ESTIMATION OF AGRICULTURAL SOIL EROSION AND SURFACE WATER QUALITY TRENDS IN THE CHENEY LAKE WATERSHED

by

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Abstract

Phosphorus and sediment runoff are the primary cause of eutrophication in Cheney Lake, the primary water source for Wichita, Kansas. Best Management Practices (BMPs) such as no-till farming practices and nutrient management can be implemented to reduce phosphorus runoff on high-risk agricultural fields. Past efforts have established BMP use in this watershed, although the effectiveness of these efforts has not been evaluated. The goals of this project were to identify any existing water quality trends in the Cheney Lake Watershed, estimate the current distribution of erosion in the watershed, and evaluate the placement of BMPs with regards to field-scale erosion risk. Parametric, multi-linear regression and non-parametric, seasonal Mann-Kendall analyses were used to identify trends in the Total Suspended Solids (TSS) and Total Phosphorus (TP) of grab samples from the North Fork Ninnescah River. A Geographic Information System (GIS) model based on the Revised Universal Soil Loss Equation (RUSLE) was used to estimate watershed-scale erosion, prioritize agricultural land for BMP placement, and evaluate existing placement of BMPs within the Cheney Lake watershed. No detectible trends were identified in the water quality data due to stream variability, frequency of sampling, or absence of actual improvement in water quality. Additional sampling must be done to detect any trends in the future. BMPs were implemented on 13% of prioritized field area, and 11% of non-prioritized field area. Conservation Reserve Program (CRP) fields were placed on 14% of prioritized field area, and 5% of non-prioritized field area. No-till practices were implemented on 13% of prioritized field area, and 18% of non-prioritized field area. The top 20% eroding fields were identified given current conditions, and account for approximately 56% of the watershed-wide erosion. The GIS method has demonstrated utility in evaluating past erosion control measures for the watershed and in informing future decisions concerning BMP placement.

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CHAPTER 1 - Introduction

Soil conservation and water quality are two of the most pervasive environmental concerns across the Great Plains region of the United States. These concerns are primarily due to the extent of land under intensive agricultural use which, if improperly managed, may contribute simultaneously to soil erosion and non-point pollution of surface and ground water.

The Cheney Lake Watershed, located in South-Central Kansas, is home to both of these environmental concerns. The eventual lifespan of the Cheney Reservoir is being determined by the rate at which it fills with sediment, slowly diminishing its ability to store water. The lake has also experienced water quality concerns, when repeated algal blooms have resulted in taste and odor issues for the city of Wichita, which draws the majority of its municipal drinking water from the lake. These algal blooms are caused by the presence of excess nutrients in the lake, which may be transported in either dissolved or sediment-bound forms from the nutrient-rich agricultural land within the watershed.

Best Management Practices (BMPs) have been implemented in the Cheney watershed to improve the water quality of the streams and reservoir. However, BMP placement did not account for the vulnerability of specific fields. It has not been determined how effective past BMP implementations have been at improving water quality in this watershed.

In order to address these issues, there needs to be an assessment of past BMP placement, prioritization of future placement, and evaluation of past practice effects on water quality trends.

Soil Phosphorus Forms and Cycling

A full understanding of the water quality issues in the Cheney Lake Watershed requires a thorough understanding of the importance of P in agriculture and the environment. Phosphorus (P) is an essential plant nutrient that is needed for the growth of native vegetation, agricultural crops, and aquatic plants alike. Phosphorus can be found in many different forms in the soil. The Phosphorus cycle between various mineral and biological forms is complex, and it can be difficult to quantify the availability of soil phosphorus for plant uptake, or its risk of loss from the soil. Before addressing the problem of eutrophication, it is necessary to understand the role of P in the soil.

Soil phosphorus measurements

Quantifying the amount of P in the soil and the forms that it takes are important for both agronomic and environmental reasons. P does not always have distinct forms with predictable characteristics. Even while in a mineralized form, it is not always soluble or biologically available. Furthermore, changing soil or water conditions can impact the speciation and availability of P that is already present.

One way to describe P availability is to measure the total amount of the element, or Total Phosphorus. Total Phosphorus (TP) is not a reliable indicator of either plant availability or environmental concern, because the majority of P in most soils is found in recalcitrant organic or inorganic compounds or soil minerals. Total Phosphorus is meant to be an exact, quantitative measure of the P in the soil, while other measures of P are generally based on availabilities rather than exact chemical species.

A variety of extractions may be performed to estimate the amount of P available for crop use, including the Bray II, Mehlich III, and Olsen P extractions. These results are known collectively as Soil Test P (STP.) It is important to note that STP was designed to estimate P availability to crops, and not to predict P vulnerability to runoff loss. Soil P tests simulate the conditions around plant roots that enable a plant to uptake P, that differs in chemistry from runoff water conditions. In addition to this, STP is generally measured for the top 15 cm of a soil, whereas the P most likely to be lost due to runoff events is located in the top five centimeters of soil that interacts with surface runoff (Sharpley et al., 1996). This means that while STP is used by most states as a basis for P regulation (Sharpley et al., 2003), it is not the best estimation of a given soil's vulnerability to P loss.

Sharpley (1995) used a P saturation approach to predict P loss from soils in runoff conditions. Soil test P correlations to soil P loss will vary among different soils, making it difficult to predict a given soil's vulnerability to P runoff. By factoring in a soil's total ability to hold P, however, it is possible to get a better estimation of soil P-loss vulnerability (Sharpley, 1995). It is necessary to measure P sorption maximum in order to find P sorption saturation percent. This adds complexity to the analysis of soil tests, and is not currently as ubiquitous as the STP extractions that are regularly performed on agricultural soil. Soil P saturation, once determined, is a more useful measure of comparing relative BAP concentrations across different soil types.

Different forms of phosphorus can be quantified when describing the P content in water bodies or runoff. Soluble Phosphorus (SP) is the portion of this P that is easily dissolved and transported by water. This P is the most biologically available. Particulate P (PP) is a measure of the P that is bound to soil particles, in this case eroded soil particles in runoff and water body sediments. A portion of the PP will become biologically available in a water body, and is known as bioavailable particulate P (BPP). Soluble Phosphorus and BPP combine to represent the total Bioavailable Phosphorus (BAP.)

Several different methods of measuring soil P for the purpose of environmental concerns have been proposed. Simple water or NaOH extractions of particulate soil that has already been eroded can be used to determine the bioavailability of the associated P (Sharpley et al., 1991). Iron Oxide-Impregnated strips of paper have also been used to estimate available P in agricultural runoff (Sharpley, 1993). While these methods are meant to measure P that has already been lost to runoff, it is still beneficial to be able to predict P loss from a soil before it takes place.

Phosphorus Sources

In addition to quantifying the amount of P in the soil and water, it is necessary to understand the various sources that enrich soil P under natural and agricultural settings. Under natural conditions soil P is taken up by plants, consumed by animals, and then returned to the soil through their waste or decomposition. This process will naturally enrich the upper portions of the soil profile with relatively higher P content than the subsoil. This means that while P loss should be expected to accompany naturally occurring soil erosion, the enrichment of soil P is limited by the initial amount present in the soil parent material.

Agricultural settings differ from natural settings due to crop P removal as well as manure or fertilizer inputs. Any grain or forage removed from the field contains P that would otherwise return to the soil. Producers will often use organic or mineral sources to replenish soil P and avoid yield-reducing P deficiencies in future crops. In addition to P application as a fertilizer, P is often applied to cultivated land through the disposal of excess animal manure, and viewed as a form of waste management rather than soil amendment.

These deviations in the overall P balance of agricultural land can lead to increased vulnerability to P loss. The high transportation cost of moving manure means that much of the manure produced by animal productions is applied to nearby fields within the same watershed. In the United States, less than a third of grain produced is fed on farms where it is grown, resulting in a major one-way transfer of P from grain-producing to animal-producing areas (Sharpley et al., 2003). This disparity of P removed by crops and P applied by animal waste means that watersheds with a high level of animal production contain fields with excessive amounts of P in the soil. Even if total P quantities in a watershed are not increasing, it is possible for individual fields to become enriched. Nonpoint agricultural sources have been identified as the primary source of P and Sediment loss in the Cheney watershed (Starzec et al., 2008).

Sediment and Phosphorus Loss Factors

There are several factors other than soil P concentration that affect the amount of P lost in runoff. These factors also contribute to sediment loss, as the detachment and transportation of P and sediment generally take place simultaneously, with the majority of TP in water bodies bound to the sediment. In order to assess P loss or sedimentation within a watershed, it is necessary to consider these factors.

Land Use

General land use has the greatest impact on P loss. Sharpley (1995) found native prairie to contribute less to P loss than agricultural land. Agricultural land does not always have a balance of input and output P to the soil, as previously discusses. Cultivated crop land is also affected by other management practices that are not applicable to pasture or native grassland.

Land Management

If land is to be used for growing crops, the tillage practices, fertilizer application amounts, and fertilizer application methods can be altered to reduce P loss. Fertilizer placement strategies such as incorporating or injecting P fertilizer greatly reduces dissolved P loss (Sharpley, 1995). Soil amendments such as alum can be applied to areas of extremely high P in order to reduce P solubility and limit its loss from runoff (Moore Jr et al., 2000).

Erosion

The greatest percentage of total P lost in runoff is bound to soil particles and organic matter. This sediment bound P accounts for 80% of the P lost from most cultivated lands (Sharpley et al., 2003). Bennett et al. (2001) states that P generally enters aquatic ecosystems sorbed to soil particles that are eroded into water bodies and any factor that increases erosion will increase the potential P runoff to downhill aquatic ecosystems. Reducing tillage can reduce TP loss due to the reduction of soil erosion.

Rainfall and irrigation

The mechanism by which P is lost from agricultural ground and transported to water bodies relies on the flow of water from precipitation or irrigation runoff. Areas of the world with greater intensity of rainfall and higher amounts of annual precipitation will receive more runoff events, and thus, more P loss. Sharpley et al. (2003) found that irrigation can significantly increase the potential for soil and water contact and thus can increase P loss by surface runoff and erosion. Irrigation can be thought of as having a similar effect to shifting the climate of a field to that of higher precipitation, and thus higher physical and chemical weathering.

In addition to the physical or chemical effects of irrigation, the practice of irrigation may also allow for land area otherwise unsuited for crops to be cultivated. This would alter the land use from native to agricultural and have the potential impacts from land use described previously.

Proximity to water bodies

The position of a given field within the watershed can have a great impact on its contribution to P and sediment loading in surface water. Sharpley et al. (1999) found that stream flow P concentrations were more closely related to the P concentration of soils within 60m of the stream than to the soils of the entire watershed as a whole. This is because in the watershed they studied, land closer to streams contributed more surface runoff during storm flow than land further from the stream. They conclude that proper management of P in a watershed must take into account the proximity of fields to streams. Soil erosion and P runoff anywhere in the watershed may affect water quality, but the locations nearest surface water have the potential for the greatest and most immediate impact.

Outcomes of Sediment and Phosphorus Runoff

It has been determined that P runoff and sedimentation are the primary risks facing the watershed (Cheney Lake Watershed Inc., 2011). While the causes of these problems are highly related, as previously discussed, they each have uniquely negative consequences for the reservoir.

Eutrophication

Eutrophication is the increase in nutrient concentrations of a water body, which leads to overproduction of algal growth. The consequent decomposition of this plant matter consumes much of the oxygen in the water which can kill many of the fish and other organisms present, leading to a loss of fish production and biodiversity. The taste and odor effect of eutrophication can also lead to water quality issues for municipal drinking water sources as well as negatively impact any recreational value of the water body, causing a financial impact to local businesses. (Bennett et al., 2001; Dodds et al., 2008).

Both saltwater and freshwater can be affected by eutrophication. In general, the limiting nutrient for most ocean bodies is nitrogen, while the limiting nutrient for freshwater bodies is P (Schindler, 1977). This means that an increased input of P alone is enough to drastically affect the algal production of most freshwater lakes.

Reducing P inputs to a water body should in theory reduce the potential for eutrophication. Schindler (1974) found that freshwater lakes quickly recovered once external sources of P were eliminated. Little or no P was recycled within the lake from the sediments. These results indicate that the results of anthropogenic eutrophication may be solved very quickly if the source of P input into a lake is reduced. Others have found that P continues to be cycled within a lake years after the nutrient input sources have been decreased (Carpenter, 2005). Carpenter (2005) focused on lakes affected by nonpoint P inputs, which have replaced point sources as the main input of P in many regions. Their model showed that substantial changes to soil management were required to reduce eutrophication and that it may take hundreds of years for increased soil P levels to stop affecting the water quality of the watershed.

The response of an individual lake to reduced P inputs depends on the P cycling that takes place between the lake water and the previously deposited lake sediment. Pope (1998) found that the P concentration in sediment at the bottom of Cheney lake is highly variable, but averaged the relatively high value of 410 mg P kg^{-1}. It is not clear how much of this existing P would become available in the lake if the input concentrations were to decrease in the future.

Acceptable P Loss from Agricultural Land

The question of acceptable P loss from agricultural land has very real implications as far as government regulations and producer practices. In order to produce a critical value of P concentration allowed on agricultural soil, it is necessary to first determine what amount of P in runoff is historically normal and what target quality level is appropriate for the given water body.

Bennion et al. (1996) demonstrates a method of determining historical P levels in a given water body before modern human influence. They do this by analyzing diatom remnants from lake bottoms to determine past nutrient ratios and concentrations by the species of diatoms present at different times. From an ecological perspective, restoring water quality to these historic values could be considered a satisfactory goal.

From a recreational and water-use perspective, the target nutrient levels would more likely be based on preventing eutrophic conditions, which might degrade water quality. There is no definitive quantity of P that is considered the cutoff point between acceptable and unacceptable, but 100 micrograms total P per liter is generally unacceptably high, and concentrations as low as 20 micrograms total P per liter can cause eutrophication problems (Correll, 1998). This value will vary across watersheds due to the effect of nitrogen concentration and other biological or chemical balances. If a water body has experienced past eutrophication problems, this value can be determined by the P concentration present in the water during these events.

Once a water quality goal is set for the watershed, one can attempt to set soil P goals that will allow this water quality goal to be met. As discussed earlier, STP is not a reliable measure of P saturation across different soils. Because of its common use for agricultural purposes, however, most states' recommendations and regulations for maximum soil P concentration is based on STP.

Experiments have been done to relate STP to P loss for given soils (McDowell and Sharpley, 2001), but these studies are of limited use for different soils in different watersheds. Most states consider values between 75 and 200 mg/kg STP to be the limit at which no further P source should be applied (Sharpley et al., 1996).

Sedimentation

While eutrophication is the most immediate threat to the water quality of the Cheney Reservoir, the process of sedimentation is also an area of concern. All man-made reservoirs are constructed with an estimated lifespan, defined by the time it will take for their capacity to become severely reduced by the buildup of sediment within the reservoir. The Cheney Reservoir was designed with an effective life-span of 100 years. As of 1998, 34 years into its life, about 27 percent of the allocated sediment storage capacity had been used (Mau, 2001). The CMC set TSS goals which, if met, would double the life of the reservoir (Stone et al., 2009).

