedEdge, and DJI X3 under overcast and sunny sky conditions across 2016-2017 locations.

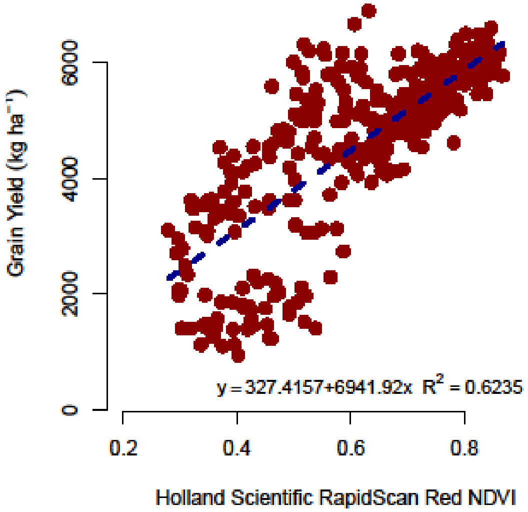


Figure 2-13. Holland Scientific RapidScan Red NDVI versus Grain Yield during Stem Elongation Across 2016-2017 Locations.

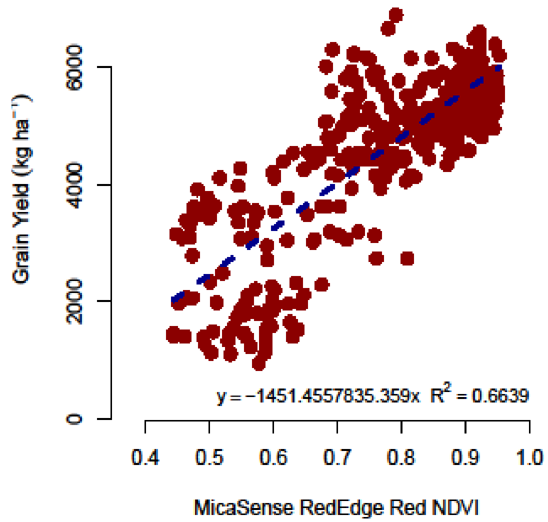


Figure 2-14. MicaSense RedEdge Red NDVI versus Grain Yield during Stem Elongation Across 2016-2017 Locations.

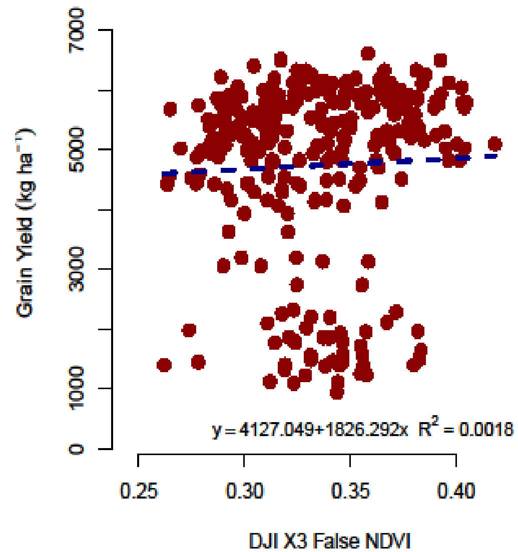


Figure 2-15. DJI X3 False NDVI versus Grain Yield during Stem Elongation Across 2016-2017 Locations.

Table 2.11 2016 Summary of Results for Grain Yield, Grain Protein, and Flag Leaf N at Athol.

Treatment	Fall/Winter	Feekes 4	Feekes 8	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	----------- N Application Rate kg ha^{-1} -----------				Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	5.15	A	108	D	26	E
2	28	0	0	28	4.93	A	119	CD	28	BCD
3	56	0	0	56	5.21	A	121	CD	29	ABCD
4	84	0	0	84	5.18	A	129	ABC	28	BCD
5	112	0	0	112	5.25	A	140	A	30	ABCD
6	140	0	0	140	5.18	A	134	AB	29	ABCD
7	91	0	0	91	4.91	A	129	ABC	27	ABCD
8	0	55	0	55	5.20	A	126	BC	27	DE
9	0	17	10	27	4.91	A	121	C	27	DE
10	0	19	0	19	5.07	A	119	CD	27	CDE
11	0	8	10	18	5.23	A	119	CD	27	CDE
SE					3.92		0.43		0.07	
Treatment Pr > F					0.8		< 0.00		< 0.00	

NS = Not significant

Treatments with same letter are not statistically different at 0.05 alpha

Table 2.12. 2016 Summary of Results for Grain Yield, Grain Protein, and Flag Leaf at Clifton.

Treatment	Fall/Winter	Feekes 4	Feekes 7	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	------------ N Application Rate kg ha^{-1} -----------				Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	3.98	E	106	A	29	F
2	28	0	0	28	4.77	D	106	A	29	EF
3	56	0	0	56	4.84	D	111	A	33	CD
4	84	0	0	84	5.72	ABC	123	A	37	AB
5	112	0	0	112	3.92	BCD	114	A	36	BC
6	140	0	0	140	6.20	A	121	A	39	AB
7	138	0	0	138	5.72	ABC	106	A	39	AB
8	0	62	0	62	5.02	CD	115	A	34	CD
9	0	31	45	76	5.77	AB	115	A	39	AB
10	0	42	0	42	5.03	CD	108	A	33	DE
11	0	18	41	59	5.82	AB	111	A	37	AB
SE					4.02		0.6571		0.12	
Treatment Pr > F					< 0.00		0.64		< 0.00	

NS = Not significant

Treatments with same letter are not statistically different at 0.05 alpha

Table 2.13. 2016 Summary of Results for Grain Yield, Grain Protein, and Flag Leaf N at Sabetha.

Treatment	Fall/Winter	Feekes 4	Feekes 7	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	------------ N Application Rate kg ha^{-1}-----------				Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	5.10	B	114	C	35	D
2	28	0	0	28	5.50	AB	123	AB	39	A
3	56	0	0	56	5.25	AB	122	AB	38	AB
4	84	0	0	84	5.58	AB	124	AB	38	ABC
5	112	0	0	112	5.33	AB	125	A	39	A
6	140	0	0	140	5.59	AB	126	A	38	AB
7	0	0	0	0	5.70	AB	123	AB	35	CD
8	0	16	0	16	5.99	A	119	BC	36	BCD
9	0	21	0	21	5.48	AB	123	AB	37	BCD
SE					4.73		0.21		0.83	
Treatment Pr > F					0.4		0.02		0.00	

NS = Not significant

Treatments with same letter are not statistically different at 0.05 alpha

Table 2.14. 2016 Summary of Results for Grain Yield, Grain Protein, and Flag Leaf N at Valley Center.

Treatment	Fall/Winter	Feekes 4	Feekes 7	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	---------- N Application Rate kg ha^{-1} ----------				Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	0.96	E	108	G	21	E
2	28	0	0	28	1.48	CD	116	F	26	D
3	56	0	0	56	2.04	AB	127	DE	31	BC
4	84	0	0	84	2.10	AB	134	CD	33	AB
5	112	0	0	112	2.40	A	143	AB	36	A
6	140	0	0	140	2.28	A	148	AB	36	A
7	110	0	0	110	2.08	AB	139	BC	33	AB
8	0	37	0	37	1.46	CD	120	EF	24	DE
9	0	50	33	84	1.70	BC	126	EF	30	C
10	0	35	0	35	1.16	DE	118	F	25	D
11	0	32	0	32	1.08	DE	121	EF	25	D
SE					2.11		0.25		0.12	
Treatment Pr > F					< 0.00		< 0.00		< 0.00	

NS = Not significant

Treatments with same letter are not statistically different at 0.05 alpha

Table 2.15. 2016 Summary of Results for Grain Yield, Grain Protein, and Flag Leaf N at Victoria.

Treatment	Fall/Winter	Feekes 4	Feekes 9	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	---------- N Application Rate kg ha^{-1} ----------				Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	2.30	E	105	E	19	E
2	28	0	0	28	3.37	BC	110	E	24	D
3	56	0	0	56	3.62	BC	119	CD	28	C
4	84	0	0	84	3.63	BC	119	CD	29	BC
5	112	0	0	112	3.60	BC	133	B	31	BC
6	140	0	0	140	4.30	A	143	A	33	A
7	110	0	0	110	3.76	B	140	A	33	A
8	0	56	0	56	3.28	C	118	D	28	C
9	0	22	31	53	3.44	BC	117	D	29	BC
10	0	18	0	18	2.80	D	106	E	23	D
11	0	16	44	60	2.49	DE	124	C	30	BC
SE					2.54		0.20		0.09	
Treatment Pr > F					< 0.00		< 0.00		< 0.00	

NS = Not significant

Treatments with same letter are not statistically different at 0.05 alpha

Table 2.16. 2017 Summary of Results for Grain Yield, Grain Protein, and Flag Leaf N at Ashland Bottoms.

Treatment	Fall/Winter	Feekes 4	Feekes 7	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	------------ N Application Rate kg ha^{-1} ---------				Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	1.40	AB	98	D	29	F
2	28	0	0	28	1.50	AB	108	CD	34	F
3	56	0	0	56	1.66	AB	111	CD	33	EF
4	84	0	0	84	1.90	A	130	AB	36	DE
5	112	0	0	112	1.67	AB	134	A	36	CD
6	140	0	0	140	1.89	A	130	AB	37	BCD
7	140	0	0	140	1.70	AB	136	A	39	AB
8	0	104	0	104	1.76	AB	132	AB	34	BCD
9	0	17	41	59	1.78	AB	123	B	33	BCD
10	0	101	0	101	1.34	B	136	A	35	AB
11	0	66	52	118	1.62	AB	135	A	34	ABC
SE					2.66		0.38		0.16	
Treatment Pr > F					0.40		< 0.00		< 0.00	

NS = Not significant — Treatments with dame letter are not statistically different at 0.05 alpha

Table 2.17. 2017 Summary of Results for Grain Yield, Grain Protein, and Flag Leaf N at Belleville.

Treatment	Fall/Winter	Feekes 4	Feekes 7	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	---------- N Application Rate kg ha^{-1} -----------				Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	5.44	B	103	D	29	C
2	28	0	0	28	5.74	AB	108	CD	34	BC
3	56	0	0	56	5.91	AB	109	BCD	33	C
4	84	0	0	84	5.84	AB	114	BCD	36	ABC
5	112	0	0	112	5.85	AB	116	A	36	ABC
6	140	0	0	140	5.99	A	118	A	37	AB
7	53	0	0	53	5.88	AB	114	AB	39	A
8	0	37	0	37	5.76	AB	108	BCD	34	BC
9	0	20	0	20	5.69	AB	107	CD	33	C
10	0	41	0	41	6.11	A	109	BCD	35	BC
11	0	21	0	21	5.68	AB	104	D	34	BC
SE					2.72		0.23		0.15	
Treatment Pr > F					0.37		0.00		0.00	

NS = Not significant

Treatments with same letter are not statistically different at 0.05 alpha

Table 2.18. 2017 Summary of Results for Grain Yield, Grain Protein, and Flag Leaf N at North Farm.

Treatment	Fall/Winter	Feekes 4	Feekes 7	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	---------- N Application Rate kg ha^{-1} ---------				Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	3.25	G	98	BC	23	D
2	28	0	0	28	3.88	F	94	C	27	C
3	56	0	0	56	4.38	EF	94	C	28	ABC
4	84	0	0	84	4.74	CDE	107	AB	30	ABC
5	112	0	0	112	5.22	BC	110	AB	31	AB
6	140	0	0	140	5.35	AB	105	ABC	31	AB
7	104	0	0	104	5.80	AB	109	AB	32	A
8	0	68	0	68	4.74	CDE	109	AB	28	BC
9	0	57	39	96	4.65	DE	109	AB	31	AB
10	0	93	0	93	5.01	BCD	112	A	32	AB
11	0	61	24	84	4.72	CDE	108	AB	31	AB
SE					3.34		0.47		0.13	
Treatment Pr > F					< 0.00		0.04		0.00	

NS = Not significant

Treatments with dame letter are not statistically different at 0.05 alpha

Table 2.19. 2017 Summary Results for Grain Yield, Grain Protein, and Flag Leaf N at Salina.

Treatment	Fall/Winter	Spring	Feekes 4	Feekes 7	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	------------------ N Application Rate kg ha^{-1}------------------					Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	0	4.12	B	122	EGH	23	H
2	28	0	0	0	28	4.42	AB	128	EFG	27	EFG
3	56	0	0	0	56	4.31	AB	130	DE	27	DEFG
4	84	0	0	0	84	4.57	A	135	BCD	30	BCDE
5	112	0	0	0	112	4.70	A	140	AB	30	BCDE
6	140	0	0	0	140	4.43	AB	142	A	32	A
7	0	0	0	0	0	4.42	AB	121	GH	26	FG
8	0	0	0	0	0	4.51	AB	121	H	26	FG
9	0	0	0	0	0	4.37	AB	128	EF	25	GH
10	Na	Na	Na	Na	Na	Na	Na	Na	Na	Na	Na
11	Na	Na	Na	Na	Na	Na	Na	Na	Na	Na	Na
SE						2.31		0.24		0.09	
Treatment Pr > F						0.54		<0.00		<0.00	

NS = Not significant

Na = Not applicable, Within 5 miles of Salina airport, sUAS flights not permitted

Treatments with same letter are not statistically different at 0.05 alpha

Table 2.20. 2017 Summary of Results for Grain Yield, Grain Protein, and Flag Leaf N at Solomon.