Sedimentation is caused by eroded soil particles that are transported by rainfall and stream flow into a lake or reservoir. Soil particles that are easily transported by stream flow settle permanently to the bottom of the reservoir when they encounter still or slow water movement. While this process is inevitable in man-made reservoirs, the rate at which it takes place can be slowed by reducing the amount of soil eroded from the watershed and transported into the lake.

Water Quality Analysis

The major factors influencing sediment erosion and P runoff have been identified. While this is important to consider on a per-field basis, it is also important to be able to quantify the effect that these factors have on the actual water quality of the watershed. It is important to identify and quantify water quality trends over time, as this is the final result of what is happening in the field.

Determining trends in water quality data has several inherent difficulties. Water quality, especially of streams or rivers, can exhibit extreme variability over time. Even substantial effects of conservation efforts can be overwhelmed by the effects of individual precipitation events or long term climatic variability. Sample timing and consistency, serial correlation, and non-normal data distribution are other issues that commonly affect the analysis of water quality trends. Helsel and Hirsch (1993) describe methods used by the United States Geological Survey to analyze water quality data. Non-parametric statistical methods are particularly well-suited to analyzing water quality data because they do not require the same assumptions about the data, such as normality (Hirsch et al., 1991). The Mann-Kendall test is a popular non-parametric method used to test for trends in water quality (Darken et al., 2000; Yue and Wang, 2004).

Before prioritizing BMP placement within the watershed, it is necessary to determine whether or not there are any watershed-wide trends in water quality based on the existing implementation of BMPs. The results of this analysis will inform the predictions and observations made by subsequent GIS analyses and watershed modeling.

Best Management Practices

In the context of the Cheney Watershed, BMPs are meant to reduce the environmental impact of agricultural land use. They include a wide variety of practices may address the source of pollutant, the transportation of the pollutant into vulnerable waters, or both. Common BMPs that have been implemented include reduced-tillage crop rotations, terrace construction, and nutrient management planning. Nutrient management planning addresses the source of P, as well as other nutrients, that may threaten surface water quality.

As previously discussed, the amount of tillage that cropland receives can have a strong impact on soil erosion. By minimizing tillage, or eliminating it all-together, it is possible to minimize the amount of sediment and soil-bound P from entering nearby surface water.

Terraces are erosion control structures that are commonly implemented in fields containing steep hills or slopes. They modify the speed and direction of runoff flow to minimize the occurrence of concentrated flow during precipitation events. In addition to reducing soil erosion and P runoff, they can also benefit the producer with greater efficiency of a field to utilize precipitation.

Prioritizing BMP Placement

Once an area has been identified as a major contributor to P contamination within a watershed, it is possible to implement measures to remediate the environmental concern. In order to do that, it is necessary to know what BMPs are most effective for reducing P runoff in a watershed in order to eliminate or reduce eutrophication.

Revised Universal Soil Loss Equation

As mentioned previously, P loss from agricultural land is highly correlated with soil erosion, therefore, identification of areas with high potential for erosion should also identify areas with high potential for P loss. The Revised Universal Soil Loss Equation (RUSLE) is a widely accepted model for predicting soil erosion. RUSLE uses a series of factors in order to produce an estimated average of soil loss from sheet and rill erosion. The R factor is based on yearly rainfall intensity.. The K factor is based on soil properties. The L factor accounts for slope length and the S factor accounts for slope steepness. The L and S factors are often collectively referred to as LS factor. The C factor is based on vegetative cover and soil surface conditions resulting from land use type and management. The P factor accounts for conservation practices that are otherwise not accounted for by the other factors.

There are several important factors that influence P and sediment runoff risk that are not accounted for by RUSLE, including the distance from the field to the nearest water body and the transport factors that carry the sediment beyond the boundary of the field. RUSLE also does not take into account the amount of P within a given soil, or the ability of the soil to retain or lose dissolved P to runoff. It also does not account for P loss directly from fertilizer or manure sources.

P-Index

Several states have developed P indices as a tool for ranking the vulnerability of fields for P loss in runoff (Sharpley et al., 2003). The Kansas P Index is based on factors which are divided into source and transportation factors, and assigned numerical values based on their impact on relative P loss vulnerability (Sonmez et al., 2009). The summed transport factors are multiplied with the summed source factors to produce a final P Index value that does not quantify any physical amount of P lost, but instead gives a relative assessment of risk. These values correspond to maximum P application rates, which producers may be required to follow when field-applying manure from animal feeding operations of a given size.

P-index calculations are a useful for ranking individual fields based on P-loss risk, but they must be performed manually for each field in consideration. Geographic Information System (GIS) methods can be used in order to target fields within an entire watershed based on risk of P loss. Prioritizing fields based on potential P-loss allows BMPs to be placed more strategically within a watershed.

Watershed Modeling and Prioritization Strategies

There are many ways to prioritize the placement of conservation practices within a watershed. As we have seen, there are many factors, both inherent to the location and dependent on land management, which can greatly affect the likelihood of a given location to contribute sediment or P runoff to a nearby water body.

Qui (2009) describes a method used to prioritize agricultural lands for conservation buffer placement in a New Jersey watershed. In this study, the watershed was classified based multiple criteria, and about one-third of the agricultural land prioritized for conservation efforts.

These criteria included soil erodibility, hydrological sensitivity, wildlife habitat, and impervious surface rate. The final value determined spatially for the watershed is not a quantifiable measure, but rather a weighted score or index of these criteria.

Settimi et al. (2010) used a GIS containing soil parameters, slope, and water features to evaluate the past placement of conservation practices within the Little River Experimental Watershed in Georgia. They found that conservation practice placement was effected more by proximity to a water body and soil hydrologic group than by slope class. They determined that fields participating in federally funded conservation programs coincided with high resource concern areas 35% of the time.

Watershed modeling efforts have already been performed for the Cheney Watershed. U.S. NRCS (2006) used computer modeling to identify and predict the locations of ephemeral gullies in the watershed. They estimate that gully erosion, which is not accounted for by the RUSLE model, may be responsible for as much as 35% of the sediment load to the reservoir. This analysis produced the estimated locations of ephemeral gullies and their contribution to sediment loading, which can be used to evaluate the placement of BMPs within the watershed. Other watershed modeling efforts, such as the use of AnnAGNPS (Wang et al., 2003) and SWAT (Parajuli et al., 2009), do not give field-scale predictions of P loss or erosion, but are meant to give larger-scale estimations of these values using comprehensive, process-based simulations.

Cheney Reservoir History

Construction on the Cheney Reservoir, in Reno County, Kansas, began in 1962 and was completed in 1965. It was built by the U.S. Bureau of Reclamation, the government agency under the Department of the Interior, which is responsible for many dams, power plants, and canals in the western US. The city of Wichita Kansas funded half of the cost for the project. The purpose of the reservoir was to provide flood control, wildlife habitat, recreation, and to be a municipal water supply for the city of Wichita.

The Cheney Reservoir serves as the primary water source for around 350,000 people (Starzec et al., 2008). Historically, the lake has supplied anywhere from 60 to 80 percent of Wichita's water use. As of the year 2005, the reservoir has supplied the city with approximately

315 billion gallons of water, or nearly six times the total capacity of the reservoir (Wichita City Council, 2005).

Conservation Efforts in the Cheney Lake Watershed

Given the reservoir's use for drinking water and recreation, the utility of the Cheney reservoir relies on the quality of its water. The reservoir has experienced water-quality problems in the last few decades (Pope et al., 2002; Starzec et al., 2008; Stone et al., 2009; Wang et al., 2003). Cheney Lake experiences occasional algal blooms, which result in taste and odor problems in the drinking water and compromise the lake's use for recreation.

In 1992, due to concerns about the water quality of the reservoir, the Reno County Conservation District and Agricultural Stabilization and Conservation Service formed a task force to identify the problems affecting the water quality and identifying courses of action to address these problems. The task force identified agricultural sources, fertilizer and animal manure, as the primary sources influencing the high levels of P within the lake. In 1994 an EPA grant of $170,000 was used to fund the establishment of a Citizens Management Committee (CMC) to lead the conservation effort within the watershed (Cheney Lake Watershed Inc., 2011) This money was used by the CMC to manage the watershed and implement BMPs. In 1999, the CMC established Cheney Lake Watershed Inc. (CLW). CLW is a non-profit organization that seeks to improve the water quality within the watershed through private funding sources. The city of Wichita has pledged $200,000 annually from 2000 to 2006 towards watershed conservation efforts.

Numerous cost-share and educational programs have been implemented by the various organizations and agencies at work in the watershed in order to reduce sediment, nutrient, and pesticide transport into the reservoir. Cost-sharing of BMP contracts has been used to provide economic incentive for producers to adopt land management practices such as reduced tillage, terracing, and nutrient management planning. From 1994 to 2006 more than 1,300 BMP contracts of 39 different types have been implemented (Starzec et al., 2008). In addition, more than 77,000 acres of cultivated cropland has been converted into native grass as part of the Conservation Reserve Program (CRP.) The city of Wichita has assisted this effort by funding 50% of the cost for fencing recently converted CRP land.

Previous assessment findings

Previous studies have been conducted to document water quality in Cheney Reservoir as well as watershed factors that impact water quality. Efforts have been made to identify the causes of P and sediment runoff, document the current situation, and suggest goals for improvement.

To determine historic soil P concentrations, Pope et al., (2002) performed an extensive soil core sample study across the watershed. Soil cores from land that had never been under agricultural use or fertilization were collected from sites across the watershed, mostly from old country cemeteries. Based on these samples, they determined that, on average, agriculture is responsible for an increase of about 2.9 times the amount of P found under natural conditions. They concluded that about 65% of the total historical input of P to the reservoir is from agricultural sources. However, they estimated that even under natural conditions, the TP concentration in the flowing surface water would still be above the goal of 0.10 mg L^{-1} set by the Cheney Reservoir task force in 2004, given the amount of P found in the natural soils and the amount of sediment expected to erode under natural conditions. According to a U.S. NRCS (2006) study that modeled ephemeral gulley erosion, only 10% of the area within the watershed is responsible for 76% of the sediment load caused by this type of erosion. This indicates that erosion rates and sediment transport are highly variable across the watershed.

A recent analysis by Stone et al. (2009) describes water quality data collected from 1997 to 2008 from USGS streamflow data. They found that the TP and total suspended sediment (TSS) concentrations for stream baseflow exceeded the goals set by the Cheney Reservoir task force in 2004. However, the runoff concentrations during rainfall events rarely exceeded the higher concentration goals set for them. They didn’t detect a significant trend in TP or TSS concentrations over time, but they note that 1997 to 2008 experienced lower than average streamflow, which may increase the variability of the data from year to year.

In 2004, the Cheney Lake Watershed was selected by the NRCS to be part of the Conservation Effects Assessment Project (CEAP) program. The purpose of CEAP watersheds is to study the implementation of BMPs within watersheds and what effects they have had on water quality. In 2006, the watershed was granted an additional 3 year grant to further study the watershed trends and to identify BMP strategies. Specifically, the purpose of the project is to answer three main questions: 1. How do the timing, location, and array of conservation practices affect water quality at the watershed scale? 2. How do social and economic factors affect conservation practices and implementation? 3. What is the optimal placement and suite of conservation practices for this watershed?

Conclusions

It is clear that the Cheney Lake Watershed merits additional research regarding its water quality concerns. Many efforts have been made to decrease the amount of sediment and P that agricultural land contributes to the reservoir. However, the effectiveness of these efforts has not been quantitatively determined, and their spatial implementations have not been evaluated. The goal of this project is to assess past BMP placement, prioritize future placement, and evaluate past practice effects on water quality trends. To do this, it is first necessary to detect the presence of significant trends in the surface water quality measurements. Then, it is necessary to use some modeling effort to evaluate the placement of BMPs within the watershed, and to provide guidance for future BMP placement.

CHAPTER 2 - Water Quality Trend Analysis

Introduction

The most direct way to evaluate the water quality of a waterbody is to collect and analyze water samples over a period of time. From the data it is possible to determine the current level of water quality as well as any trends of improvement or worsening conditions. The implementation of BMPS may impact water quality, as well as changes in weather, land use, or water management. Ideally the impact of BMPs can be measured by pairing a treatment watershed with a control watershed, but this setup is often impractical or impossible depending on the area being studied.

A variety of water quality data have been collected from the Cheney Watershed in the past. These data have been summarized and described, but they have not been analyzed thoroughly with detailed trend-analysis statistical methods, and significant trends have not been detected. Previous studies have found that the North Fork Ninnescah River has not been meeting the TP and TSS concentration goals during base flow conditions, although it has generally met the goals set for storm runoff conditions (Stone 2009).

It is necessary to perform a trend analysis on water quality data to determine the efficacy of BMPs in the Cheney Watershed. The current summaries of the data provide information about the water quality, but do not confirm whether these conditions are improving or worsening. Extensive efforts have been made to improve water quality in this watershed in the past, but their efficacy must be examined to inform future strategies.

Concerns, limitations, and challenges in determining trends

While surface water quality data are becoming more abundant, it often has complexities that must be addressed when being analyzed. Non-normality, censoring due to detection limits, unequal sampling intervals, seasonality, serial correlation, covariate effects, and the presence of outliers are all issues that must be addressed when dealing with water quality data. (Darken 2000.)

Serial correlation

Serial correlation occurs when sample measurements are not independent of one another, and any given sample result is highly correlated with the previous sample (Helsel and Hirsch, 2002). In water quality, this can be because two samples are collected during the same runoff event, or due to seasonal effects. Data collected within a short time interval is especially prone to this. Serial correlation can greatly skew the results of trend analysis, so it must be detected if it exists.

The Durban-Watson statistic describes the presence of serial correlation in parametric data. A non-parametric test for serial correlation can be performed by pairing each data-point with the next chronological point as a new two-variable dataset. A non-parametric test such as the Kendall-Mann can then test for a trend between these two variables.

Sample frequency and bias

The frequency of sample collection is also a concern for analyses of water quality data. Non-parametric trend tests generally require data to be collected in evenly-spaced intervals. Parametric tests can also become unevenly weighted due to many samples taken during one period of time and less taken during another.

Sample collection times may not always be random or unbiased. The intensity of data collection and water quality testing may vary by season, during storm events, or over the course of project and funding changes. If samples are taken more often at a given time of year, then any detected trends may not account for the overall water quality. Samples may be more likely to be taken during high stream flow events, such as storms. This would lead to a dataset that is highly biased towards runoff conditions, rather than average base flow. If a long term trend is to be collected in some watersheds, data from several different sampling efforts may be required, and any difference between these collection strategies may affect the resulting trend.

Seasonality and other covariates

Water quality often fluctuates over the course of the year, due to seasonal patterns in climate as well as agricultural operations. This may add a great deal of variability to the dataset, as lower flow seasons such as January may have drastically different water quality than high flow seasons such as July. If seasonal variability is not dealt with, it may mask the presence of a trend in the water quality.

Trend Analysis Strategies

Statistical methods used to detect trends in water quality data, can be classified as either parametric or non-parametric. Parametric methods include linear regressions, multi-linear regressions, and statistical tests that assume errors to be normally distributed. Non-parametric tests are generally rank-based methods that do not require distributions to be normal, only consistent. If the data follow a linear relationship and the residuals are normally distributed, the parametric tests have the greatest statistical power to detect a trend. Water quality data, however, often violate those assumptions, making the non-parametric tests more appropriate to use. (Helsel and Hirsch, 2002).