Treatment	Fall/Winter	Spring	Feekes 4	Feekes 7	Total N	Grain Yield	GY LSD Group	Grain Protein	GP LSD Group	Flag leaf	GP LSD Group
	-------------- N Application Rate kg ha^{-1} -----------------					Mg ha^{-1}		g kg^{-1}		g kg^{-1}	
1	0	0	0	0	0	5.65	A	124	DEF	29	A
2	28	0	0	0	28	5.44	A	130	CDE	31	A
3	56	0	0	0	56	5.70	A	134	BC	32	A
4	84	0	0	0	84	5.54	A	136	BC	29	A
5	112	0	0	0	112	5.22	A	137	BC	32	A
6	140	0	0	0	140	5.60	A	135	BC	33	A
7	0	0	0	0	0	5.27	A	124	EF	29	A
8	0	0	24	0	24	5.32	A	124	DEF	31	A
9	0	0	64	0	64	5.62	A	123	F	30	A
10	0	0	63	0	63	5.54	A	124	DEF	31	A
11	0	0	0	0	0	5.35	A	123	EF	29	A
SE						3.11		0.30		0.15	
Treatment Pr > F						0.78		<0.00		0.79	

NS = Not significant

Treatments with same letter are not statistically different at 0.05 alpha

Conclusions

The results from the optical sensor comparison indicates that the MicaSense RedEdge provides reliable spectral data during overcast and sunny conditions and was able to produce strong relationships between NDVI and Grain Yield. Additional development is necessary for improving spectral reflectance calibration methods for the MicaSense RedEdge under overcast conditions to compensate for potentially inflated NDVI values. Thus, improving its accuracy and reliability for assessing winter wheat health across varying sky conditions throughout the growing season. Uncalibrated RGB cameras such as the DJI X3 can be used to calculate indices like False NDVI to map in field variability. However, uncalibrated False NDVI is inadequate for assessing crop health over time across varying sky conditions and has no relationship with grain yield.

The results from the field studies conducted had shown soil test and optical sensor based N recommendation systems can produce optimal grain yields at a reduced N rate under most conditions. At the majority of locations, the optical sensor based N recommendations performed better than the soil test based N system in regard to reducing N rates without sacrificing grain yield. However, at two locations the soil test based N recommendation system was superior to the optical sensor based N recommendations by achieving the same grain yield at a lower N rate. Reasoning for the degraded performance at these locations by the N recommendation algorithms that process the optical sensor spectral data will need to be investigated.

This project indicates that enhancing nitrogen use efficiency through the adoption of soil testing and/or the use of optical sensors is possible and should be encouraged. Both methodologies provide N recommendations that would allow Kansas wheat producers to maintain or increase grain yield, reduce N inputs, and enhance profitability while reducing environmental impact.

References

ArcGIS. (2016). ArcGIS System Software. Redlands, California.

Agisoft. 2017. Agisoft PhotoScan software. St. Petersburg, Russia.

Aparicio, N., D. Villegas, J. Casadesus, J.L. Araus, and J.L. Royo. 2000. Spectral vegetation indices as non destrictive tools for determining durum wheat yield. Agron.J. 92:83-91.

ArcGIS. 2016. ArcGIS System Software. Redlands, California.

Barnes, E.M., T.R. Clarke, S.E. Richards, P.D. Colaizzi, J. Haberland, M. Kostrzewshi, P. Walker, C. Choi, E. Riley, T. Thompson, R.J. Lascano, H. Li, and M.S. Moran. (2000). Coincident detection of crop water stress, nitrogen status and canopy density using ground-based multispectral data. Processing's of the 5th International Conference on Precision Agriculture. American Society of Agronomy: Madison, Wisconsin.

Bauer, M.E, and J.E. Cipra. 1973. Identification of agricultural crops by computer processing of ERTS MSS data. LARS Technical Reports. Paper 20. http://docs.lib.purdue.edu/larstech/20. W. Lafayette, IN: Purdue Univ.

Bhatte, A.U., D.J. Mulla, and B.E. Frazier. 1991. Estimation of soil properties and wheat yields on complex eroded hills using geostatistics and thematic mapper images. Remote Sensing Environment. 37:181-191.

DJI Matrice 100.2016. http://www.dji.com/matrice100/info#specs.Nanshan District, Shenzhen, China. Accessed September 7, 2017.

Flowers, M., R. Weisz, and R.W. Heinger. 2001. Remote sensing of winter wheat tiller density for early season nitrogen application decisions. Agron. J. 93:783-789.

Flowers, M., R. Weisz, and R.W. Heingiger. 3003b. Quantitative approaches to using color infrared photography for assessing in-season nitrogen status in winter wheat. Agron. J. 95:1189-1200.

Flowers, M., R. Weisz, R. Heiniger, D. Osmond, and C. Crozier. 2004. In-season nitrogen optimization and site-specific management in soft red winter wheat. Agron. J. 96:124-134.

Fuglie, K.O., and C.A. Kascak. 2015. Adoption and diffusion of natural-resource-conserving agricultural technology. Rev. Agric. Econ. 23:386-403. doi: 10.1111/1467-9353.00068.

Fitzgerald, G.J. 2010. Characterizing vegetation indices derived from active and passive sensors. International Journal of Remote Sensing. 31:4335-4348.

Grant, C.A., and D.N. Flaten. 1998. Fertilizing for protein content in wheat. P. 151-168. *In* D.B. Fowler et al. (ed.) Wheat protein production and marketing. Proc. Wheat Protein Symp., Saskatoon, Sask., Canada. 9-10 Mar. 1998. Univ. Ext. Press, Univ. of Saskatchewan.

Hatfield, J.L., A.A. Gitelson, J.S. Schepers, and C.L. Walthall. 2008. Application of spectral remote sensing for agronomic decisions. Agron. J.100:S-117-S-131.

Hatfield, J.L., J.H. Prueger, and W.P. Kustas. 2004. Remote sensing of dryland crops. p. 531-568. *In* S.L. Ustin (ed.) Remote sensing for natural resource management and environmental monitoring: Manual of remote sensing. 3rd ed. John Wiley, Hoboken, NJ.

Heege, H.J., S. Reusch, and E. Thiessen. 2008. Prospects and results for optical systems for site-specific on-the-go control of nitrogen-top-dressing in Germany. Prec. Agi. 9:115-131.

Holland Scientific. 2012. RapidSCAN CS-45 User's Guide. (Lincoln, NE: Holland Scientific).

Jain, N., S.S. Ray, J.P. Singh, and S. Painigraphy. 2007. Use of hyperspectral data to assess the effects of different nitrogen applications on a potato crop. Precis. Agric. 8:225-239. doi:10.1007/s11119-007-9042-0

Jensen, A., B. Lorenzen, H. Spelling-Ostergaard, and E. Kloster-Hvelplund. 1990. Radiometric estimation of biomass and N content of barley grown at different N levels. Int. J. Remote Sens. 11:1809-1820.

Kim, Y., J.F. Reid, A. Hansen, and M. Dickson. 2000. Evaluation of a multi-spectral imaging system to detect nitrogen stress of corn crops. An ASAE meeting paper. Paper no. 003128. American Society of Agricultural Engineers (ASAE), St. Joseph, MI.

KSU Mesonet. (2017). Available at http://mesonet.k-state.edu.

LaRuff, J.M., W.R. Raun, S.B. Phillips, J.B. Solie, M.L. Stone, and G.V. Johnson. 2001. Optimum field element size for maximum yields in winter wheat, using variable nitrogen rates. J. Plant Nutr. 24:313-325.

MicaSense Atlas. 2015. (Seattle, WA). https://atlas.micasense.com/app/login. Asscessed September 7, 2017.

MicaSense RedEdge. 2015. MicaSense RedEdge Multispectral Camera. (Seattle, WA).

Microsoft (2016). Microsoft Excel computer software. Redmond, Washington: Microsoft.

Mistele, B., R. Guster, and U. Schmidhalter. 2004. Validation of field-scaled spectral measurements of nitrogen status in winter wheat. In: Mulla, D. (Ed.), 7th International Conference on Precision Agriculture and other Precision Resources Management. Minneapolis, Minnesota, USA, pp. 1187-1195.

Mulla, David J. 2012. Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems Engineering. 114:358-371.

Oklahoma State University. Calculation of growing degree days and heat units). http://www.nue.okstate.edu/GDD_calc.html. Accessed September 12, 2017.

Pinter, P.J., Jr., J.L. Hatfield, J.S. Schepers, E.M. Barnes, M.S. Moran, C.S.T Daughtry. 2003. Remote sensing for crop management. Photogrammetric Engineering and remote sensing. 69:647-664.

Raun, W.R., J.B. Solieb, G.V. Johnson, M.L, Stone, R.W. Mulle, K.W. Freeman, W.E. Thomason, and E.V. Lukina, 2002. Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. Agron. J. 94:815-820.

Rouse, J.W., R.H. Hass, J.A. Schell, and J.W. Deering. 1973. Monitoring vegetation systems in the Great Plains with ERTS. Third ERTS Symposium, pp. 309-317. NASA SP-351.

R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

RStudio (2012). RStudio: Integrated development environment for R (Version 3.4) [Computer software]. Boston, MA.

SAS University Edition. (2016). SAS INST., Cary, NC.

Schepers, J.S., D.D. Francis, M. Vigil, and F.E. Below. 1992. Comparison of corn leaf nitrogen concentration and chlorophyll meter readings. Communications in Soil Science and Plant Analysis. 23:2173-2187.

Spratt, E.D. 1974. Effect of ammonium and nitrate forms of fertilizer-N and their time of applications on utilization of N by wheat. Agron.J. 66:57-61.

Stokes, D.T., R. Sylvester-Bradley, R.K. Scott, R. Clare, J. Hopkinson, G.F. Milford, and S.E. Salmon. 1998. An integrated approach to nitrogen nutrition for wheat. Home-Grown Cereals Authority Project Rep.159. Caledonia House, London.

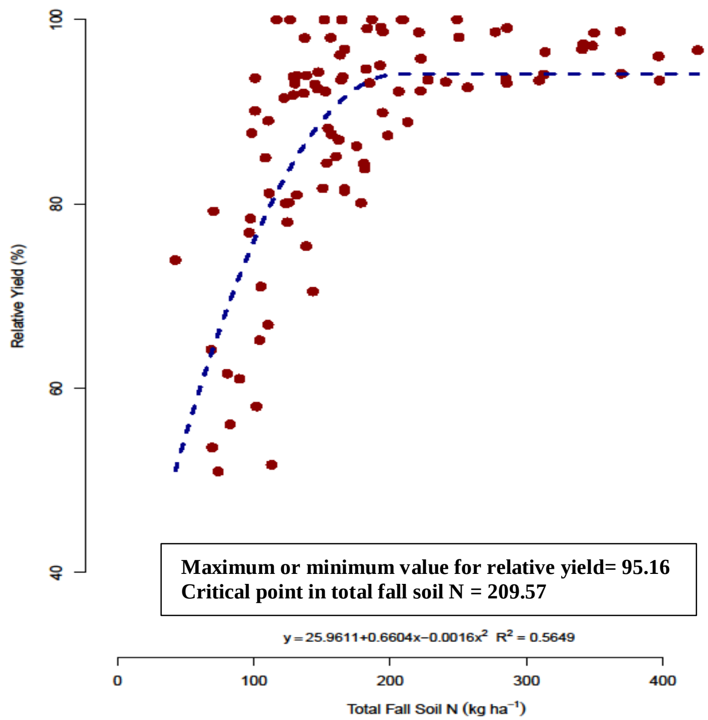
Stone, M.L., J.B. Solie, W.R. Rauan, R.W. Whitney, S.L. Taylor, and J.D. Ringer. 1996. Use of spectral radiance for correcting in-season fertilizer nitrogen deficiencies in winter wheat. Transactions of the ASAE/ 39:1623-1631.

Thenkabail, P.S., R.B. Smith, and E.D. Pauw. 2002. Evaluation of narrowband and broadband vegetation indices for determining optimal hyperspectral wavelength for agricultural crop characterization. Photogrammetry and Remote Sensing. 68:607-621.

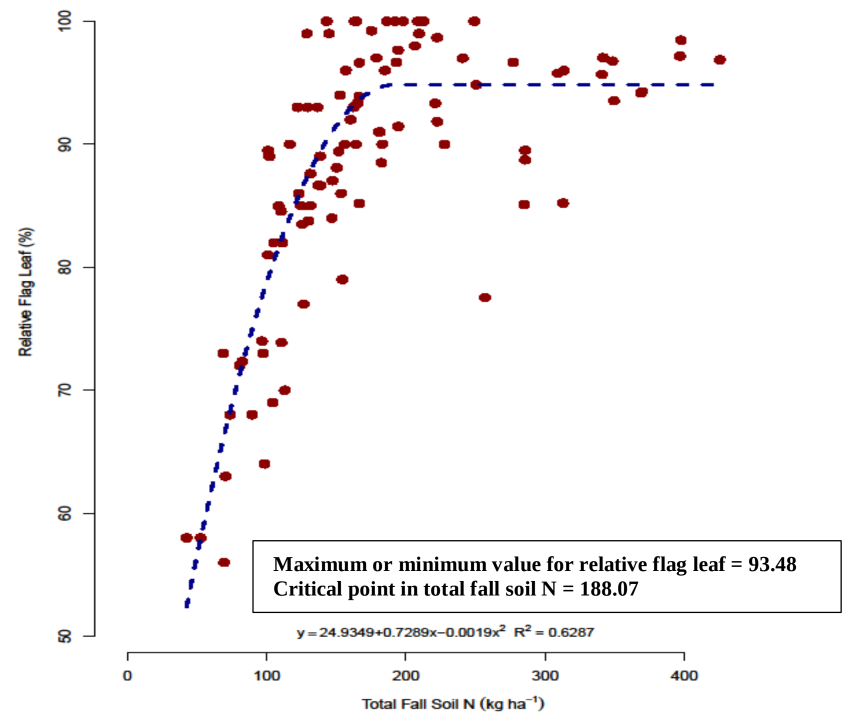
Tremblay, N., Z. Wang, and C. Belec. 2007b. Evaluation of the Dualex for the assessment of corn nitrogen status. J. Plant Nutr. 30:1355-1369.

Wanjura, D.F., and J.L. Hatfield. 1987. Sensitivity of spectral vegetation indices to crop biomass. Trans, ASAE 30:810-816.

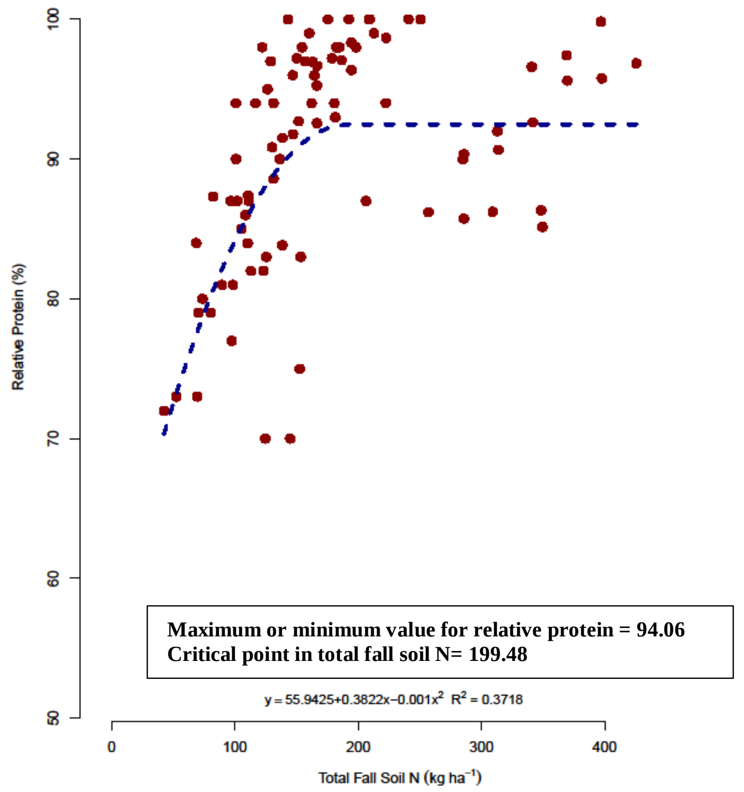
Appendix A - Chapter 2 Site Location Winter Wheat Raw Data



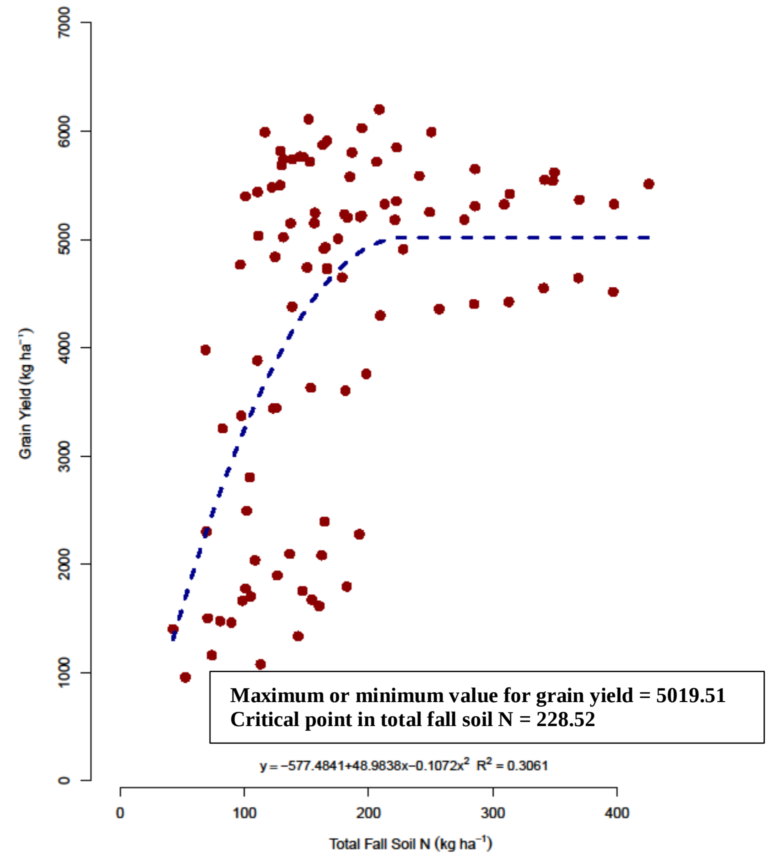
Total Fall Soil N versus Relative Yield Across Locations for 2016 & 2017 years.



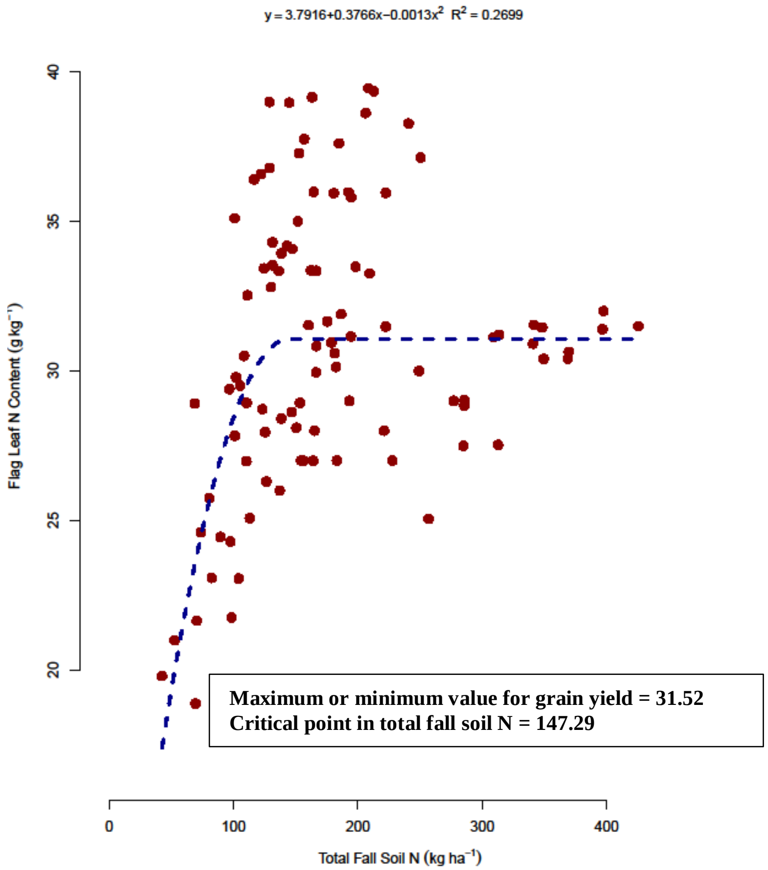
Total Fall Soil N versus Relative Flag Leaf Across Locations for 2016 & 2017 years.



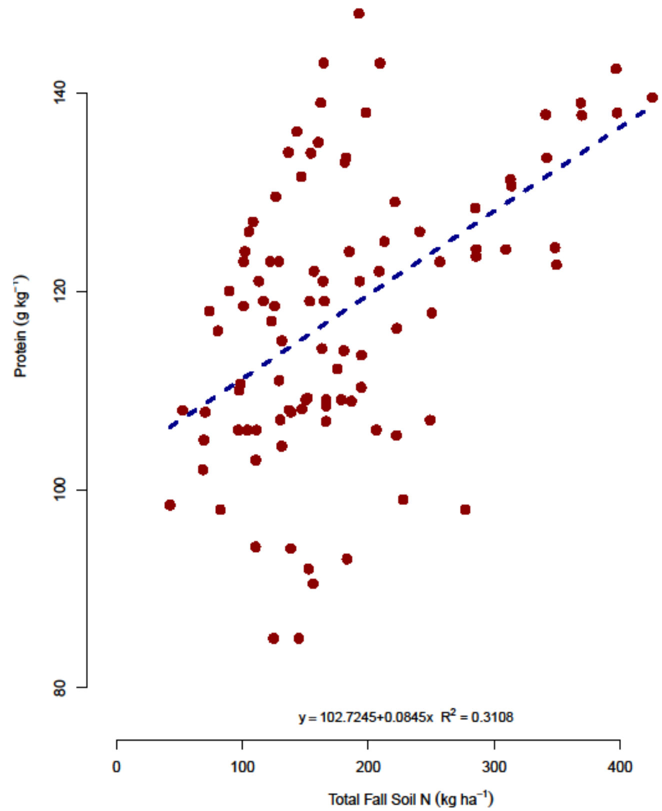
Total Fall Soil N versus Relative Grain Protein Across Locations for 2016 & 2017 years.



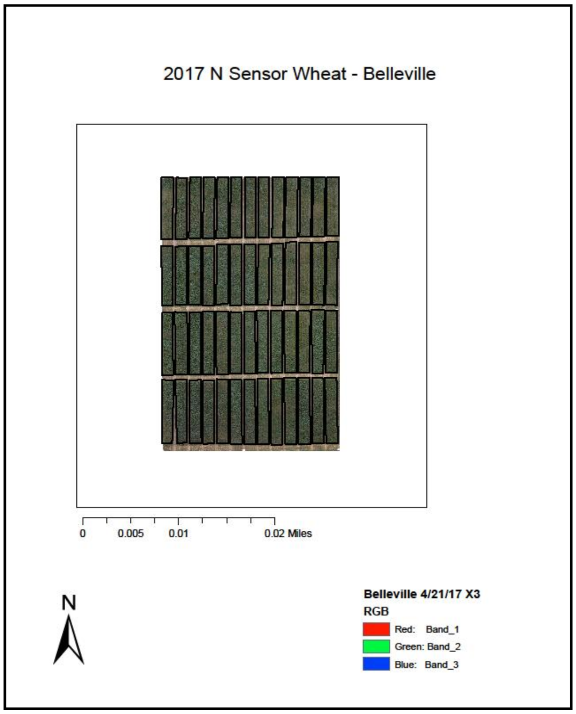
Total Fall Soil N versus Grain Yield Across Locations for 2016 & 2017 years.



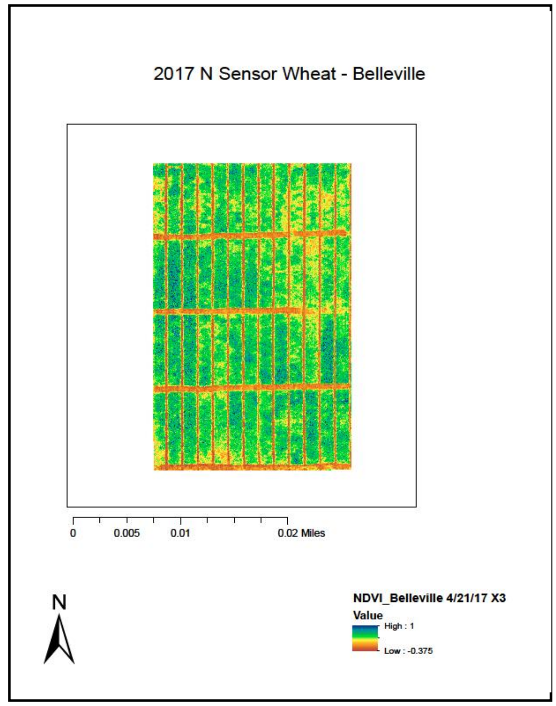
Total Fall Soil N versus Flag Leaf N Content Across Locations for 2016 & 2017 years.



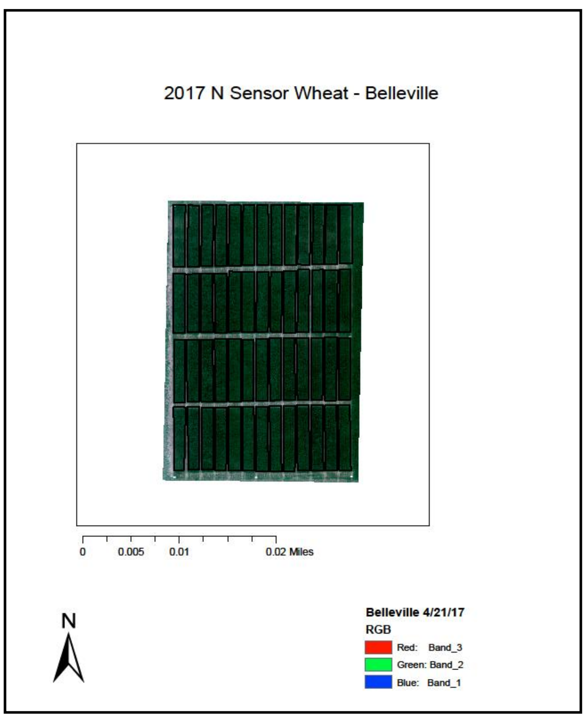
Total Fall Soil N versus Grain Protein Across Locations for 2016 & 2017 years.



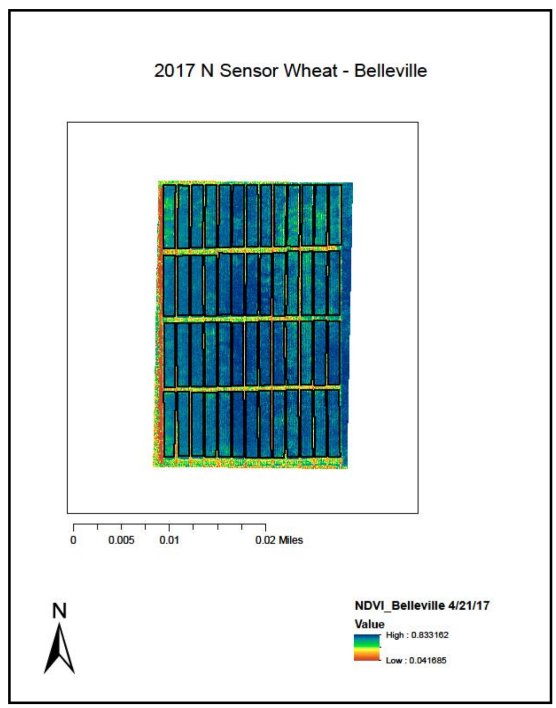
DJI X3 Image of Belleville 4/21/17.