Esterby (1998) details some of the strengths and weaknesses of parametric and non-parametric trend detection techniques. They find that non-parametric methods are simpler to implement in most cases, because they require less assumption-checking than parametric tests. Water quality data may never meet the assumptions required for parametric tests, including normality of errors. Parametric tests are, however, more flexible for the inclusion of covariates, such as flow rate and seasonality.

Helsel and Hirsch (2002) provide reference for several parametric and non-parametric trend analyses as well. The multiple linear regression method is used as a parametric test that can take into account covariates as previously noted. The Seasonal Kendal trend test is used as a non-parametric test that accounts monthly cycles in water quality. They also explain how the LOWESS smoothing procedure can be used to account for the effect of flow rate at the time of sampling on the concentration of pollutant in the water sample. The smoothing procedure is used to model the interaction between these two variables, and the Seasonal Kendall test is performed on the residuals of the smoothing, rather than on the concentration values themselves.

Other studies have used methods similar to the ones described in these texts. Walker (1994) employed multiple linear regressions on a series of water quality data. A stepwise multiple linear regression procedure was used to select which variables had significant effects on the suspended sediment load. The possible variables included total storm precipitation, maximum 15 and 30 minute rainfall intensities, USLE erosivity index, and serial date. These statistical techniques were used to detect changes in three rural watersheds in Madison County, Illinois, but did not detect any statistically significant trends. This is primarily due to the small degree of BMP implementation in these watersheds and due to errors in the estimates of the sediment mass-transport (Walker, 1994).

Several studies have used simulated scenarios to test the effectiveness of the Mann-Kendall trend analysis given different data concerns and techniques (Berryman et al., 2007; Darken et al., 2000; Hirsch et al., 1982; Thas et al., 1998; Yue et al., 2003; Yue and Wang, 2004). They have found this trend detection technique to be effective at detecting trends while being more flexible than other tests for handling data with non-normal error distributions.

Many trend analysis techniques can be applied to water quality data, each with their own strengths and weaknesses. The seasonal Mann-Kendal trend analysis and multilinear regression are both well accepted tests that can be applied to stream flow water quality data.

The objective of this study is to determine if there are temporal trends in Total Phosphorus (TP) and Total Suspended Solids (TSS) in the North Fork Ninnescah River from 1997 until present. Multiple trend analyses will be used, each with its own strengths and weaknesses. This will provide an evaluation of past efforts to improve water quality in the watershed

Materials and methods

Full description of sample collections

Water quality data is available for multiple locations and collected by several different methods. The data used for trend analysis were selected based on the consistency in sampling method and availability over multiple years. Data from 207 samples collected by the USGS are available from 1997 to 2009. The majority of sampling data from 2006 to 2009 were collected by Kansas State University, as an additional 90 samples (Figure 2-1, Figure 2-2).

The water samples were collected manually by lowering a collec tion jar over the side of a bridge that crosses the Ninnescah River at the location of the USGS sampling station number 07144780, at Latitude 37°51'45", Longitude 98°00'49". The sample was taken from mid-stream, to obtain a representative sample. The slowly-filling nature of the jars collected caused the sample to be collected over a range of depths as they were lowered into the stream. The measured variables that were relevant to this study are sample date and time, instantaneous stream flow at the time of sampling, total suspended solids, and total phosphorus. In addition, the average stream discharge of the seven days prior to each sample was collected from the USGS online data for the sampling location.

Some filtering and data preparation was required before analyzing trends in the USGS and KSU water quality samples. In the original USGS data, some variable measurements had been recorded as separate sampling events, one minute apart, and were combined into a single measurement containing all of the needed variables. Any duplicate measures taken less than 12 hours apart were removed.

The timing of sample collection at this location has varied over time. From January 1997 to January 2000, there was an average of 4.4 samples per month, after preparing the data for this study. High streamflow events were more likely to receive sampling than times of low streamflow. From January 2000 to January 2006, an average of 0.5 samples per month were collected. From January 2007 until December 2009 an average of 3.1 samples were collected each month, most of them collected by KSU, which began collecting samples in May 2007.

Simple parametric method

Two different parametric analyses of increasing complexity and a non-parametric method were used to detect the presence of trends in the time-ordered sediment and phosphorus data (Table 2-1, Table 2-2). The first method was a linear regression analysis. This simple analysis helped to determine whether or not the data violates the assumptions of the analysis and requires additional, more complex analyses to be performed.

First, the water quality data were filtered to select only discrete samples that measured both stream discharge and TSS concentration. SAS 9.2 was used to perform a linear regression using the “proc reg” procedure. Time and TSS concentration were regressed to determine a parameter estimate and test of significance for the change of TSS over time. The residuals of this test were then analyzed for normality of distribution and possible serial correlation. The same method was also used for TP concentration data.

Parametric method

The second method used for trend detection was a multilinear regression using modified and log-transformed input data. These modifications produce a better fitting model and address the concerns of cofactor influence, serial correlation, and residual distribution.

Data Preperation

For this analysis, individual TSS, TP, and stream discharge measurements were used to find month-averaged values. This was done to evenly space the data and minimize the effects of serial correlation. The concentration values were also log-transformed to normalize the distribution of the data of the effect of stream discharge on TSS concentration.

Multilinear regression

A stepwise multilinear regression selection was used to determine which variable to include in the final parametric model. The factors that were tested included instantaneous stream discharge, seven-day average stream discharge, thirty-day average stream discharge, and a binary variable for each month. A requirement of P<=0.15 was used to determine factor selection.

The factors found to be significant in the stepwise regression were then used as inputs for a multilinear regression that accounts for autocorrelation. The Proc Autoreg SAS procedure was performed with a fourth-order lag option. The time variable was included whether or not it was shown to be significant in the multilinear regression, because it is this factor significance that will reveal any trending increase or decrease in water quality.

Determine "power" of test to find trend

The results of the parametric test were used to determine how great the actual trend must be for the given test to positively detect a trend eighty percent of the time. Because the parameter estimate of the multilinear regression model involves a log-transformed scale, it is necessary to un-transform the values at the beginning and end of the dataset to express the trend in actual concentration values.

Non-parametric trend analysis methods

Non-parametric tests are used to detect trends in data that does not meet the assumptions of normal distribution. This allows analysis of data without log transformation. TSS and TP concentrations were analyzed non-parametrically with the seasonal Mann-Kendall method in combination with a two-factor LOWESS smoothing to account for variations in stream discharge rate.

LOWESS smoothing to remove covariant factors

One of the difficulties in employing a non-parametric test is removing the effect of covariant factors before testing the data. The stream discharge rate at the time of sample collection has been seen to have an effect on the phosphorus loading. This is likely because the increased discharge after a rainfall has removed phosphorus and sediment from the soil surface during runoff. This causes a positive relationship between discharge and concentration (Renwick 2008). In order to remove this effect, stream discharge is plotted against Phosphorus flux, and a Locally Weighted Scatterplot Smoothing (LOWESS) method is used to describe the relationship between the explanatory and response variables. LOWESS is a non-parametric smoothing technique that fits 2^n weighted least squares equations to the data, rather than using a single equation to describe the relationship between the the explanatory and response variables. The residuals between the expected and actual Phosphorus flux are then tested for trend.

Mann Kendal trend analysis

The Seasonal Mann-Kendall Trend analysis (Hirsch et al., 1982; Mann, 1945) was used as to detect possible trends in the LOWESS residual concentration values. This is a common non-parametric method for detecting trends in water quality data. It is based on the ranking of the data, which allows it to be used on data that is bounded by zero, or that follows a non-normal distribution. This test is also less skewed by outliers than are parametric methods and is not affected by transforming the x or y variable prior to testing.

The S test statistic is calculated by subtracting the total number of discordant pairs of data by the number of concordant pairs. This is divided by the total number of pair combinations to find the Kendall's tau correlation coefficient. A tau value of 1 would mean that as x increases, y always increases. A value of -1 would mean that as x increases, y always decreases. A value of 0 would represent a completely random response of y with respect to increasing x. 0.7 is considered a strong correlation value, on par with a correlation of 0.9 from a linear correlation.

$$S = P - M$$

Where P = "number of pluses", the number of times the y's increase as the x's increase, or the number of $y_i<y_j$ for all $i < j$, M = “number of minuses,” the number of times the y’s decrease as the x’s increase, or the number of $y_i > y_j$ for I < j,

For all i = 1,…(n-1_ and j = (i+1),…n.

Kendall’s tau correlation coefficient

$$\tau = \frac{S}{n(n-1)/2}$$

To determine the p-value, the S statistic is divided by the variance, which is calculated by:

d = 2 (S can vary only in jumps of 2),
μS = 0, and
σS = $\sqrt{(n/18) \times (n-1) \times (2n+5)}$

This produces a Z-value, that is then used to determine the P-value:

$$Z_S = \begin{cases} \dfrac{S-1}{\sigma_S}, & S > 0 \\ 0\,, & S = 0 \\ \dfrac{S+1}{\sigma_S}, & S < 0 \end{cases}$$

The null hypothesis is that S=0. It is rejected at a significance level of α if |Zs| > Zcrit where Zcrit is the value of the normal distribution with a probability of excedance of α /2 (Helsel and Hirsch, 2002).

The seasonal trend present in the data must be accounted for by the test. This is done by using the Seasonal Kendall trend test (Hersch et al., 1982.) This modification to the Mann-Kendal test finds the test statistic for individual seasons and then sums the test statistics as well as their expectations and variances (Hersch et al., 1991).

For this seasonal test, an overall statistic S_k is calculated by summing the S_i statistics from individual seasons. If the product of seasons and years is more than 25, then the distribution of S_k can be approximated by a normal distribution. The null hypothesis would expect S_k to equal zero, and to have variance equal to the sum of S_i variance. S_k is standardized and then evaluated against the standard normal distribution:

$$S_k = \sum_{i=1}^{m} S_i$$

$$Z_S = \begin{cases} \dfrac{S_k - 1}{\sigma_{Sk}}, & S_k > 0 \\ 0\,, & S_k = 0 \\ \dfrac{S_k + 1}{\sigma_{Sk}}, & S_k < 0 \end{cases}$$

where:

$\mu_{Sk} \ = \ 0,$

$\sigma_{Sk} \ = \ \sqrt{\sum_{i=1}^{m}(n_i/18) \times (n_i - 1) \times (2n_i + 5)}$, and

$n_i \ = \$ number of data in the ith season.

Results

Simple Linear Regression

The simple linear regression of the raw TSS data provided a time parameter estimate of -0.0338 mg L^{-1} day^{-1}, which would be a -12.3 mg L^{-1} decrease in TSS concentration every year (Figure 2-3). This relationship is statistically significant, with P <.0001. However, the model has very poor fit with an R-square value of only 0.0823. The TP regression showed a decreasing trend, but was not statistically significant (Figure 2-4).

As stated in the methods, the results of a simple linear regression on raw water quality data is highly suspect. The TSS regression showed a first-order autocorrelation of 0.804 using the Durbin-Watson analysis. Figure 2-5 provides a visual representation of serial correlation by plotting each residual value of the linear correlation against the next chronological data point. The TP regression had a first-order autocorrelation of 0.905, as visually apparent in Figure 2-6. These results indicate that both datasets are greatly affected by serial correlation that is not being accounted for. The simple linear regression also fails to account for covariables, sampling bias, or any of the other concerns previously mentioned. The residual distributions from this test do not display normality (Figure 2-7, Figure 2-8), which is an assumption that must be met for a parametric trend test to be valid.

Multilinear Regression

The multilinear regressions employed in the second analysis of the datasets met the required assumptions for parametric testing, but failed to detect a significant trend in either TSS or TP data over time. The TSS data had a non-significant trend of -0.00120 log mg L^{-1} $month^{-1}$ with a p-value of 0.311. TP showed a non-significant trend of 0.0000881 log mg L^{-1} $month^{-1}$, with a p-value of 0.914.

Instantaneous stream discharge was found to be a significant covariable of both TSS and TP concentration, and was included in both multilinear regressions. The parameter estimate for the effect of discharge on TSS concentration is 0.0117 log mg L^{-1} m^{-3} s (Figure 2-9). For TP, the parameter estimate for discharge was 0.00890 log mg L^{-1} m^{-3} s (Figure 2-10). Other covariables were identified as significant by the stepwise selection method, but none of them had a great effect on the other variable estimates or caused the time variable to become statistically significant. The explanatory variables for each month, as well as the average 7-day and 30-day discharge were considered.

Other concerns from the simple linear regression were addressed in this method. Autocorrelation was identified and corrected by the Proc Autoreg SASS procedure. In the TSS data, the first-order lag had a t value of -3.80, while the TP data had a first-order lag t value of -2.13. The higher-ordered lags were not significant for either dataset after correcting for first-order autocorrelation. The residuals of the multilinear regressions were approximately normally distributed in both TSS and TP data (Figure 2-11, Figure 2-12).

Trend detection power

The standard errors of measurement, as determined by this multilinear regression, allowed for an analysis of this method's power to detect trends of varying intensity. Based on the regression model, it is estimated that the TSS concentration decreased from 94.1 mg L^{-1} to 61.2 mg L^{-1} over the period of measurement during discharge conditions. However, a decrease from 94.1 mg L^{-1} to 28.8 mg L^{-1} would be necessary for this method to have an 80% probability of detecting a trend.

The multilinear model estimates that TP concentration increased from 0.162 mg L^{-1} to 0.168 mg L^{-1} over the period of measurement during discharge conditions. However, a decrease from 0.162 mg L^{-1} to 0.072 mg L^{-1} would be necessary for this method to have an 80% probability of detecting a downward trend.

Non-parametric trend analysis methods

The residuals from the LOWESS smoothing between discharge, 7-day discharge, and 30-day discharge were approximately normally distributed (Figure 2-13, Figure 2-14). This smoothing process revealed a complex relationship between these two variables, with few points appearing outside of the general trend (Figure 2-15, Figure 2-16). A Mann-Kendal analysis of the time-offset residuals indicated that autocorrelation is likely in both of the datasets, with a p-value of 0.0003 for TSS residuals (Figure 2-17), and a p-value of 0.0004 for the TP residuals(Figure 2-18).

Visually, there does not appear to be a time trend in the residuals from the LOWESS procedure, either for TSS (Figure 2-19) or TP (Figure 2-20).

First-order lag autocorrelation is not a concern when using the Seasonal Kendal method, however, because trends are observed for each month of the year, rather than consecutive months.

Seasonal Mann Kendal trend analysis

The seasonal implementation of the Mann Kendal trend analysis did not result in a significant trend for either the TSS or TP data (Table 2-3, Table 2-4). The TSS data had an S statistic of -2, with a p-value of 0.972. The TP data had an S statistic of 44 with a p-value of 0.136. These results agree with the results of the parametric analysis, where TSS was estimated to decrease and TP was estimated to increase, but neither trend was statistically significant.

Discussion

Neither of the trend analysis techniques attempted by this study succeeded in detecting a significant trend in TP or TSS concentration in the North Fork Ninnescah, once seasonal effects and stream discharge covariates were accounted for. This could be due to several reasons.

The most obvious explanation is that there has not been any increase or decrease in actual TP and TSS concentration since 1997. While efforts have been made to decrease soil and phosphorus runoff, the placement and effectiveness of these efforts have not been comprehensively evaluated. Chapter 3 of this study includes one such evaluation.

It is possible that there has been a positive or negative trend, but that it is difficult to prove statistically given the inherent variability of the data. The data analyzed in this study were highly variable, and proved to be significantly affected by covariants other than time. It may be necessary to collect enough data that the variability can be accounted for, or to identify and measure further covariant effects that can be included in the analysis.

Future sampling advice

Past sampling efforts in the Cheney watershed have preferentially sampled from high streamflow events, in order to fully record the movement of P and sediment loading along the stream. When using non-parametric analyses, however, it is important to have evenly spaced data that has not been biased in its collection. Had this strategy been decided on before sampling began it may have been possible to supply the analysis with more individual points of data, rather than collapsing many points of data down to a much smaller subset of samples that can be assumed to be evenly-spaced.

In addition, it is recommended that samples be taken at shorter time intervals. Streamflow in the North Fork Ninnescah is highly variable, as are the TP and TSS values of each sample. Sampling has taken place at multiple points throughout the watershed, but use of a more intensive sampling regimen at a single location may produce a statistically significant trend where the current data does not.

Figures and Tables

Table 2-1. Trend analysis sumaries for Total Suspended Sediment (TSS) concentrations in the North Fork Ninnescah from 1997 to 2010.

Test	Data Input	Cofactors Considered	Trend P-value	Violations of Test Assumptions
Simple Linear Regression	Day-average TSS	none	0.0001	Missing data, biased sampling, non-normal errors, serial correlation, cofactors ignored.
Multilinear Regression	Monthly average TSS (log transformed)	Discharge, 1st order lag autocorrelation	0.3111	Missing data
Non-parametric seasonal K-M	Monthly median TSS	Discharge, 7-day discharge, month of year.	0.972	Missing data, uneven spacing, possible serial correlation.

Table 2-2. Trend analysis sumaries for Total Phosphorus (TP) concentrations in the North Fork Ninnescah from 1997 to 2010.

Test	Data Input	Cofactors Considered	Trend P-value	Violations of Test Assumptions
Simple Linear Regression	Day-average TP	none	0.1745	Missing data, biased sampling, non-normal errors, serial correlation, cofactors ignored.
Multilinear Regression	Monthly average TP (log transformed)	Discharge, 1st order lag autocorrelation	0.9140	Missing data
Non-parametric seasonal K-M	Monthly median TP	Discharge, 7-day discharge, month of year.	0.136	Missing data, uneven spacing, possible serial correlation.

Table 2-3. Seasonal Mann-Kendall test summary for the Total Suspended Sediment concentration of discrete water samples collected from the North Fork Ninnescah.

Month	Kendall Tau	Number of Samples	Z Test Factor	P-value
January	0.2000	5	0.24	0.806
February	0.4000	5	0.73	0.462
March	0.0909	11	0.31	0.755
April	0.3333	7	0.90	0.368
May	-0.1667	9	-0.52	0.602
June	-0.0606	12	-0.21	0.837
July	-0.2143	8	-0.62	0.536
August	-0.1667	9	-0.52	0.602
September	0.1111	9	0.31	0.754
October	-0.4000	5	-0.73	0.462
November	0.3333	4	0.34	0.734
December	0.0000	4	0.00	1.000
			Pooled Z Test Factor	**Overall P-value**
			-0.03	0.972

Table 2-4. Seasonal Mann-Kendall test summary for the Total Phosphorus concentration of discrete water samples collected from the North Fork Ninnescah.

Month	Kendall Tau	Number of Samples	Z Test Factor	P-value
January	0.4000	5	0.73	0.462
February	0.2000	5	0.24	0.806
March	0.3091	11	1.25	0.213
April	0.3333	7	0.90	0.368
May	0.0556	9	0.10	0.917
June	0.0606	12	0.21	0.837
July	-0.2143	8	-0.62	0.536
August	-0.1667	9	-0.52	0.602
September	0.2778	9	0.94	0.348
October	0.2000	5	0.24	0.806
November	1.0000	4	1.70	0.089
December	0.3333	4	0.34	0.734
			Pooled Z Test Factor	**Overall P-value**
			1.49	0.136

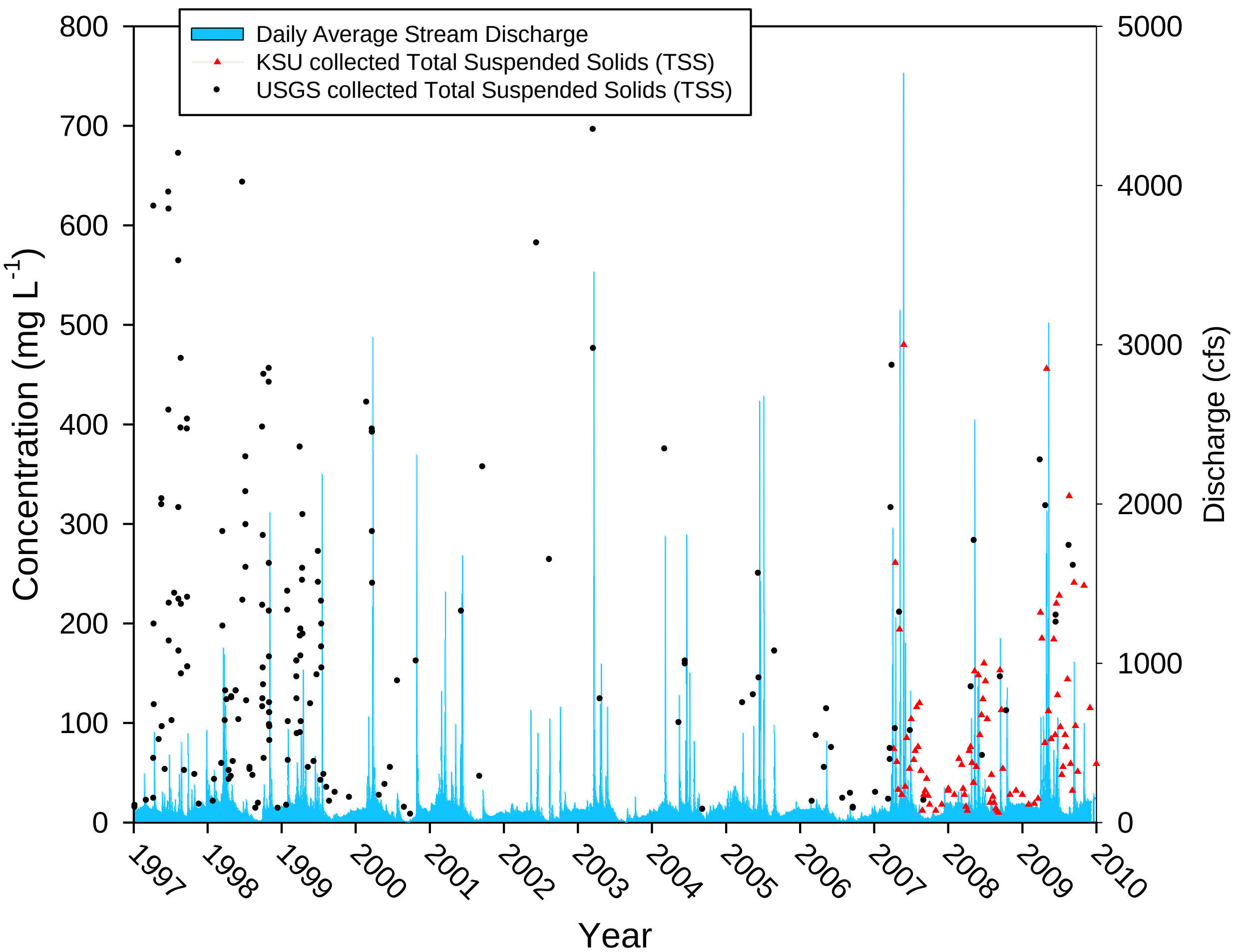


Figure 2-1. Daily average stream discharge and Total Suspended Sediment (TSS) concentrations at the USGS monitoring site 07144780 on the North Fork Ninnescah.

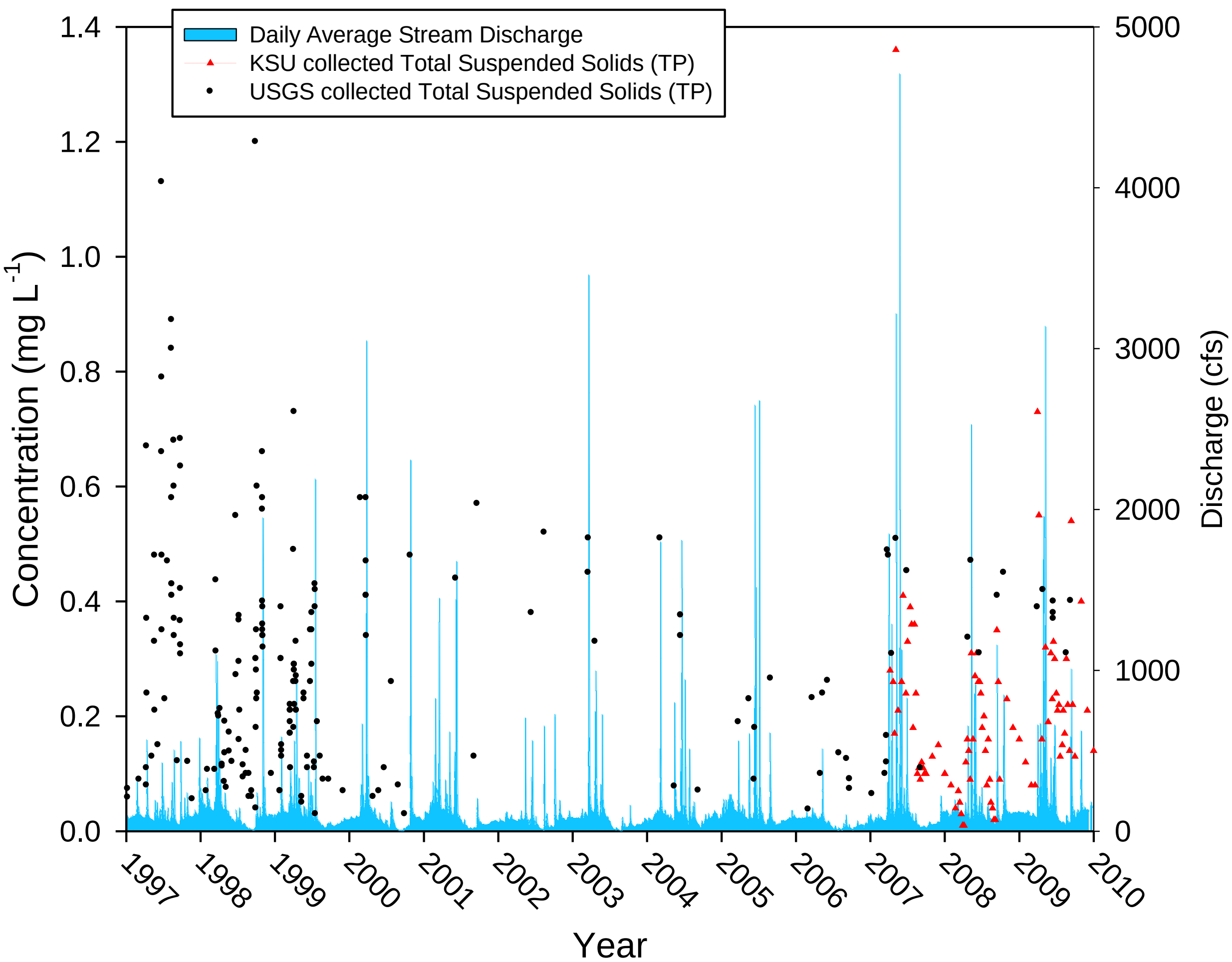


Figure 2-2. Daily average stream discharge and Total Phosphorus (TP) concentrations at the USGS monitoring site 07144780 on the North Fork Ninnescah.

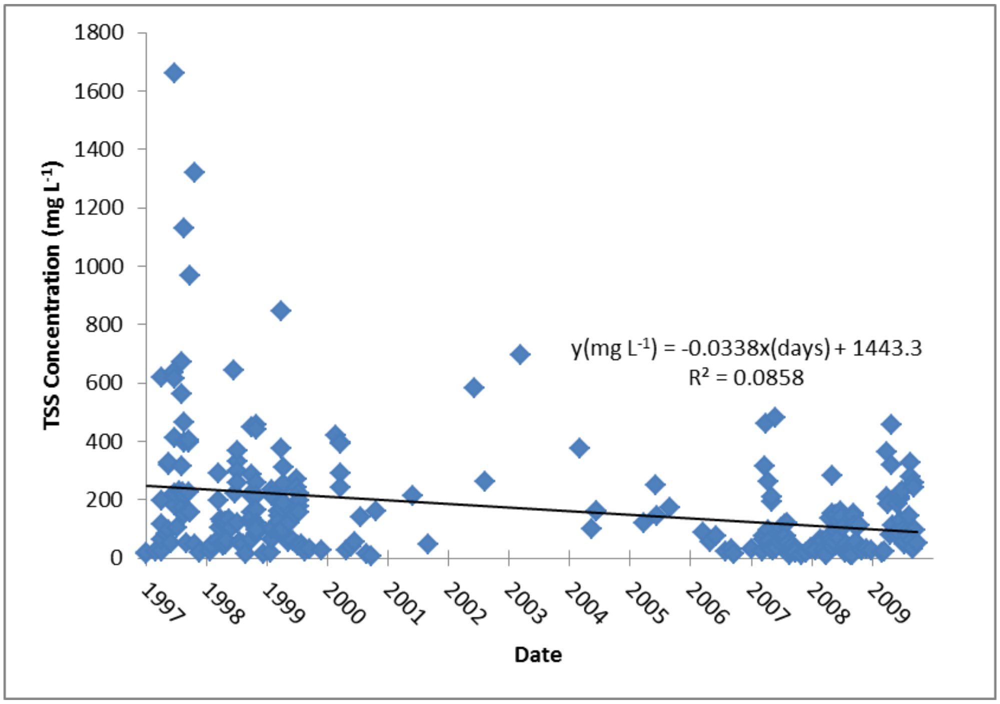


Figure 2-3. Simple linear regression of Total Suspended Solid (TSS) concentrations in discrete samples collected from the North Fork Ninnescah, showing a decreasing trend of 12.3 mg L^{-1} per year.