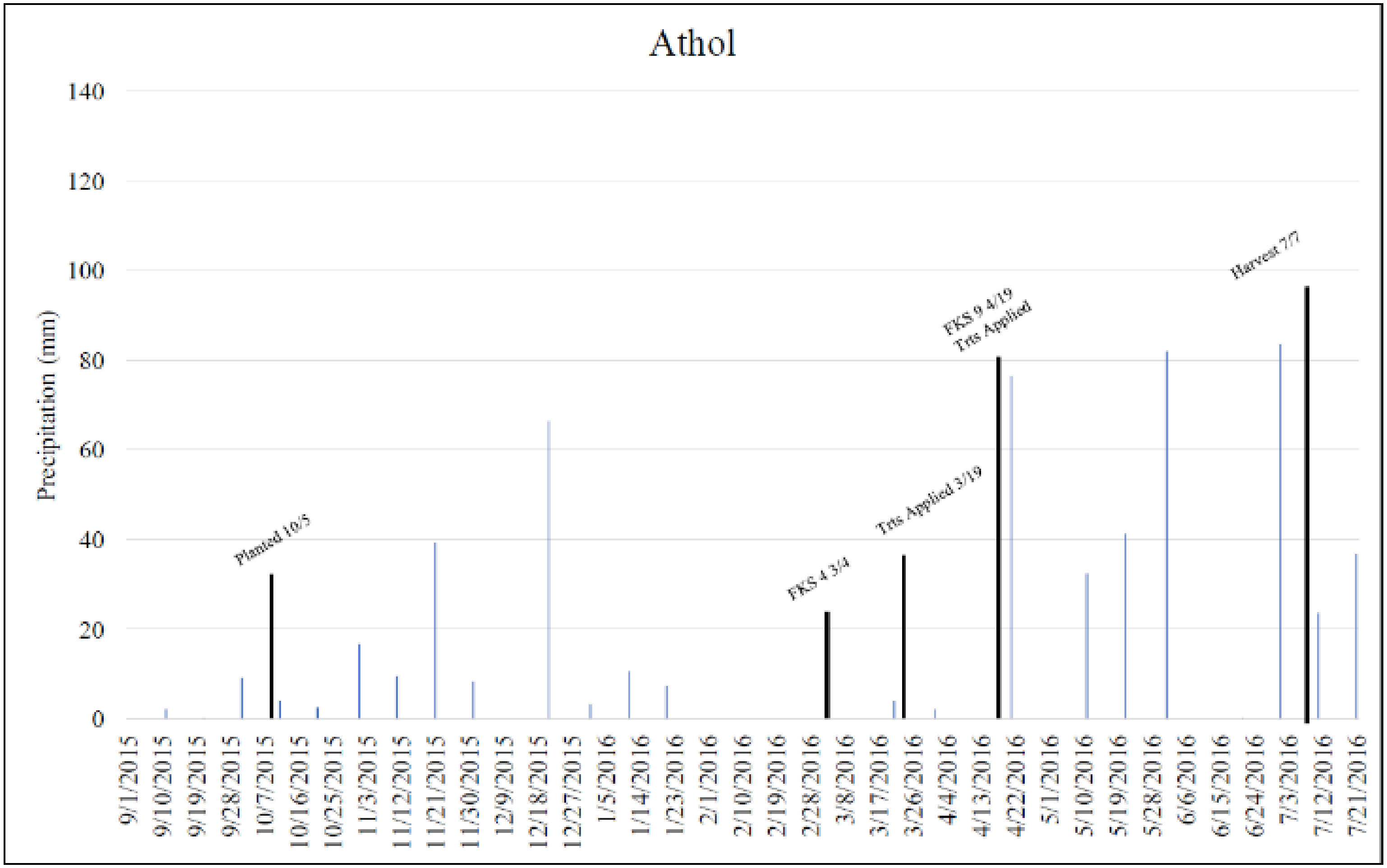
DJI X3 False NDVI Image of Belleville 4/21/17.



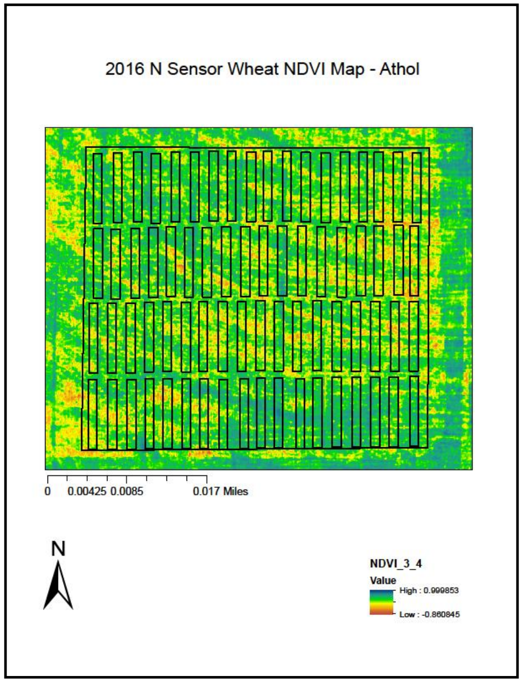
MicaSense RGB Image of Belleville 4/21/17.



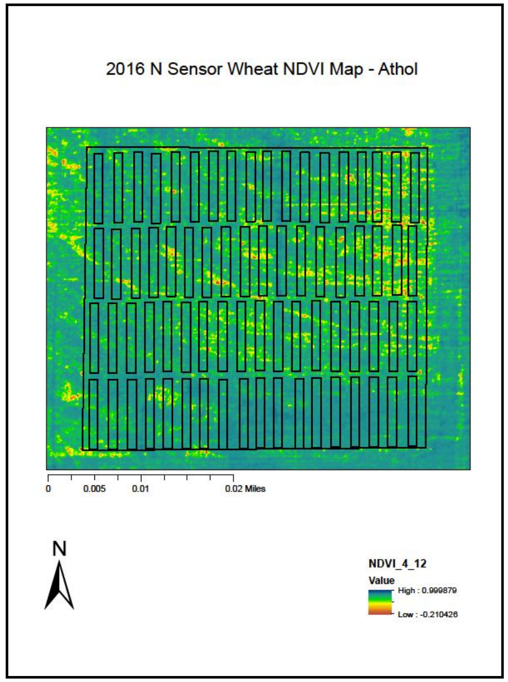
MicaSense NDVI Image of Belleville 4/21/17.



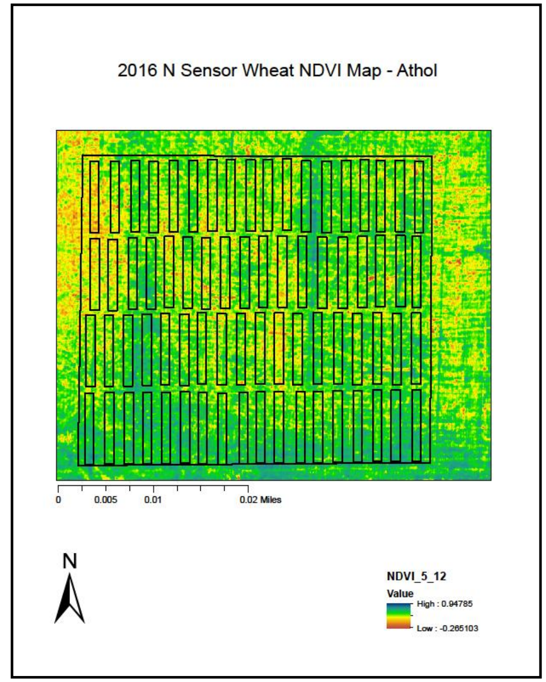
2016 Athol precipitation and key treatment dates.



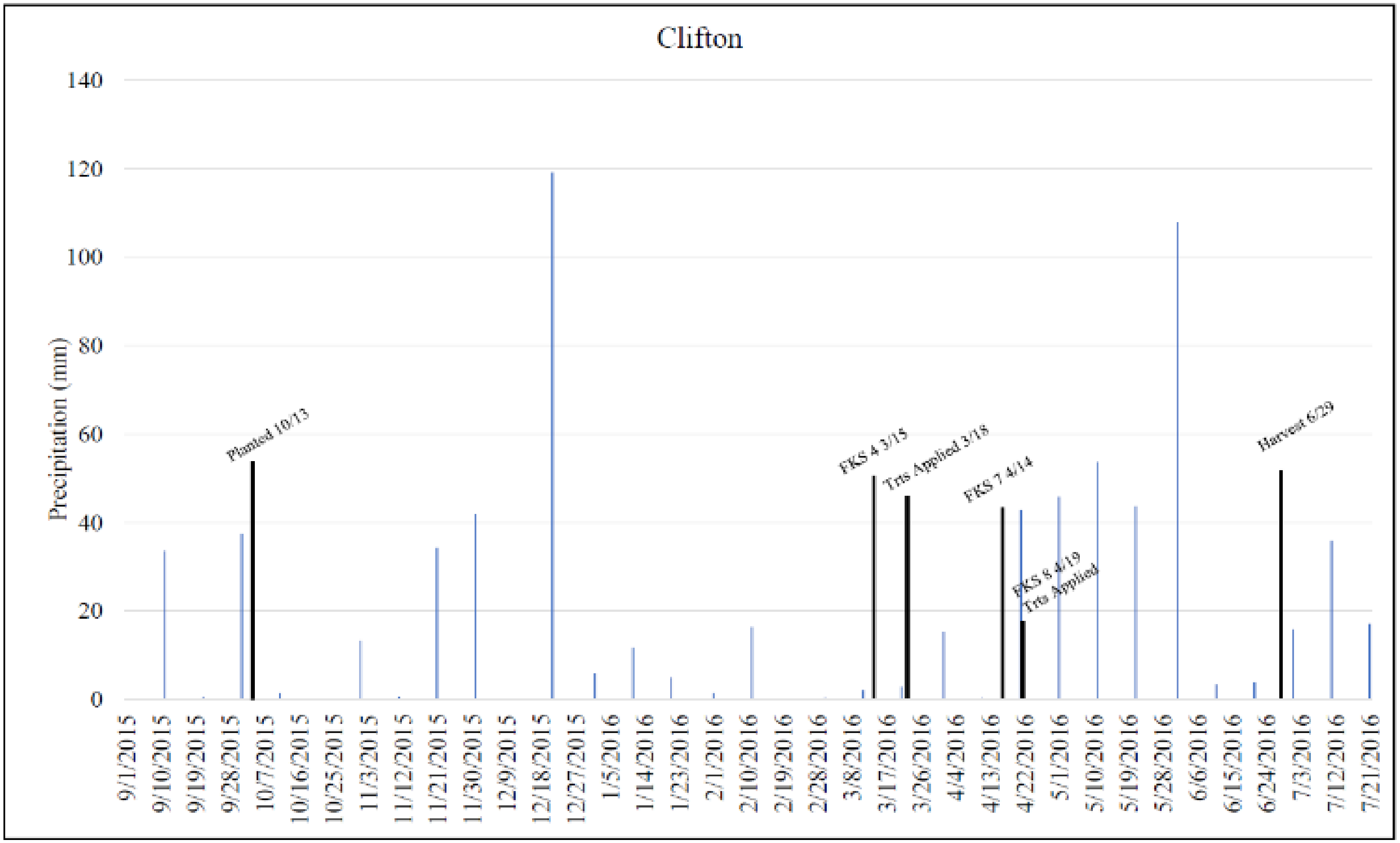
Athol NDVI Map March 4, 2016.



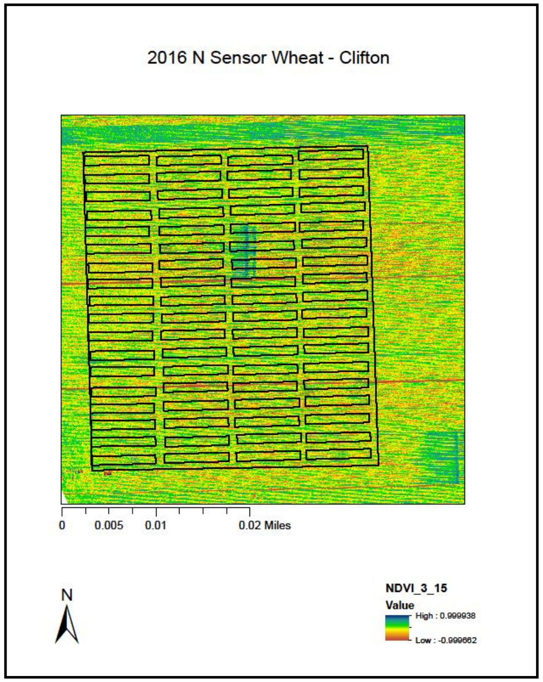
Athol NDVI Map April 12, 2016.



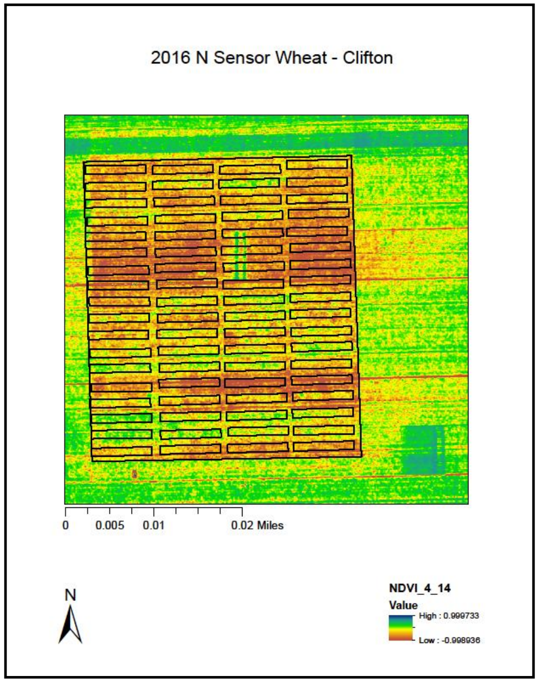
Athol NDVI Map May 12, 2016.



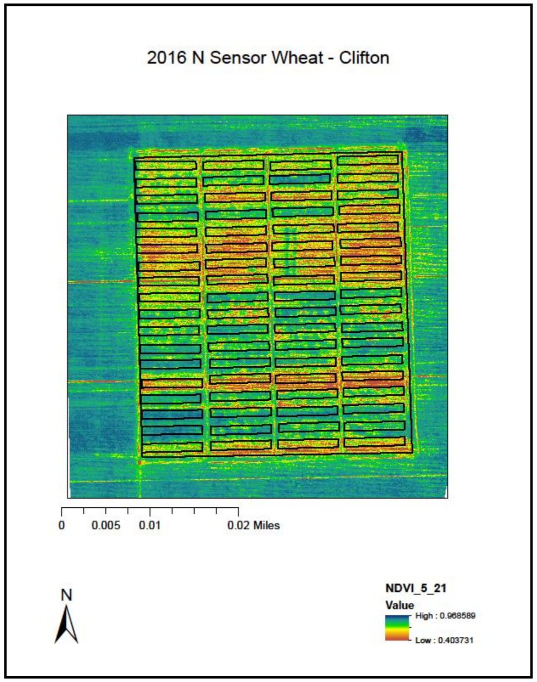
2016 Clifton precipitation and key treatment dates.