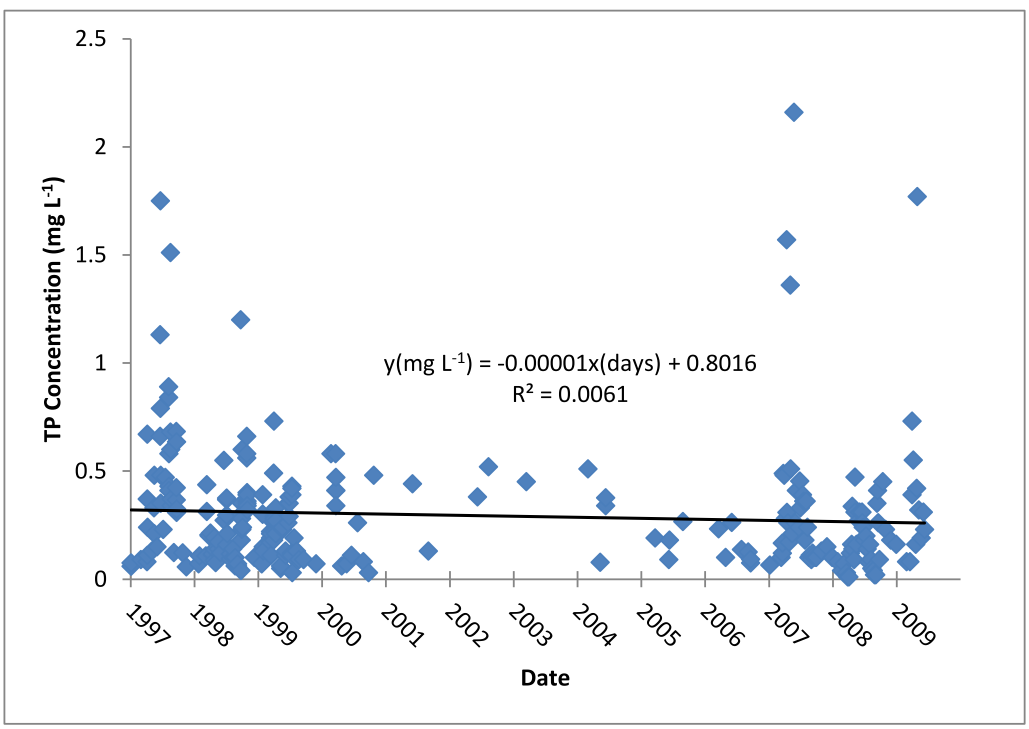


Figure 2-4. Simple linear regression of Total Phosphorus (TP) concentrations in discrete samples collected from the North Fork Ninnescah, showing a decreasing trend of 0.00475 mg L^{-1} per year.

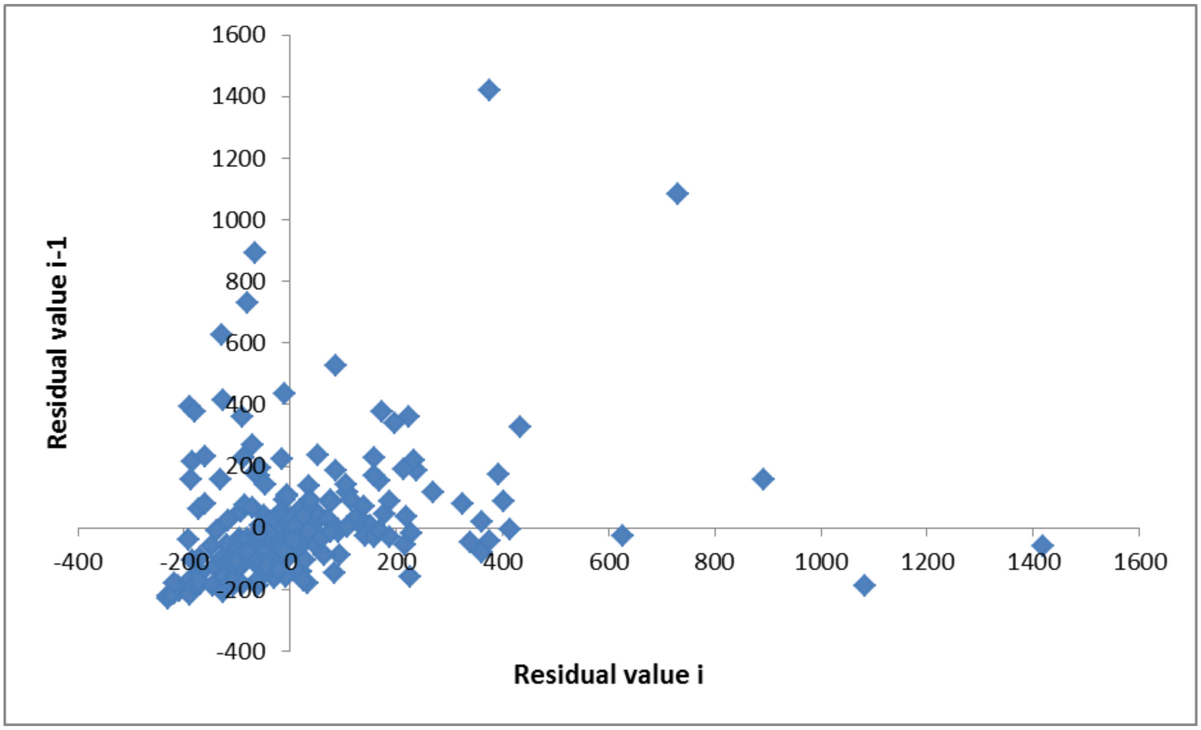


Figure 2-5. Time-offset residuals of the simple linear regression on TSS concentrations in discrete samples collected from the North Fork Ninnescah.

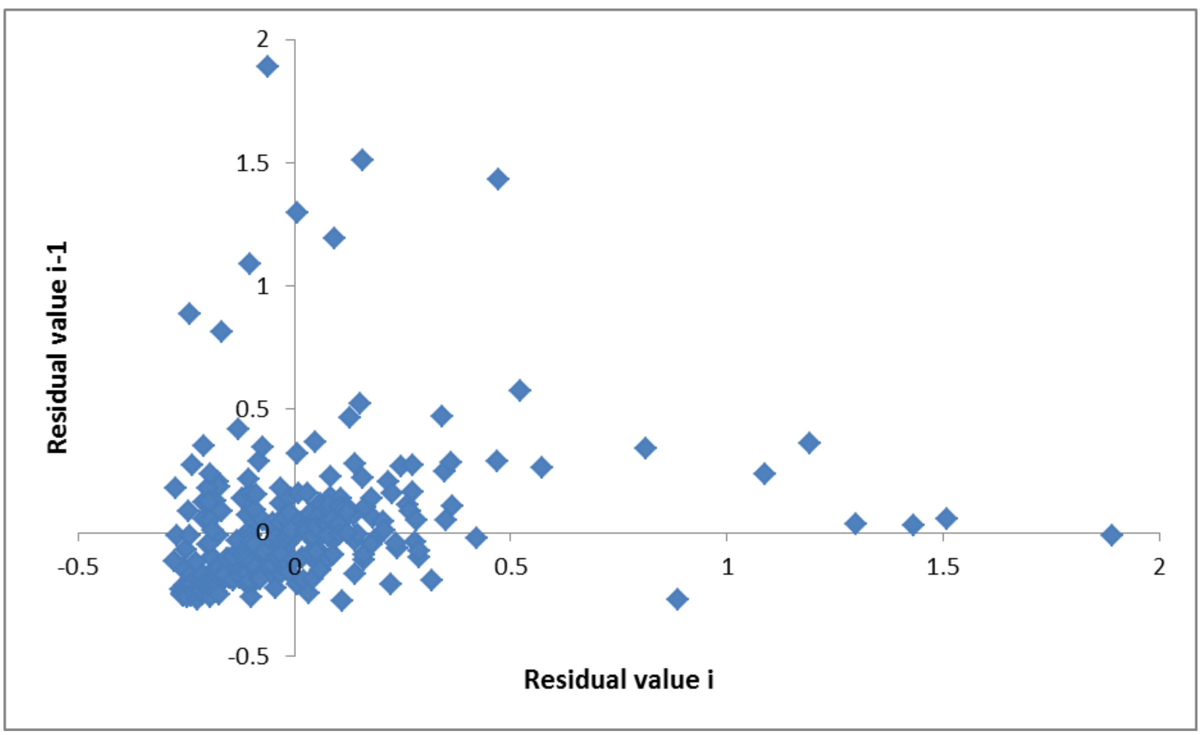


Figure 2-6. Time-offset residuals of the simple linear regression on TP concentrations in discrete samples collected from the North Fork Ninnescah.

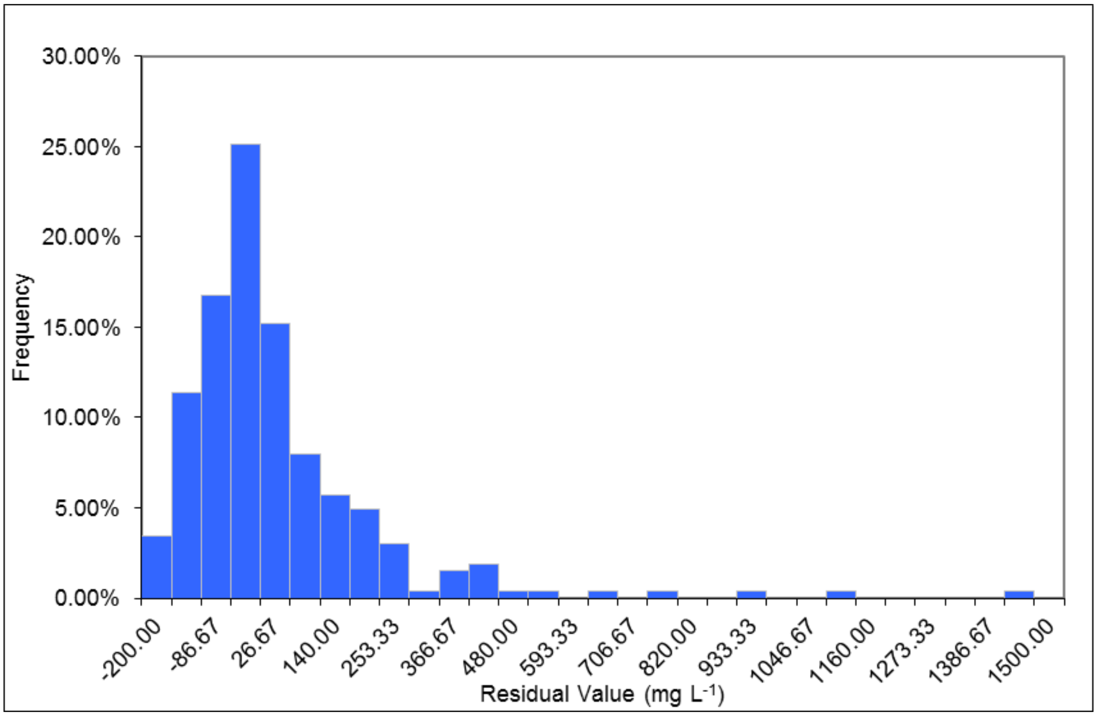


Figure 2-7. Histogram of residuals of the simple linear regression on TSS concentrations in discrete samples collected from the North Fork Ninnescah.

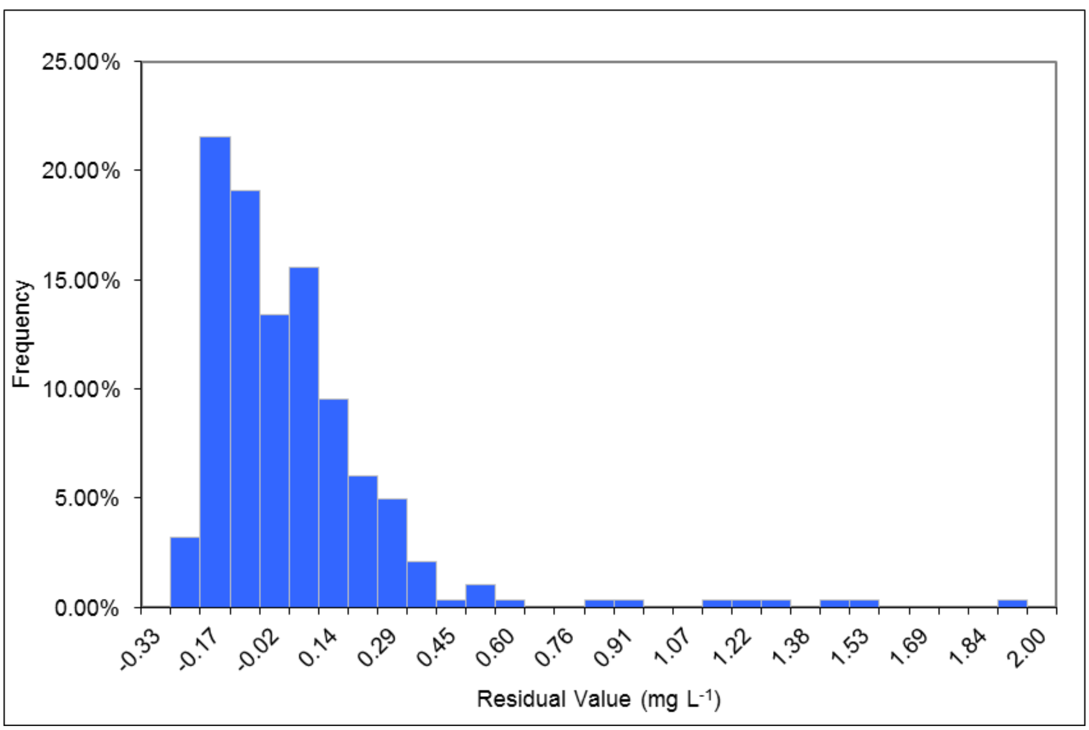


Figure 2-8. Histogram of residuals of the simple linear regression on TP concentrations in discrete samples collected from the North Fork Ninnescah.

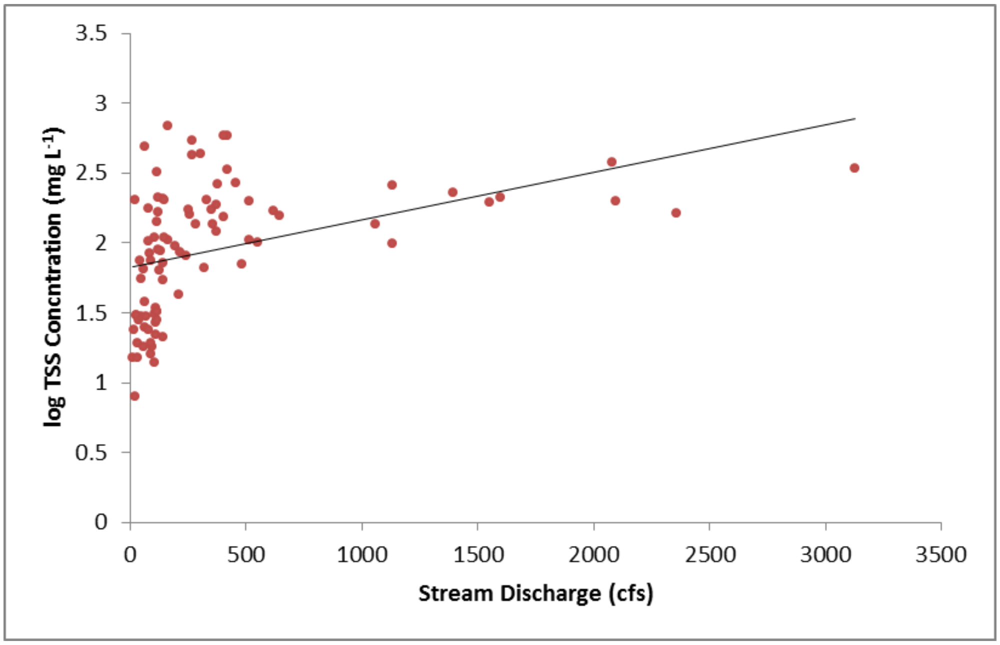


Figure 2-9. Linear correlation between log Total Suspended Solids (TSS) concentration and stream discharge at the time of sampling. The parameter estimate for stream discharge is 0.000331 log mg L^{-1} per cfs discharge in the multilinear regression accounting for time trend and autocorrelation.