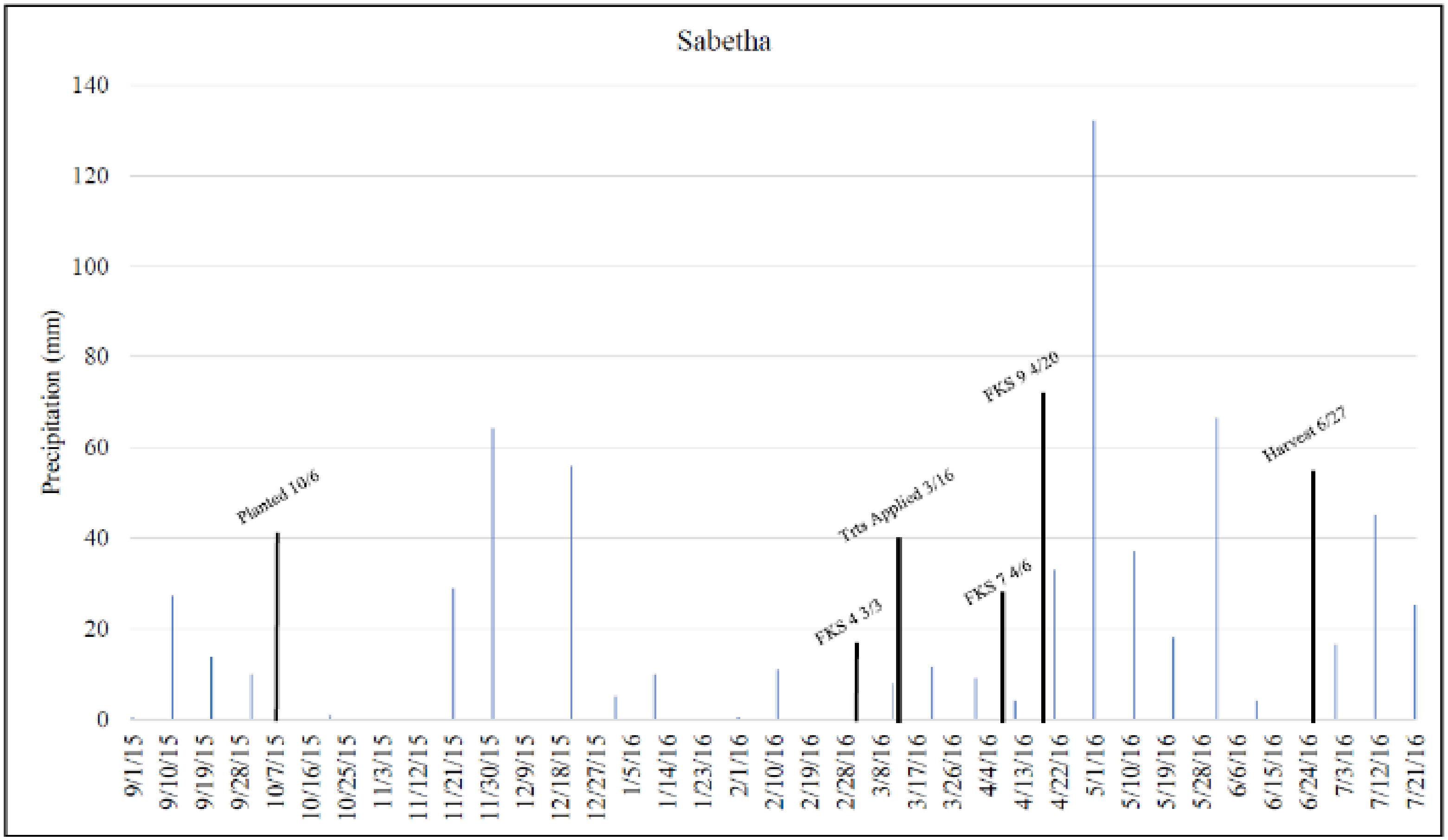
Clifton NDVI Map March 15, 2016.



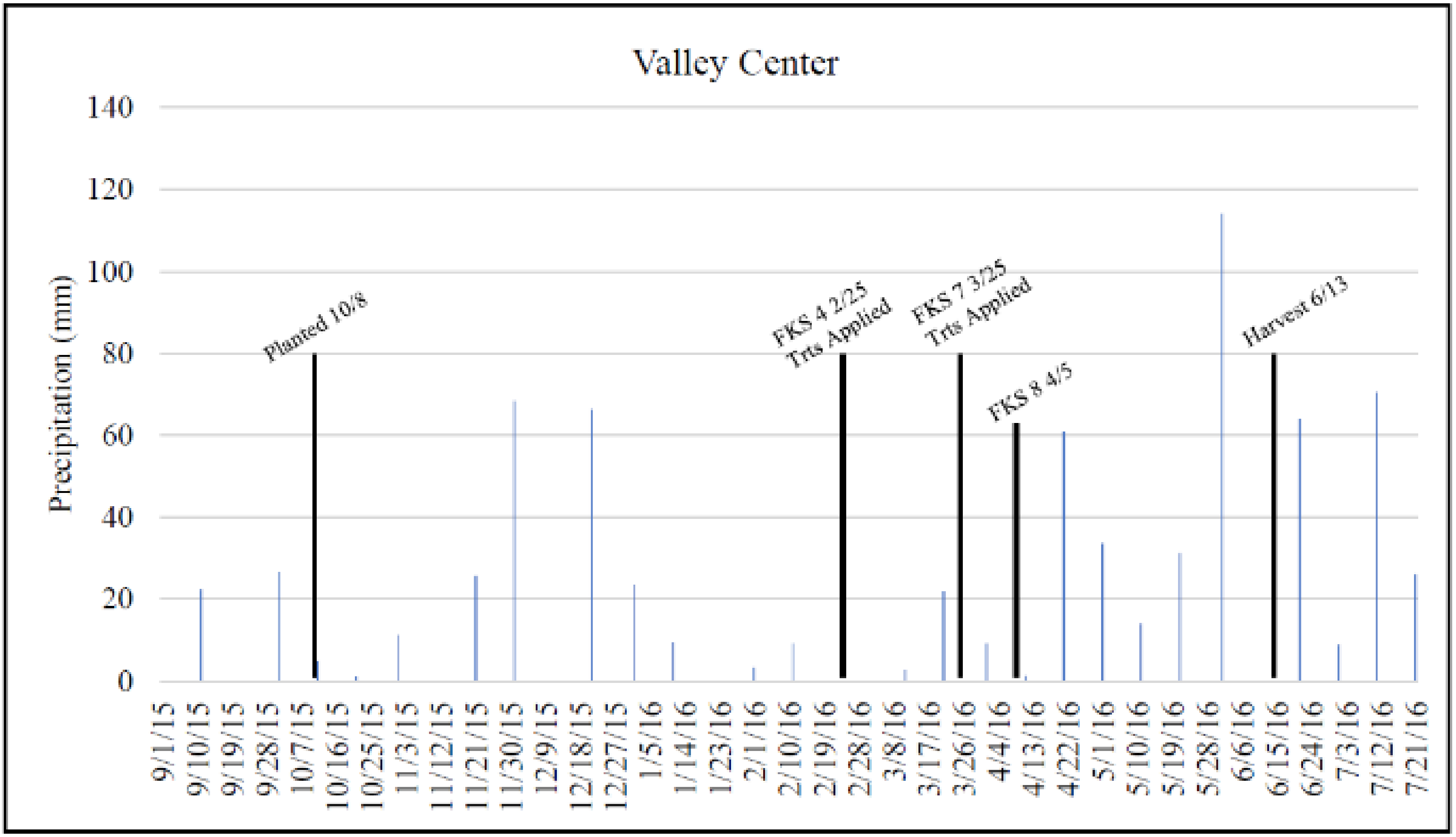
Clifton NDVI Map April 14, 2016.



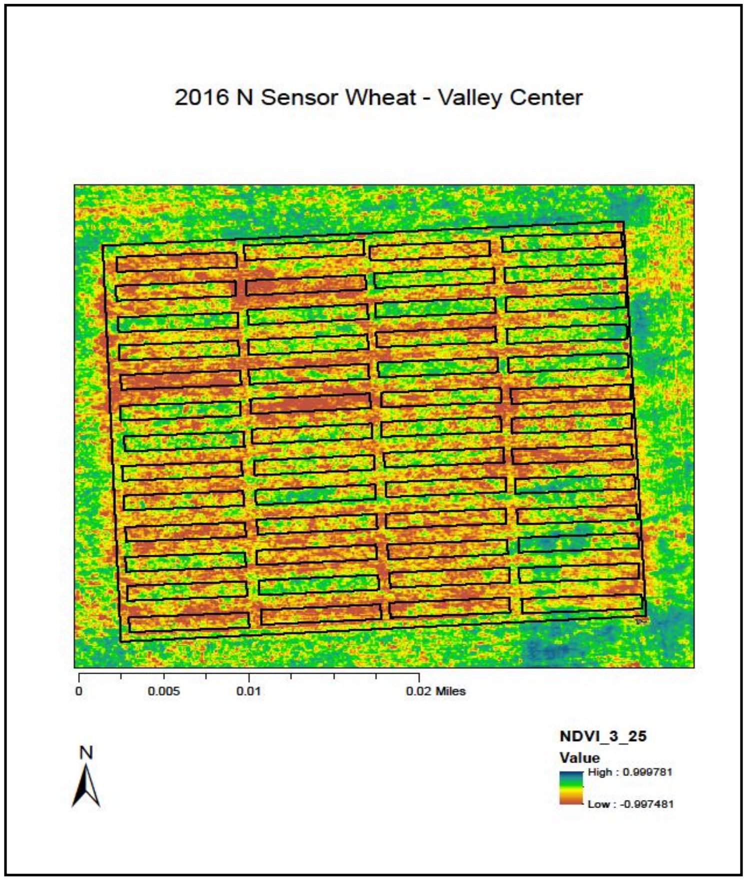
Clifton NDVI Map May 21, 2016.



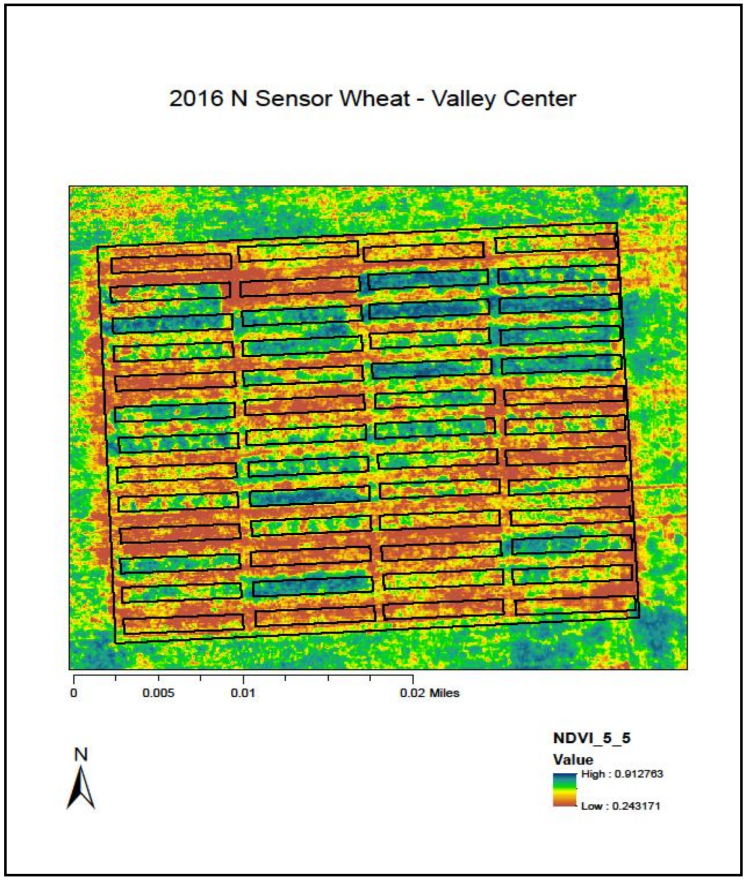
2016 Sabetha precipitation and key treatment dates.



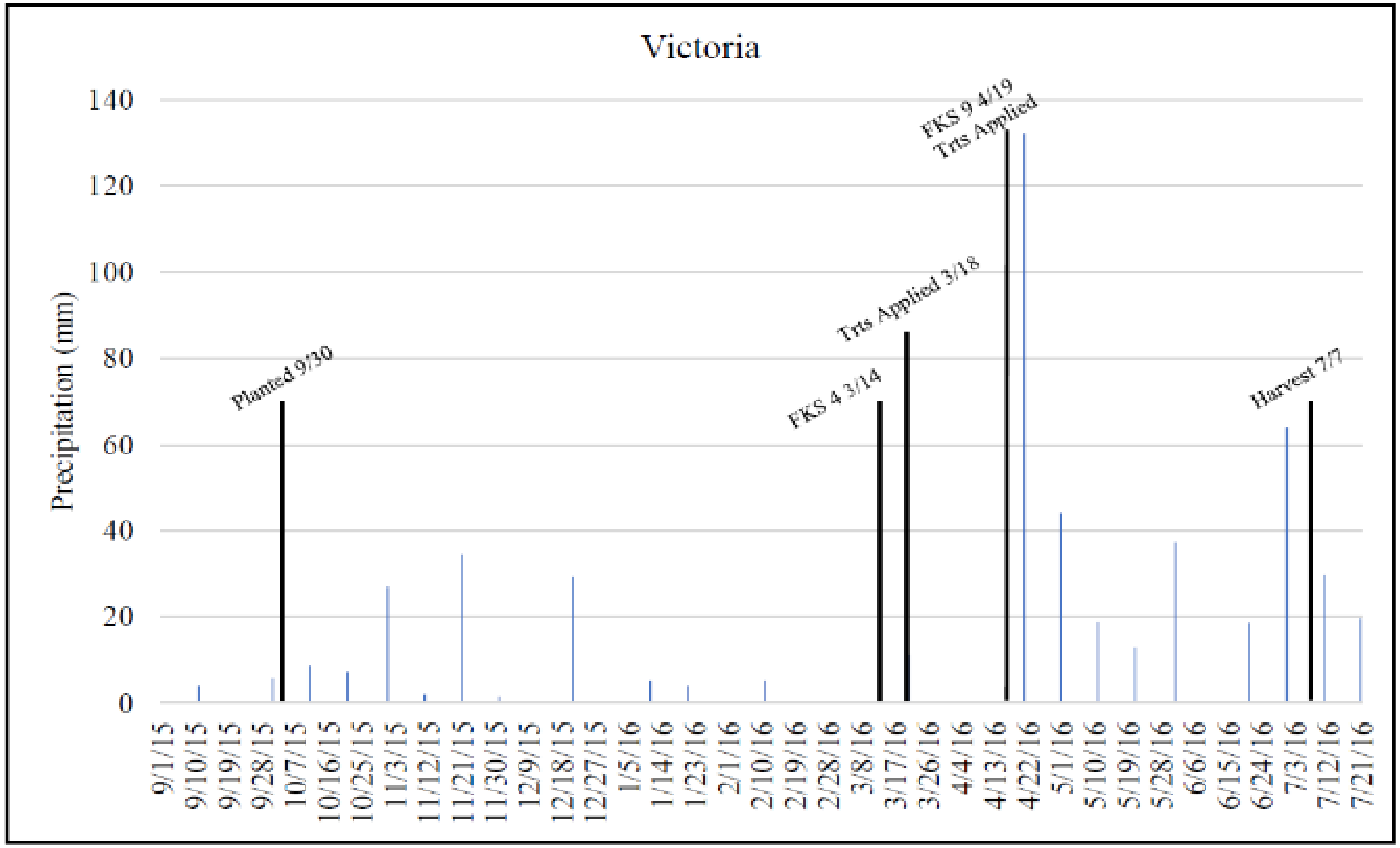
2016 Valley Center precipitation and key treatment dates.