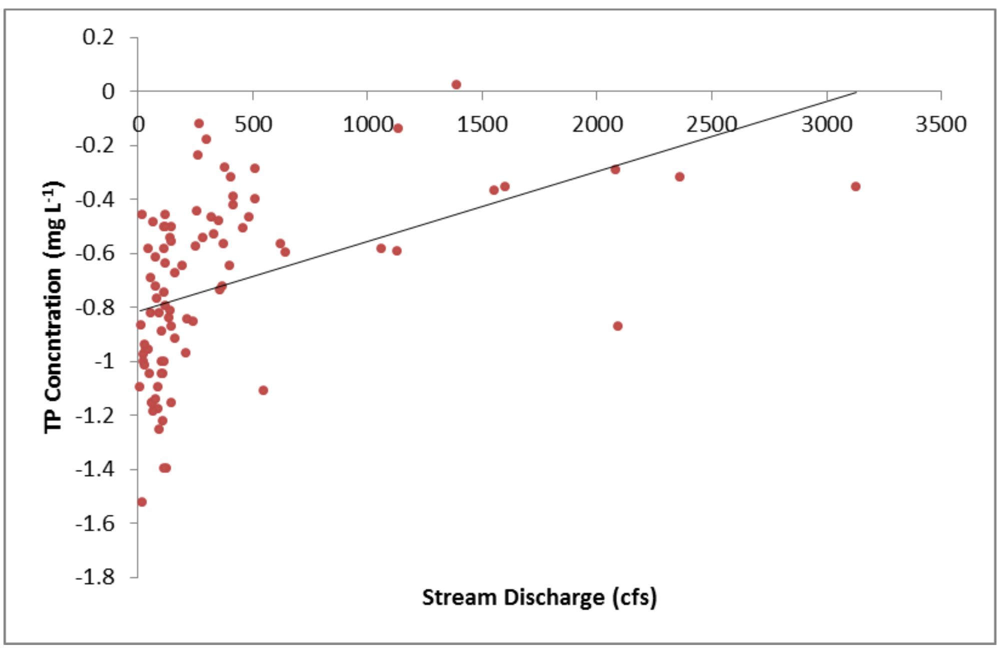


Figure 2-10. Linear correlation between log Total Phosphorus (TP) concentration and stream discharge at the time of sampling. The parameter estimate for stream discharge is 0.000252 log mg L^{-1} per cfs discharge in the multilinear regression accounting for time trend and autocorrelation.

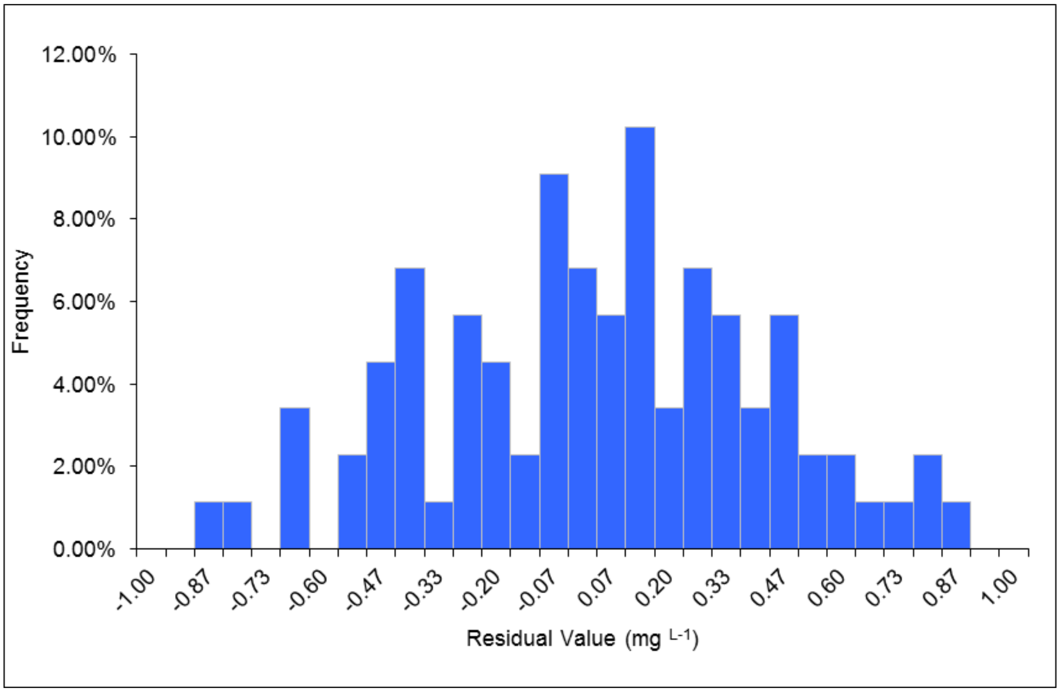


Figure 2-11. Histogram of residuals of the multilinear regression on TP concentrations accounting for instantaneous stream discharge, autocorrelation, and time in discrete samples collected from the North Fork Ninnescah.

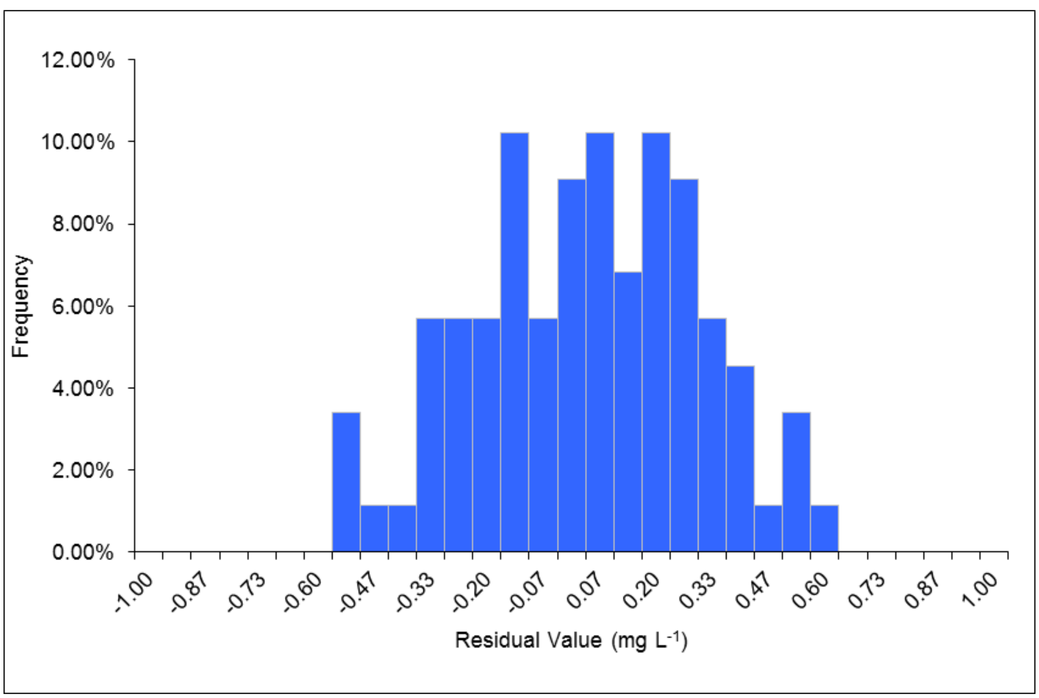


Figure 2-12. Histogram of residuals of the multilinear regression on TSS concentrations accounting for instantaneous stream discharge, autocorrelation, and time in discrete samples collected from the North Fork Ninnescah.

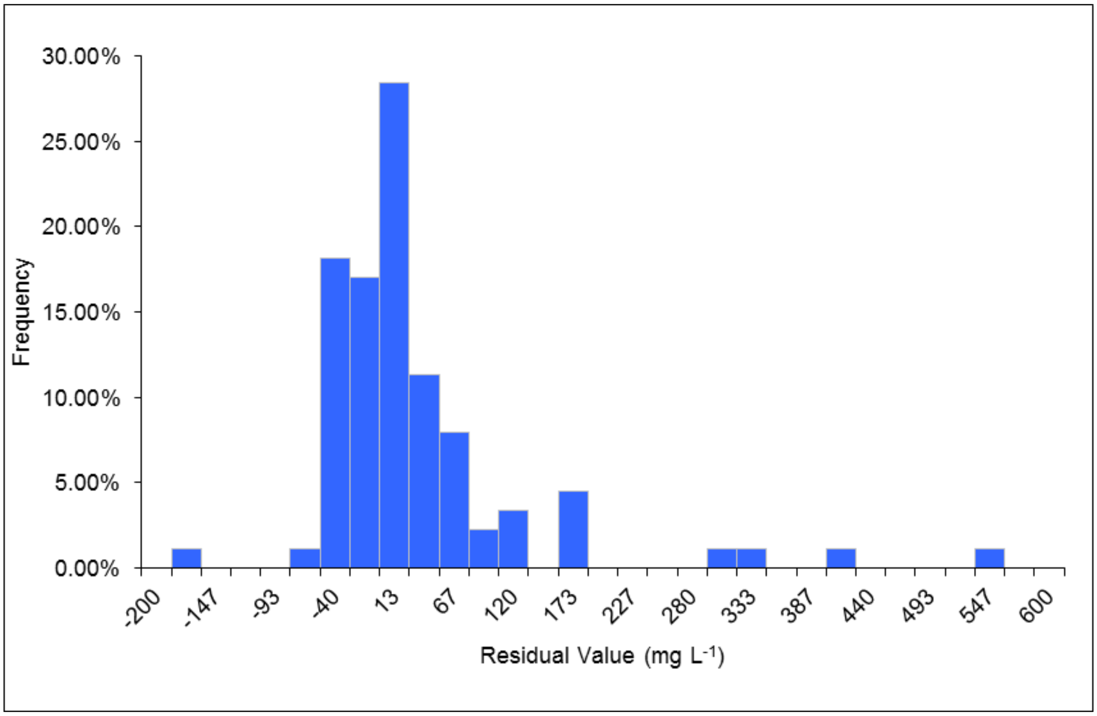


Figure 2-13. Histogram of Total Suspended Solids residuals of the two-factor LOWESS curve in discrete water samples collected from the North Fork Ninnescah.

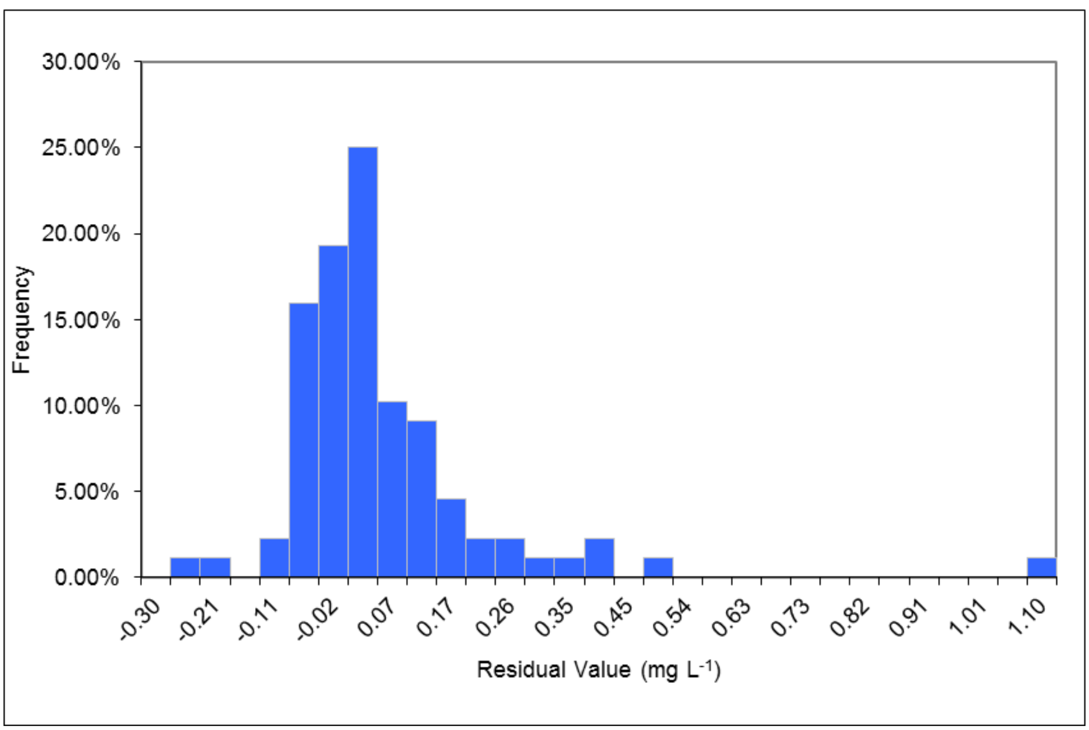


Figure 2-14. Histogram of Total Phosphorus residuals of the two-factor LOWESS curve in discrete water samples collected from the North Fork Ninnescah.

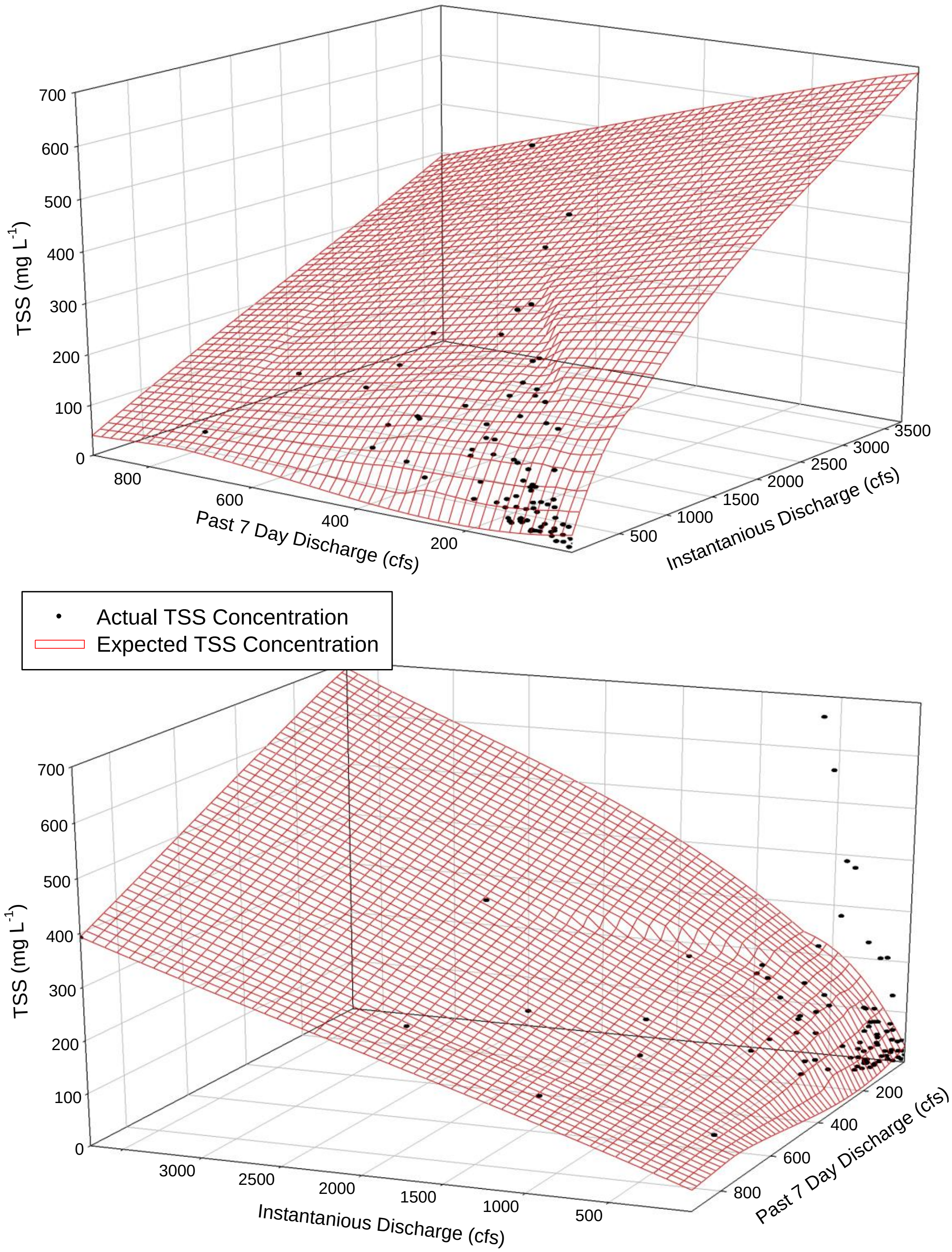


Figure 2-15. Two-factor LOWESS curve defining the expected TSS values along the continuum of instantaneous discharge and seven day average discharge values for samples collected from the North Fork Ninnescah.

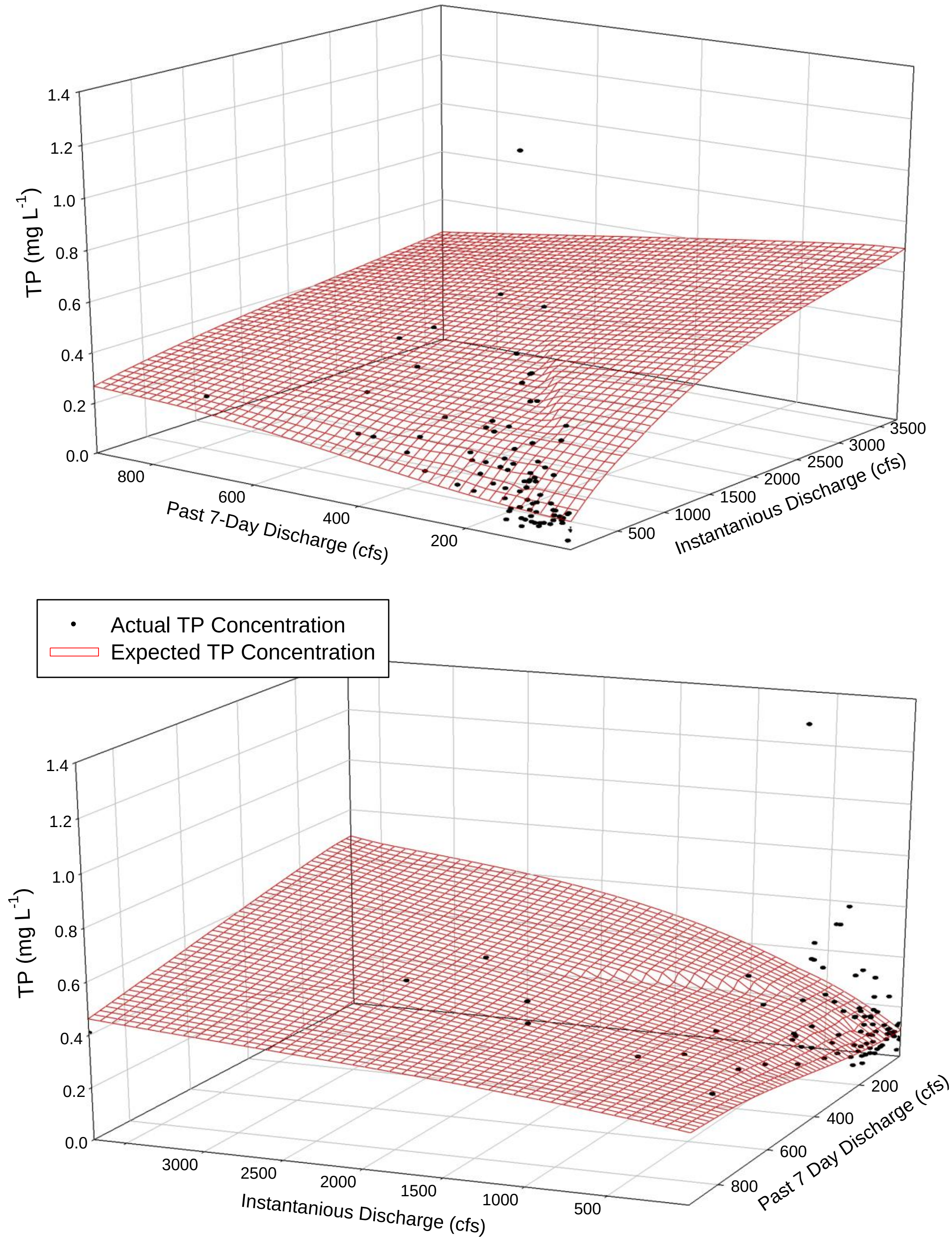


Figure 2-16. Two-factor LOWESS curve defining the expected TP values along the continuum of instantaneous discharge and seven day average discharge values for samples collected from the North Fork Ninnescah.

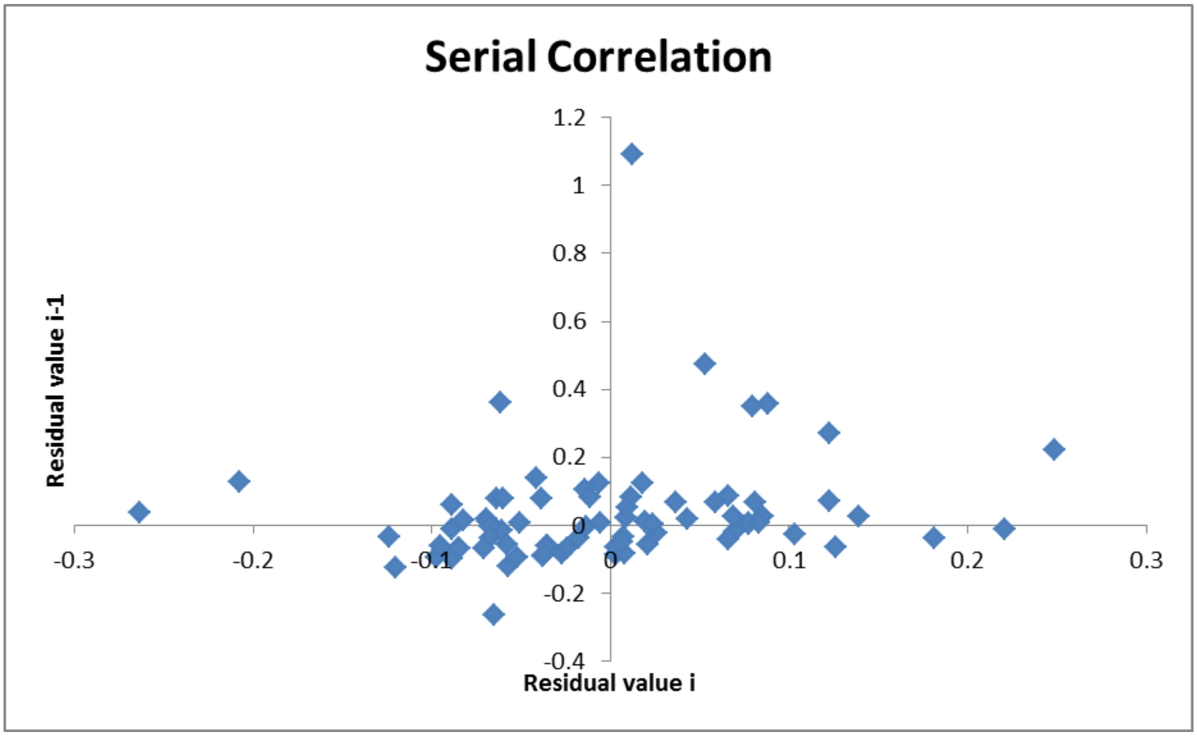


Figure 2-17. Time-offset TSS residuals from the two-factor LOWESS curve.

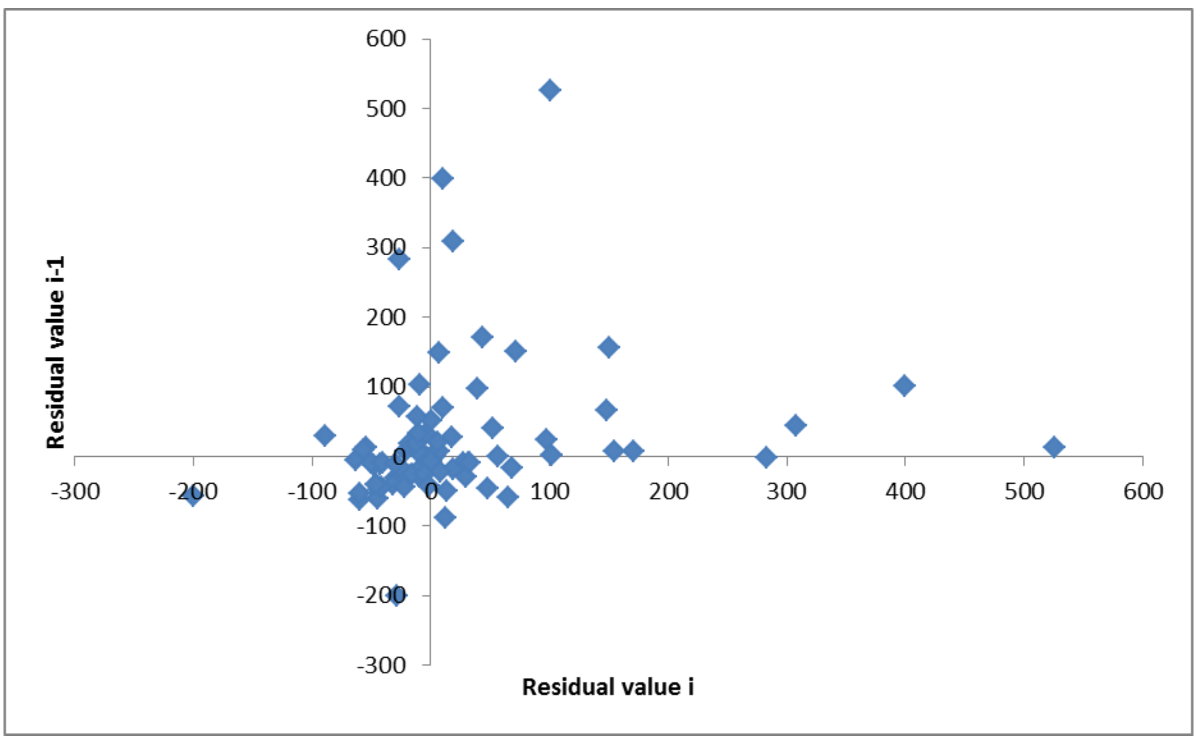


Figure 2-18. Time-offset TSS residuals from the two-factor LOWESS curve.

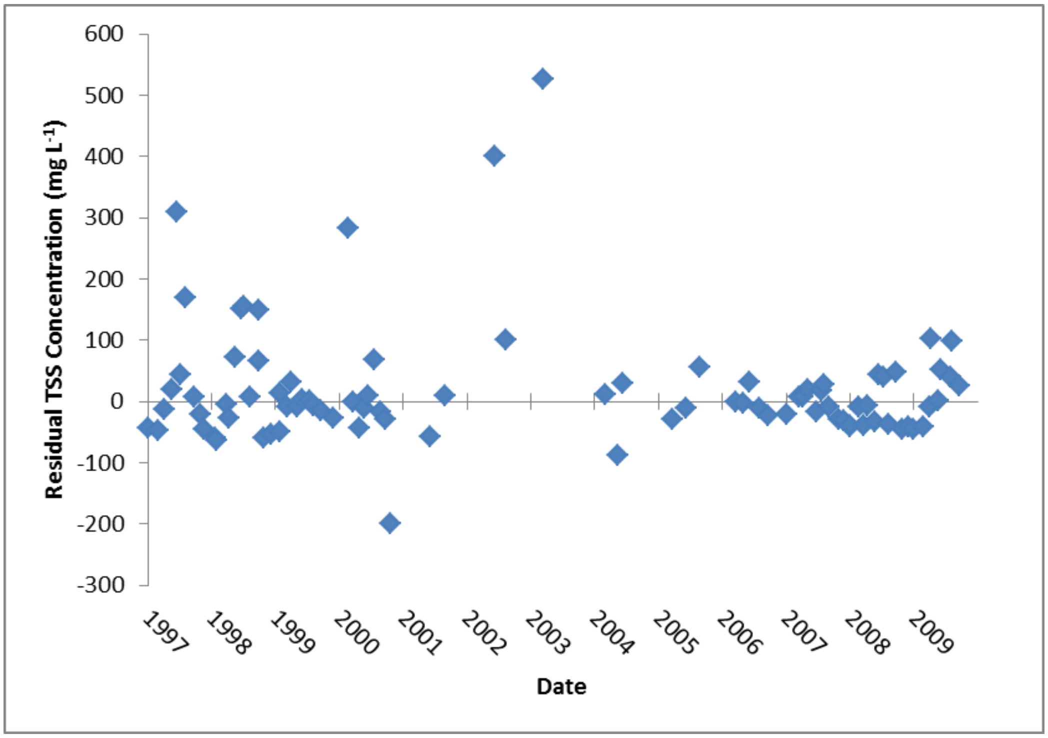


Figure 2-19. Total Suspended Solids (TSS) residuals of the two-factor LOWESS curve over time in discrete water samples collected from the North Fork Ninnescah.