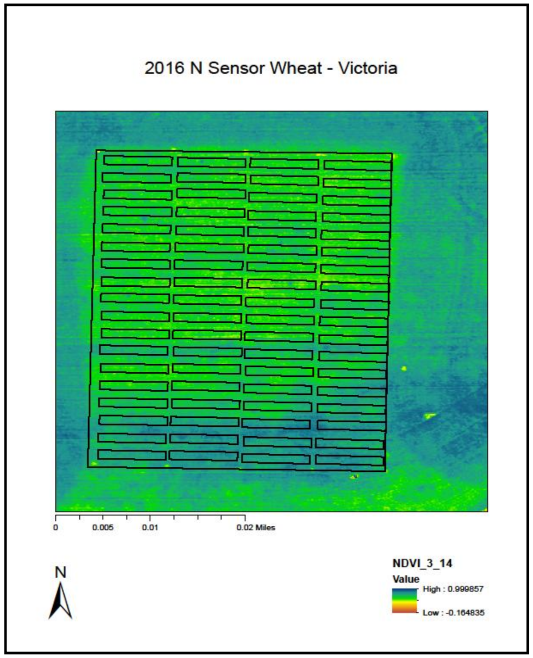
Valley Center NDVI Map March 25., 2016.



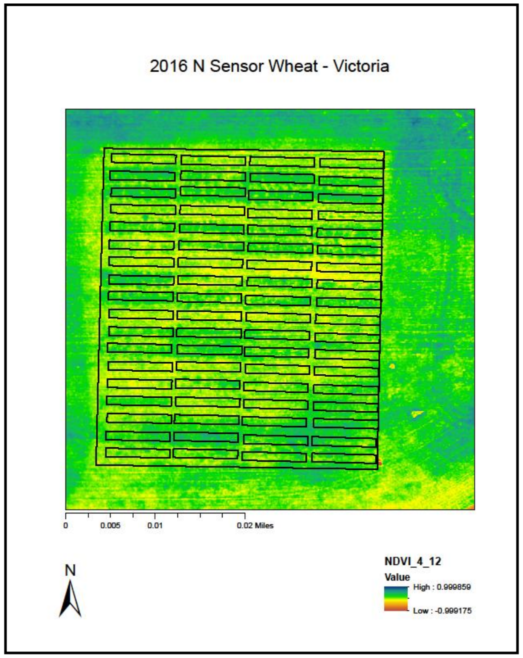
Valley Center NDVI Map May 5, 2016.



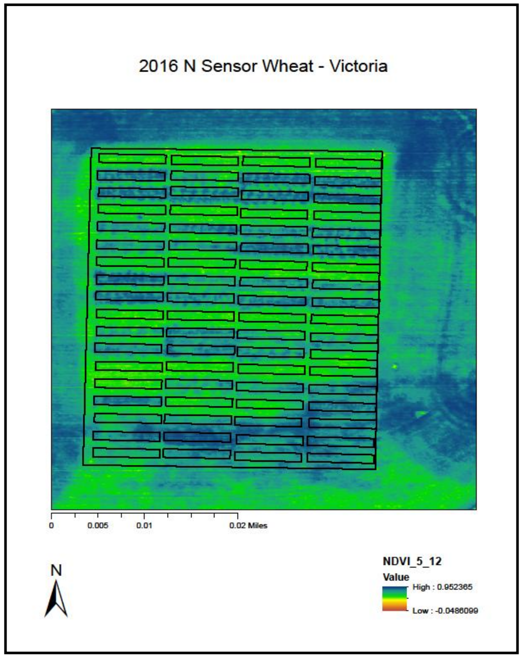
2016 Victoria precipitation and key treatment dates.



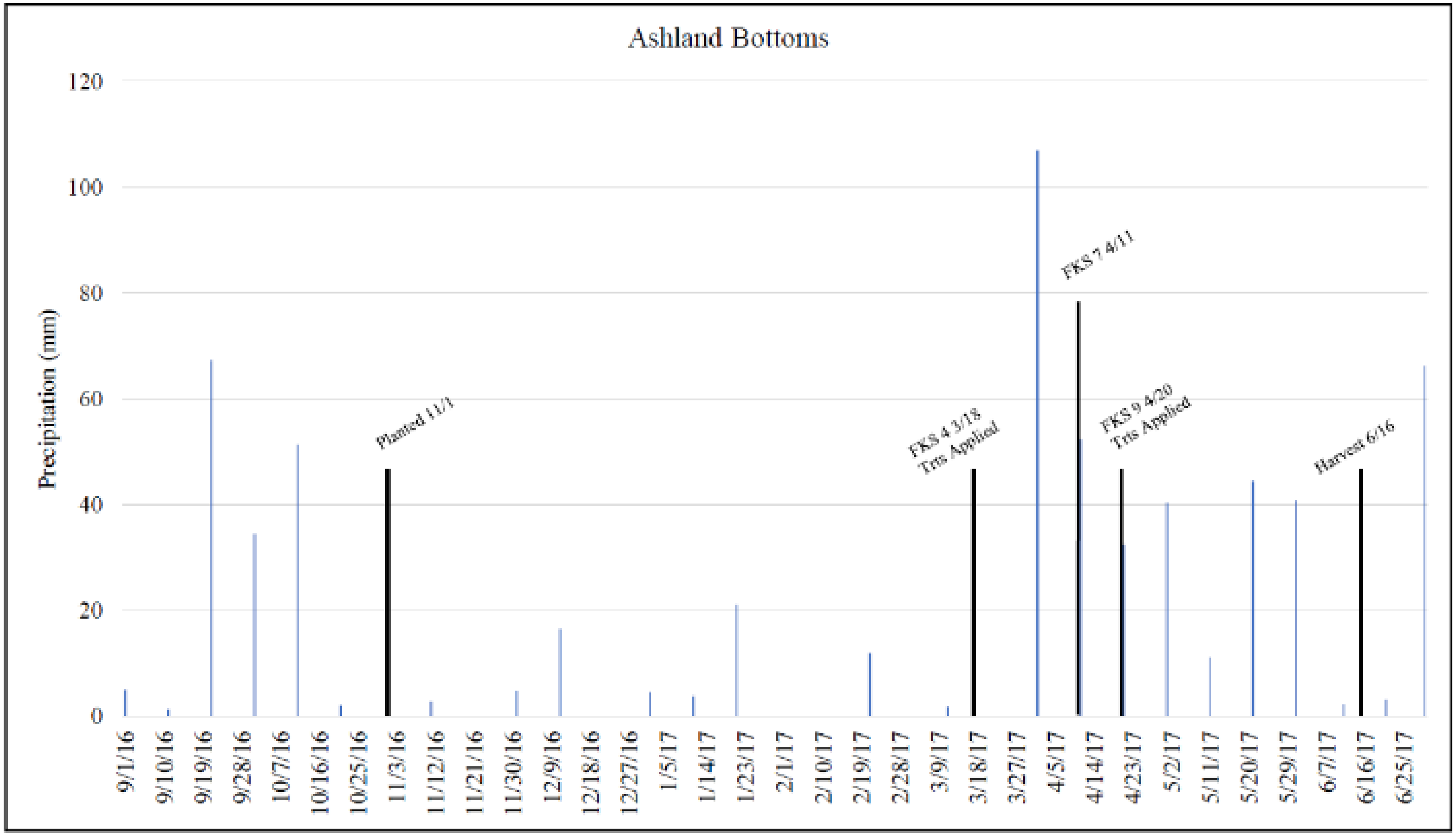
Victoria NDVI Map March 14, 2016.



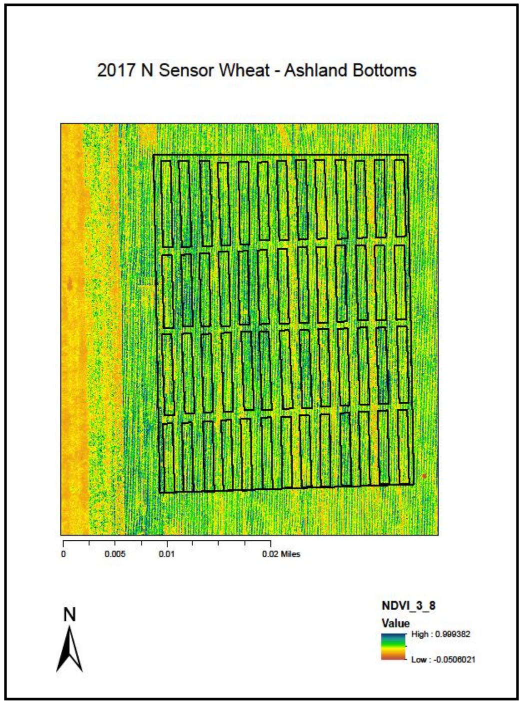
Victoria NDVI Map April 12, 2016.



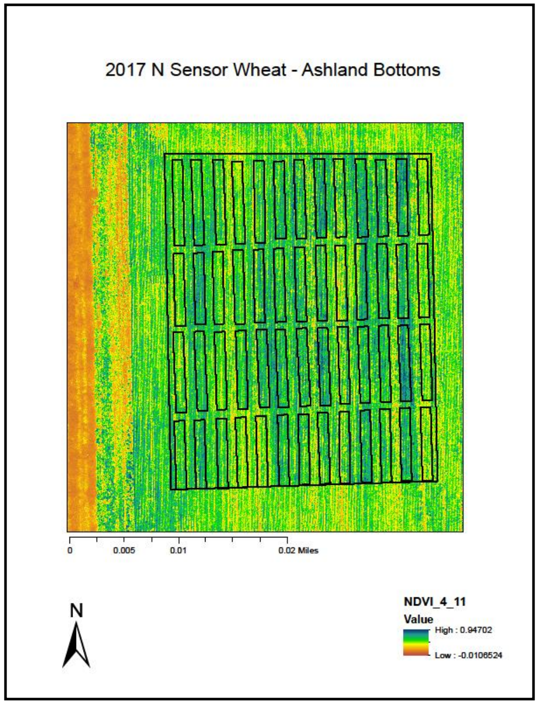
Victoria NDVI Map May 12, 2016.



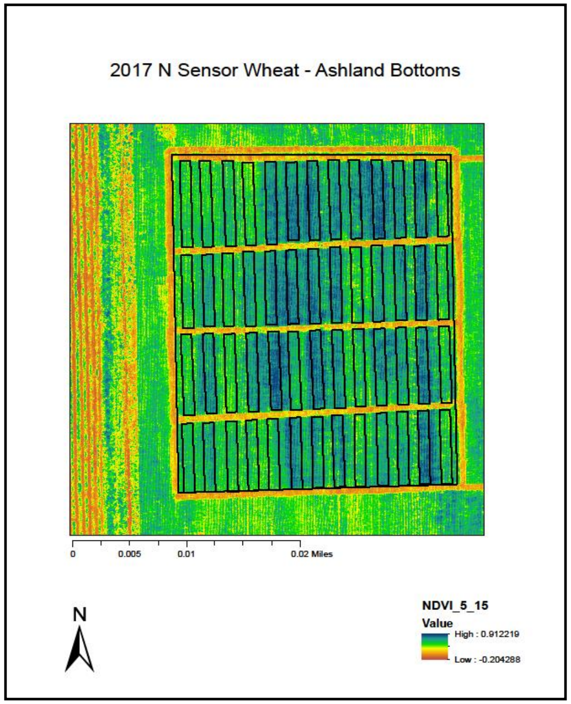
2017 Ashland Bottoms precipitation and key treatment dates.



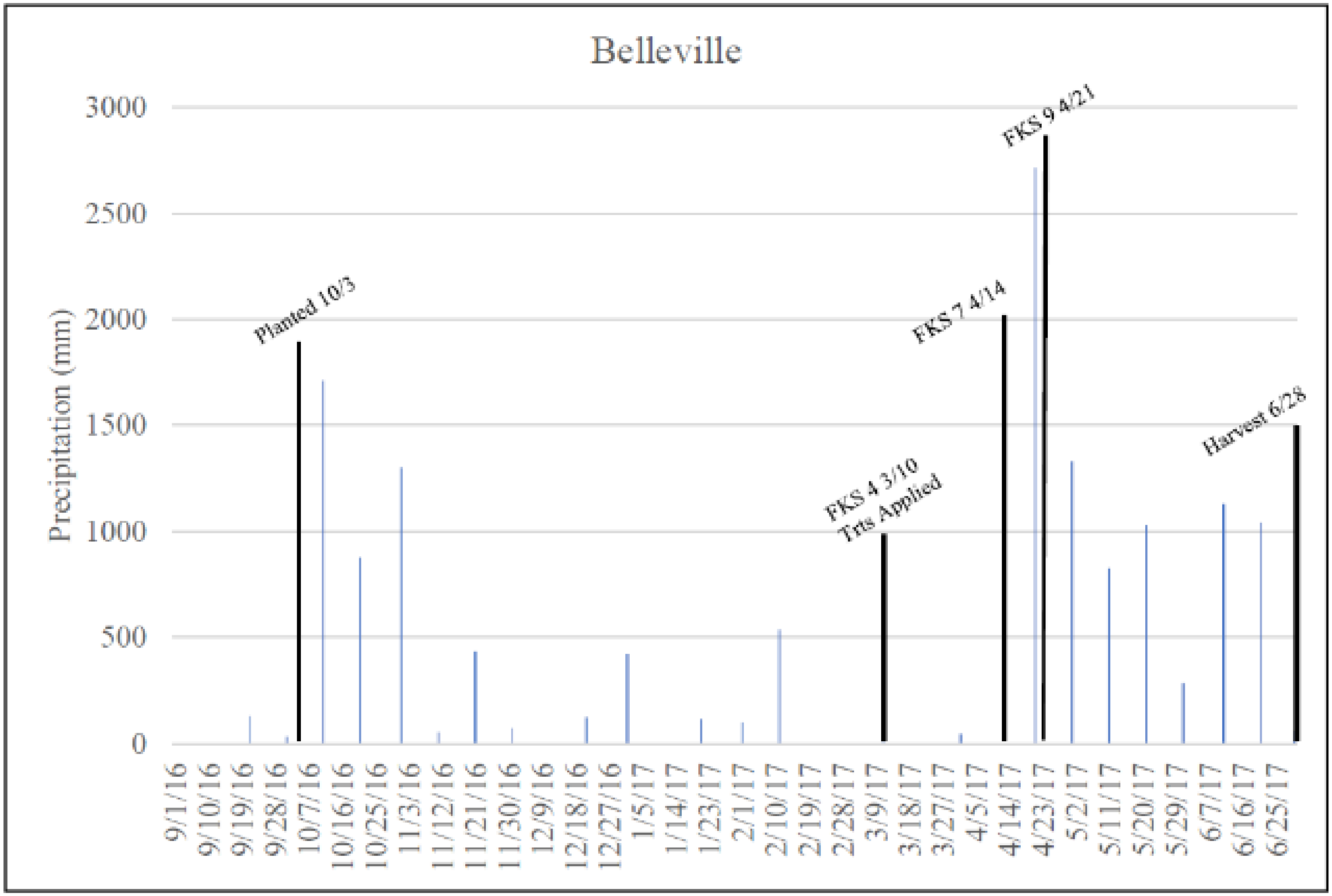
Ashland Bottoms NDVI Map March 8, 2017.



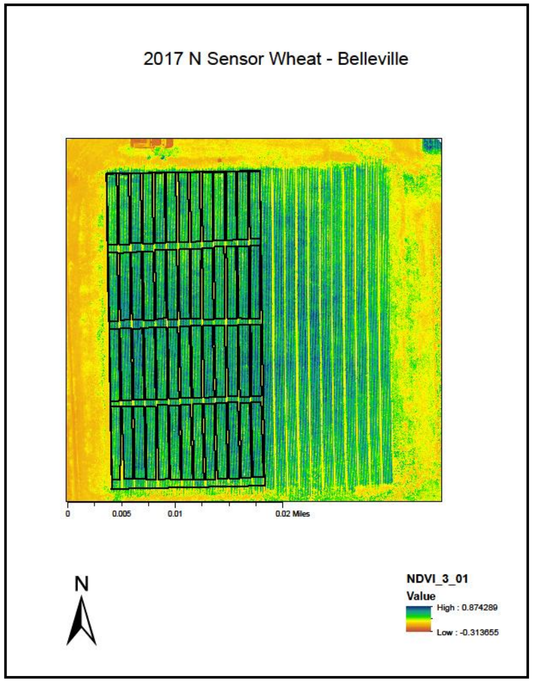
Ashland Bottoms NDVI Map April 11, 2017.



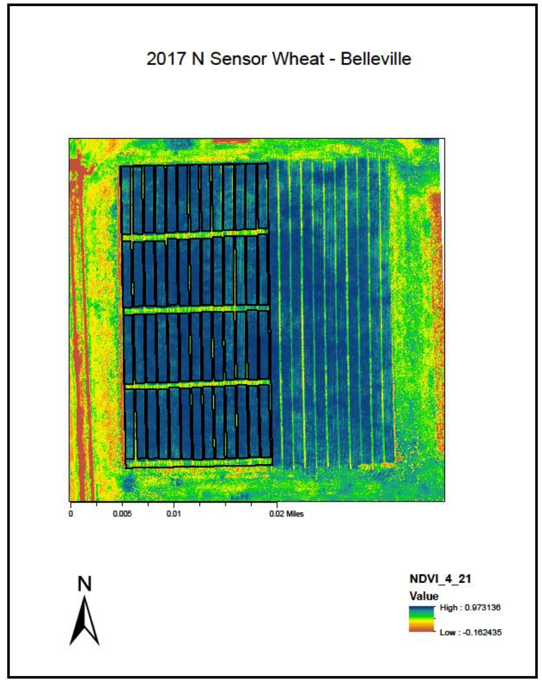
Ashland Bottoms NDVI Map May 15, 2017.



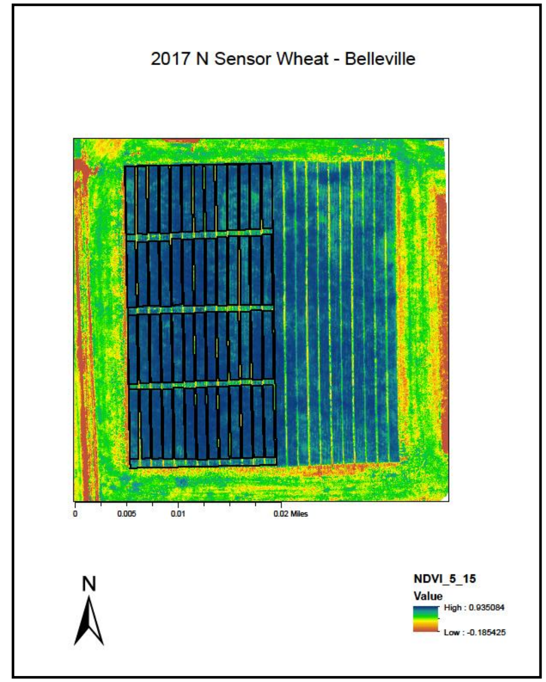
2017 Belleville precipitation and key treatment dates.



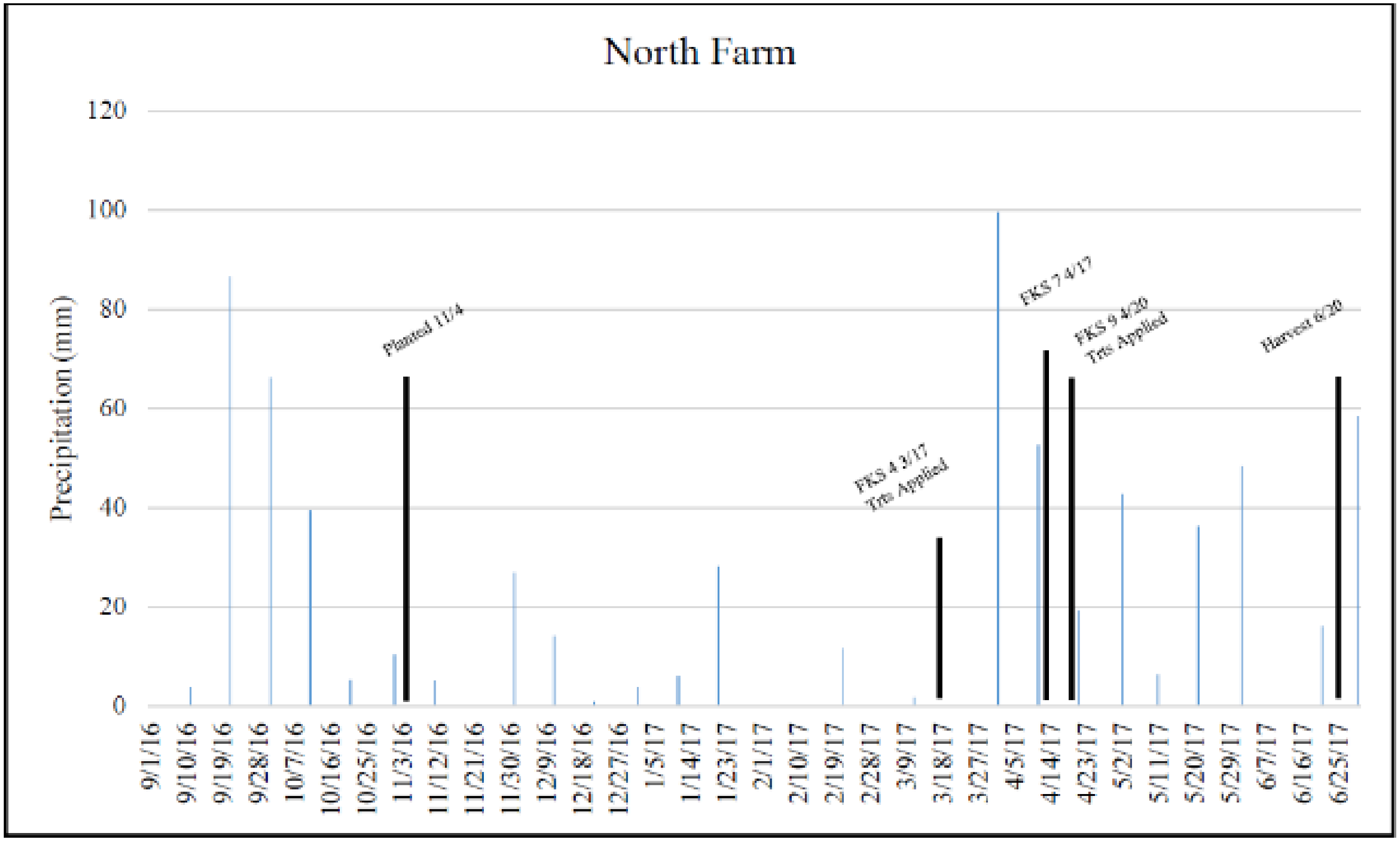
Belleville NDVI Map March 1, 2017.



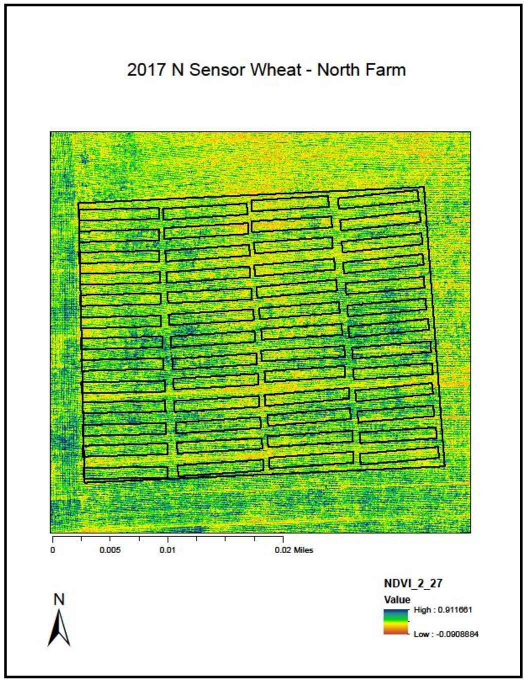
Belleville NDVI Map April 21, 2017.



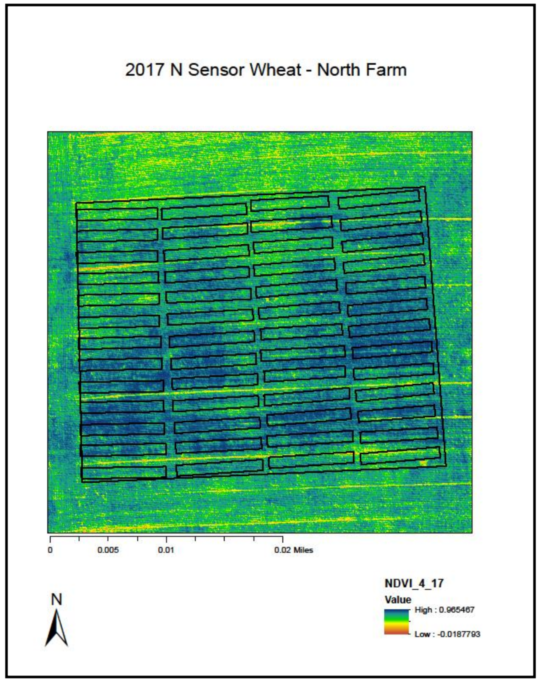
Belleville NDVI Map May 15, 2017.



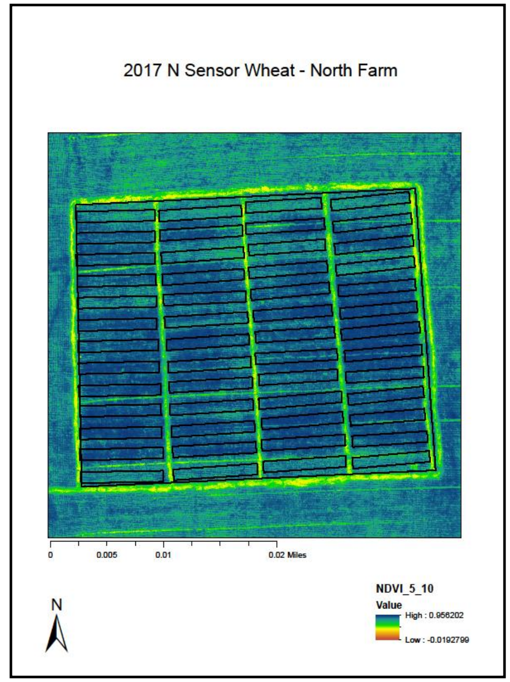
2017 North Farm precipitation and key treatment dates.



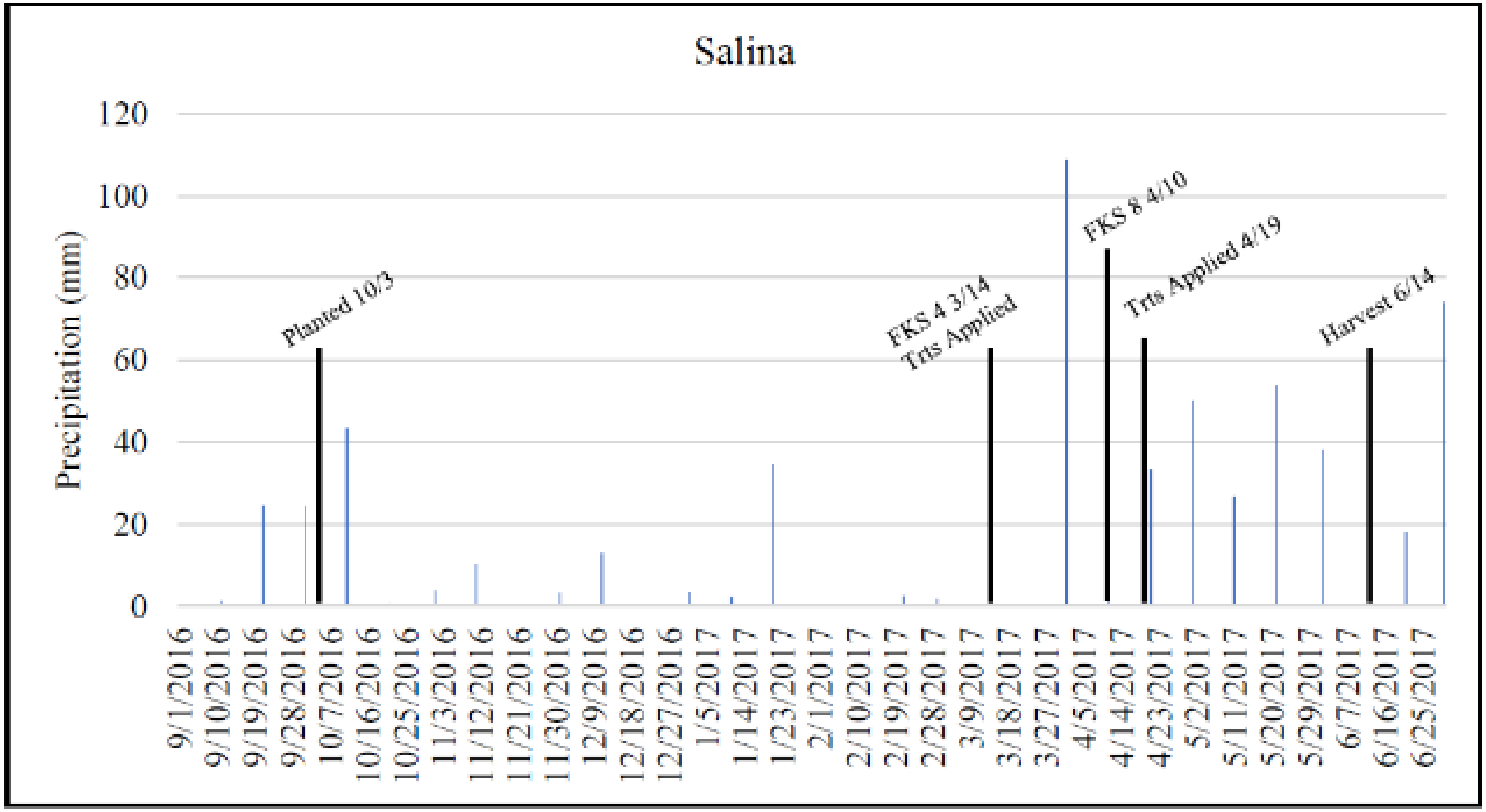
North Farm NDVI Map February 27, 2017.



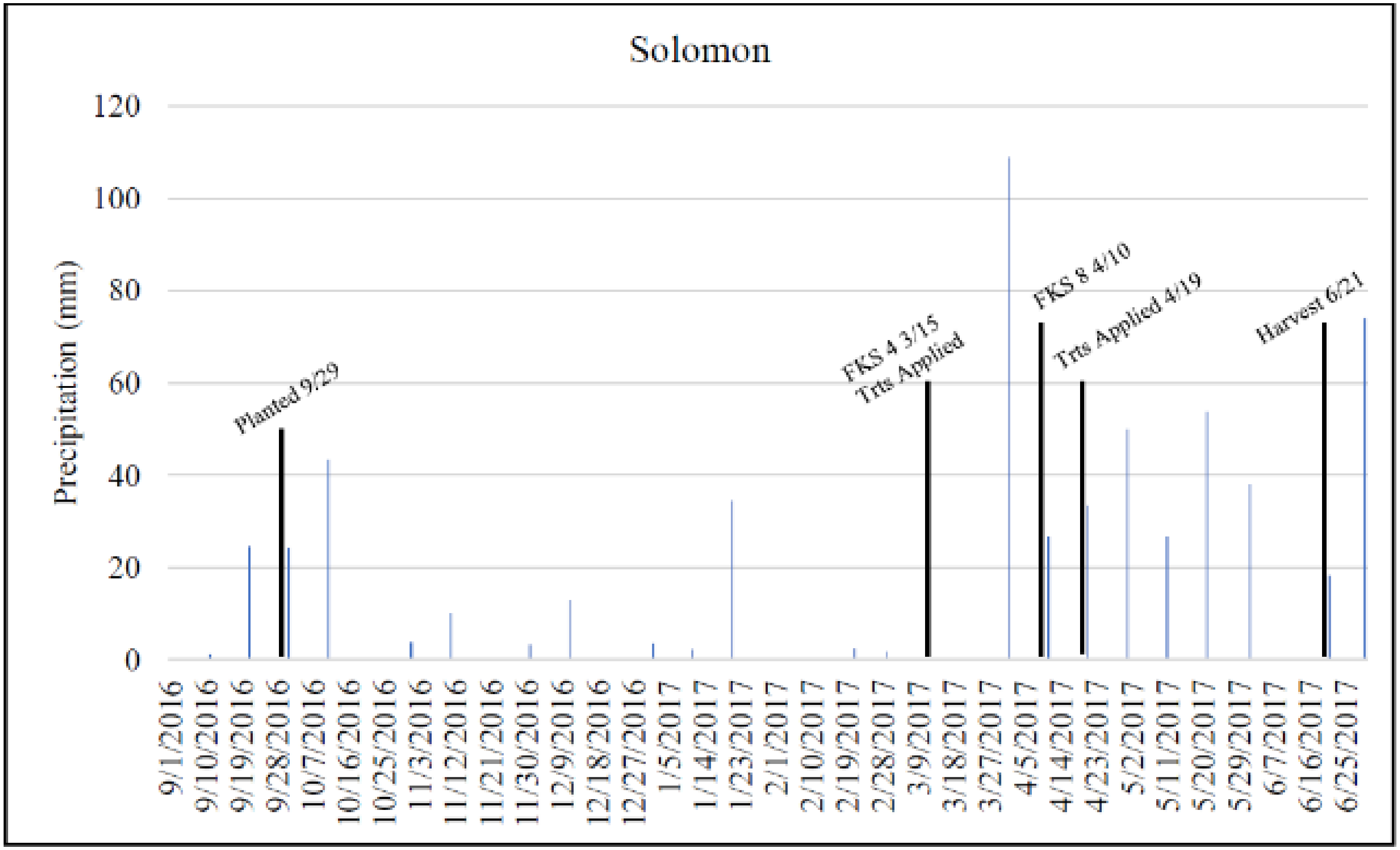
North Farm NDVI Map April 17, 2017.



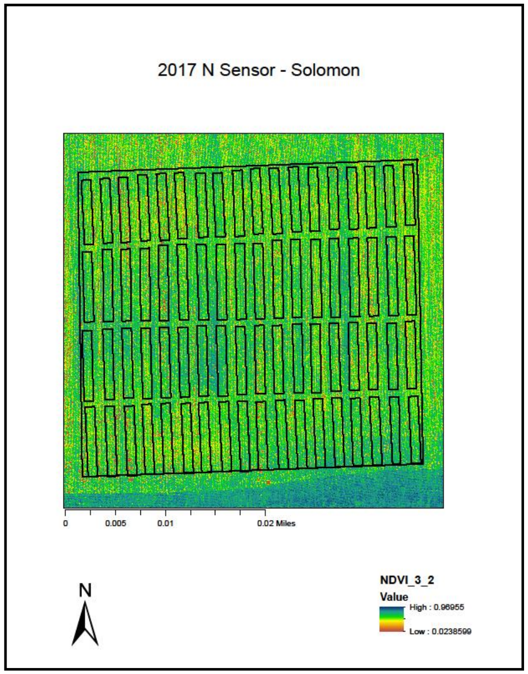
North Farm NDVI Map May 10, 2017.



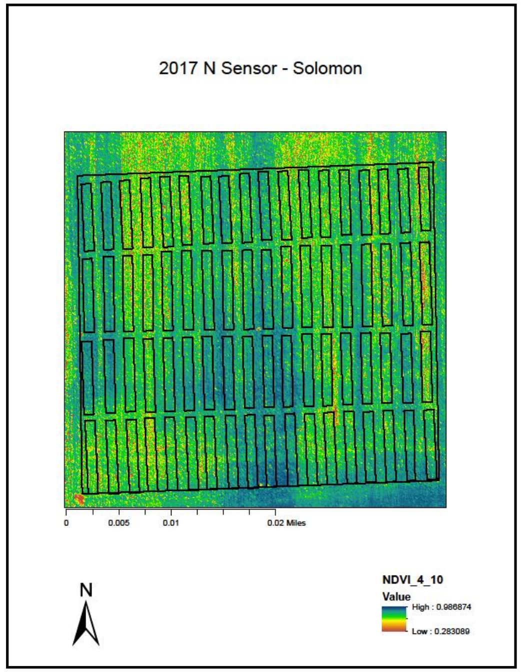
2017 Salina Precipitation and Key Treatment Dates.



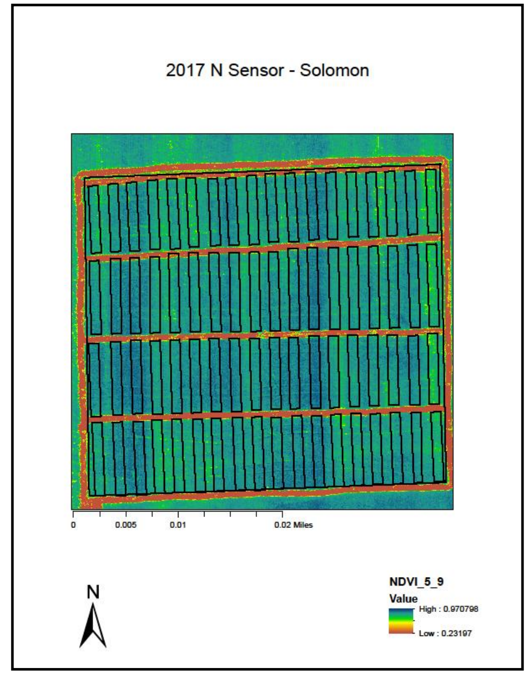
2017 Solomon Precipitation and Key Treatment Dates.



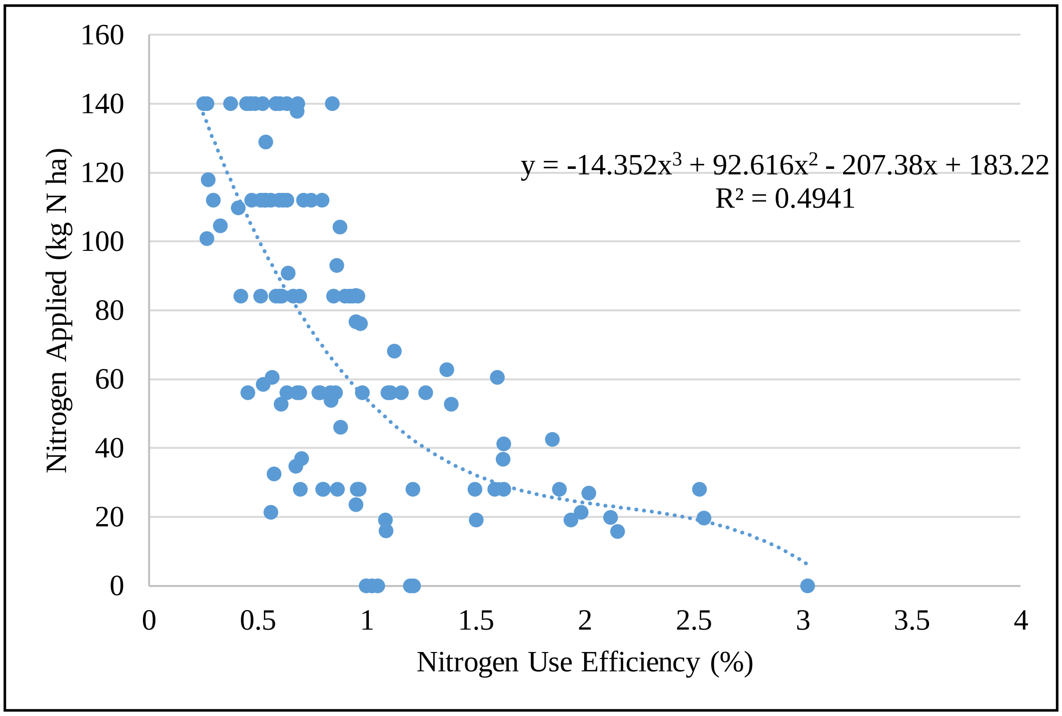
Solomon NDVI Map March 2, 2017.



Solomon NDVI Map April 10, 2017.



Solomon NDVI Map May 9, 2017.



Shows Nitrogen Use Efficiency Across Years and Locations.