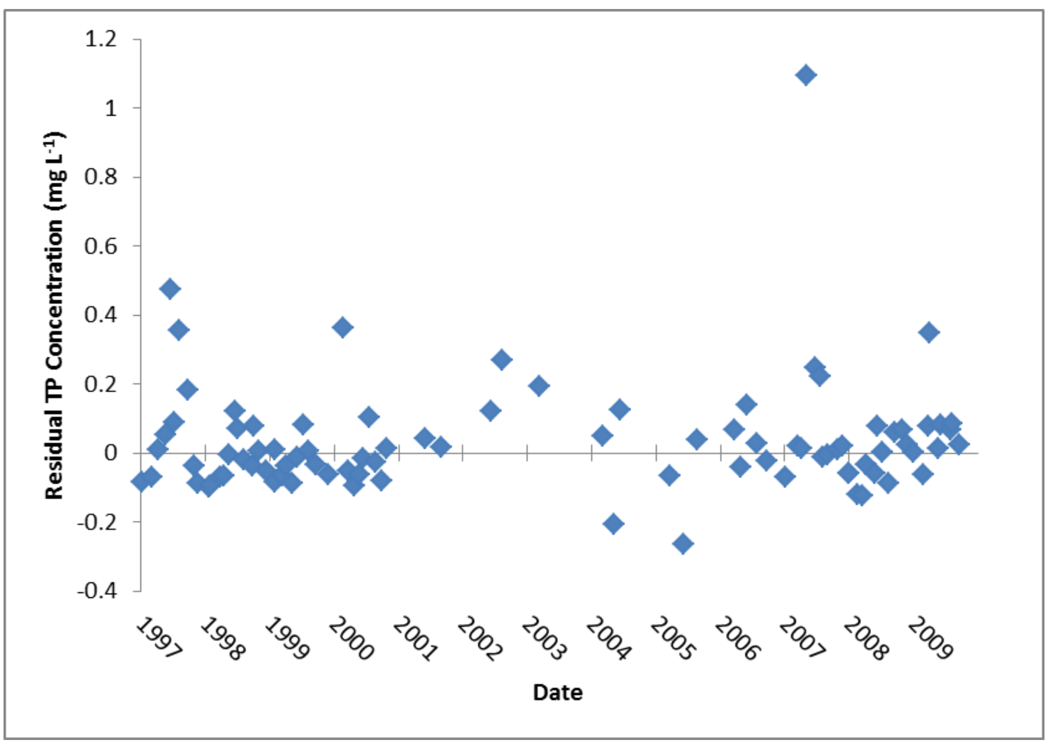


Figure 2-20. Total Phosphorus (TP) residuals of the two-factor LOWESS curve over time in discrete water samples collected from the North Fork Ninnescah.

CHAPTER 3 - RUSLE GIS

Introduction

Despite the recent conservation efforts in the Cheney watershed, there has not been an improvement in water quality that is statistically verifiable. Local producers, stakeholders, and government agencies have worked together to identify the issues affecting surface water quality, and have taken action to solve the problem of eutrophication and reduce sedimentation in the reservoir. Any possible decrease in P or TSS concentrations, however, has not been detectible in the stream quality data. This leaves the effectiveness of past efforts in question.

BMP placement evaluation

BMP placement must be evaluated before one can predict the possible improvements that could be made to water quality through their use. While BMPs may be effective at reducing phosphorus and sediment loss, it is likely that the existing contribution of sediment and phosphorus varies from field-to-field due to other soil and management factors. If a BMP is implemented on a high-risk field, it may prevent a significant amount of erosion or runoff. On a low-risk field, however, it may have a much lesser impact.

To evaluate the placement of BMPs, it is first necessary to determine which areas would benefit most from BMP placement. This can be done most effectively using GIS or spatial watershed models.

There are several methods or programs that can be used to model surface water quality in a watershed. The Soil and Water Assessment Tool (SWAT) has been used to evaluate BMPs in a watershed, (Renschler and Lee, 2005). This method provides an estimate of BMP use across the watershed and in specific sub-basins, but it does not account for field-scale erosion or P loss risk.

As previously stated in chapter one, sediment and P loss are the primary water quality impairments in the Cheney Lake Watershed. Because P loss is highly correlated with sediment loss, spatially distributed estimates of erosion could help identify priority areas for conservation practice placement and BMP evaluation.

Universal Soil Loss Equation

The Revised Universal Soil Loss Equation is a well-established model that is used to estimate field-scale erosion on agricultural lands around the world. The purpose of the RUSLE model is to guide conservation planning (Foster et al., 2003). Performing the RUSLE calculations in a GIS, using spatially varying input factors, will allow us to quickly assess the entire watershed. The RUSLE model is conceptually simple to understand, flexible about the source and detail of input data, and validated by empirical data collected over a wide range of locations and years. For these reasons, it will be used as the basis for the GIS model developed over the course of this study.

The Universal Soil Loss Equation, originally developed by (Wischmeier and Smith, 1978), is an empirical model designed to predict rainfall erosion losses in crop land. It is a multiplicative equation consisting of five factors that impact average annual erosion.

$$A=R*K*LS*C*P$$

Where A is the annual soil erosion in tons acre^{-1}, R is the rainfall and runoff factor, K is the soil erodability factor, LS is the topographic factor, C is the cover and management factor, and P is the support practice factor. These factors are discussed in-depth later in this chapter. The values used as input for the model were originally derived from more than 10,000 plot-years of data from 49 different locations ((Wischmeier and Smith, 1978).

In 1978 the model was extended to function with land uses other than cropland (Wischmeier and Smith 1978, Dissmeyer and Foster 1980), and in 1997 the model was updated to be known as the Revised Universal Soil Loss Equation (Renard et al., 1997). This revision did not alter the basic structure of the model, but introduced new ways of calculating the input factors, which incorporated additional research conducted since the original model was published. The RUSLE model included a computer program that allowed users to directly input field data to get a soil erosion estimate, rather than requiring them to look up factor values from tables and figures. RUSLE has been upgraded over time to version 1.06, while still retaining the same interface and model structure.

The latest iteration of the model is RUSLE2. RUSLE2 is not a gradual upgrade from RUSLE1.06, but represents a change in both interface and underlying calculations. RUSLE1.06 broke down it’s calculation of erosion factors into monthly averages, to account for the change in certain factors throughout the year. RUSLE2 interpolates changes in factors down to daily values, that are later aggregated into annual totals. RUSLE2 also accounts for interaction between factors that is not considered in the older, strictly multiplicative model. The RUSLE2 interface allows for more detailed input to be considered in erosion estimation, and the interface can be customized to allow for more or less complexity, depending on the user's needs and abilities.

When attempting to implement an erosion model in a GIS, it is requires much less input and processing power to use a simpler model. For this project, the RUSLE-based GIS model is designed to mimic RUSLE1.06, which is the latest version of RUSLE to use feasibly simple model. The calculations performed by RUSLE2 were not practical to implement within the context of this study, however the model results were compared to RUSLE2 estimates for the sake of model validation. This is because RUSLE2 is mathematically superior to the other RUSLE models, and uses better relationships to compute factor values.(Foster et al., 2003)

Past GIS RUSLE Watershed Studies

Past GIS analyses have used RUSLE to estimate soil erosion in various watersheds across the world, and for different purposes. It has proven to be a useful method for estimating watershed-wide erosion, simulating the impact of landuse changes, or to provide a comparison to the results of other models.

Simms et al. (2003) used a RUSLE-based GIS method to simulate and predict soil erosion in a watershed of New South Whales, Australia. They developed a model and used it to predict the erosional effects of landuse changes, specifically the impact of logging and urban expansion. The watershed in this study is about 35 km^2 in area, and features a saline lake at the mouth of the watershed that is intermittently connected to the ocean. The landscape is relatively flat and the vegetative cover is primarily forest, with only 30% of the watershed comprised of other landuses. They found that under current conditions, about 14% of the watershed area has the potential to contribute to 88% of the total erosion in that watershed. They found if logging practices were to be implemented in a specific portion of the watershed, the total watershed-wide erosion would be about 6 times greater than under current conditions, and that complete clearance of the forested area would result in 23 times the current amount of erosion.

Yui-Qing et al. (2008) developed a tool to assess soil erosion over a large watershed area in the Guizhou Province in southwestern China. This watershed exists in a fragile karst landscape that is characterized by poor soil cover, intensive landuse, and steep topography. Soil formation proceeds very slowly here because the calcareous parent material is easily dissolved during weathering. The primary goal of Yui-Qing et al. (2008) was to provide data that would be useful for local decision makers and planners to use for soil conservation efforts in the areas. There is relatively little data available for modeling purposes across the watershed, so a model such as RUSLE was needed that could operate using relatively little data input. They compared the results of the RUSLE model to local observations throughout the watershed and concluded that it was making valid predictions. Their RUSLE analysis showed that most of the watershed erosion was taking place on farmland with a gradient between 6 and 25 degrees. It also provided the spatial locations of the areas that are most at risk for erosion within the watershed.

Another example of the GIS RUSLE method being used for watershed evaluation was performed by (Ricker et al., 2008) on two tributary watersheds along the Rappahannock River in Virginia. This study is notable for two reasons. First, it was performed on a paired set of watersheds with their own water quality data to compare to the results of the model. Secondly, it incorporated a sediment delivery ratio (SDR) that was used to convert the erosion estimates of the RUSLE model into streamflow sediment concentrations. While their RUSLE/SDR model predicted that the two watersheds would have very similar sediment runoff, their streamflow data shows that one watershed has much more sediment runoff than the other. They attribute this discrepancy to an ATV trail that is present in only one watershed and isn't accounted for by the RUSLE model. This demonstrates one of the limitations of the RUSLE GIS model. While the model takes into account overall landuse, it will not automatically take into account all anthropogenic factors that can end up having a large effect on watershed water quality. Point-sources of pollution can make it difficult to use streamflow data to verify the results of non-point source estimations, such as those produced by a RUSLE GIS method.

GIS-based RUSLE models are not often thoroughly validated. Ground-based measurements of erosion across a watershed require significant time and resources, while GIS models are often used for the very reason that they do not require such extensive resources. Many studies simply state that the generalized erosion trends across the watershed, or across various land uses, follow the generally expected trends. (Fu et al., 2005a; Fu et al., 2004; Kouli et al., 2009; Yue-Qing et al., 2008) Other studies provide no reference to validation at all.(Chandramohan and Durbude, 2002; Lufafa et al., 2003; Prasad et al., 2005; Simms et al., 2003)

Several studies have used surface water quality to evaluate RUSLE accuracy, but have done so over an extremely short time scale (Molnar and Julien, 1998; Ricker et al., 2008).

RUSLE is meant to estimate average soil erosion over many years, and applying individual years or months to direct validation is beyond the scope of the model.

The goals of this project are threefold. The first goal is to estimate the current field-scale erosion that is occurring within the watershed, as well as the field-scale erosion that was taking place under past watershed conditions. This will provide valuable information about the land that is contributing most to erosion. The second goal is to evaluate the placement of BMP measures within the watershed. Extensive efforts have been made to reduce field losses of P and sediment, and the efficiency of these efforts can be assessed in part by observing whether or not they were implemented in the fields that were most at risk for erosion. The final goal of this project is to prioritize fields within the watershed for future conservation efforts. BMPs have the greatest effect on soil conservation and water quality when placed strategically in high risk areas, and this GIS will assist in placing them appropriately.

Validation of the RUSLE-based GIS model will prove that it can be used to complete the other goals of the study. In addition, it allows the model to serve as an example or guide for similar research in other watersheds.

Evaluation of BMP placement is necessary in the Cheney watershed because past BMP efforts have not lead to a detectable change in surface water quality. Evaluating the placement will help determine whether this lack of improvement is due to BMPs being placed on land where they have little effect on water quality.

Objectives

The objective of this study is to i) validate the erosion prediction potential of RUSLE-based gis method, ii) use the RUSLE-based method to evaluate BMP placement, iii) use the RUSLE based method to prioritize future BMP placement.

Methods

Each factor of the RUSLE equation can be calculated or estimated by a variety of methods. While it may be relatively simple to estimate factor values for a single field, gathering the spatially variable data to apply to a GIS can be more difficult. The following section will define the factors used for RUSLE, describe general selection processes that have used to estimate each factor, and describe how these methods were applied to this watershed.

R Factor – Rainfall-runoff erosivity

The R factor represents erosivity, or erosive power of the rainfall, which is a function of the quantity and intensity of rainfall in an area. Two areas that receive the same amount of annual rainfall may not necessarily have the same R factor because the of differences in the timing and intensity of rainfall. Large intense storm events have much more erosivity than if the same quantity of rainfall were distributed over a long, gradual time period.

There are several ways to determine the R factor for a given area. The most exact way is to calculate the erosivity of every precipitation event throughout a year and then aggregate the values into annual or monthly totals. While it is possible to calculate the R factor for a single month or year, RUSLE is meant to predict long-term averages rather than erosion for a specific year or event, so multiple years of data would be required to accurately represent the R factor for an area.

The USDA-NRCS has used historical weather data to calculate the R factor for most of the U.S. at the county level. Thirty-year average climate data was processed by the Parameter-elevation Regressions on Independent Slopes Model (PRISM) group, and aggregated into a single record for each county in the eastern states (correspondence with Dave Lightle.) Erosivity Density was determined using data from representative weather stations. The resulting R factor values are most often represented in the form of an isoline map, which can be easily used to estimate the R factor for a given location.

GIS estimation methods

Most studies using RUSLE-based GIS methods in the continental US rely on the pre-existing USDA-NRCS data to determine the R factor for their area of interest (Molnar and Julien, 1998; Prasad et al., 2005; Ricker et al., 2008). Each of these studies used NRCS isoline maps to determine a single R factor value that they applied to their entire study areas.

Fu et al. (2005a) used the hourly data from 10 rainfall gauges to find the relationship between rainfall quantity and rainfall erosivity for their watershed, and used this correlation to calculate the monthly R factor for the 52 rainfall stations in their watershed. These values were interpolated across the watershed to provide the varying R factor used in the RUSLE calculation. Chandramohan and Durbude (Chandramohan and Durbude, 2002; Yue-Qing et al., 2008) used gauges in the watershed to determine rainfall, but used estimates of the Erosivity density to convert this value into the R factors used in their RUSLE calculations. In general, the methods of manually calculating the R factor are only used in areas where NRCS R factor data is not available.

Employed method

Monthly R factor data for every county in Kansas was obtained from the NRCS office in Lincoln, Nebraska. The R factor values for each county were interpolated into a smooth, continuous raster to provide an accurate approximation for each 10x10 meter cell, using the Normal Krigging method. The monthly values were used to compute erosion in combination with monthly C factors.

K Factor – Soil erodibility

Intrinsic soil erodibility is described by the K-Factor. The K-factor is primarily a function of soil texture. Soil texture influences erosion processes of particle detachment, ease of particle transport, and tendency of precipitation to cause runoff. The K factor can be computed based on the soil texture nomograph. However, the USDA-NRCS has already computed the K factor for all soil series in the U.S. These data are available in the Soil Survey Geographic (SSURGO) dataset, that is accessible through on-line data sources (e.g. NRCS Soil Data Mart and NRCS Web Soil Survey).

GIS estimation methods

Fu et al. (2004) and Ricker et al. (2008) used the SSURGO dataset to determine the K factor for the soils in their research areas. Prasad et al. (2005) used a USGS soil survey map, which the SSURGO data is based upon. These study areas were all within the US, so they were able to directly link to the K factor for their soils. Chandramohan and Durbude (2002),Fu et al. (2005a), Kouli et al. (2009), and Yue-Qing et al. (2009) used soil particle fractions to calculate the K factors that they then linked to soil maps available for their study areas.

Employed method

SSURGO spatial and tabular data was downloaded by county from the NRCS Soil Data Mart website. The Soil Data Viewer plugin for the ArcMap software was used to link the rock-free K factor to the soil-type polygons. These polygons were then converted into a raster with 10 meter resolution, which was used for subsequent erosion computations.

LS Factor – Slope length and steepness

The topography of the landscape can have a dramatic effect on the rates of erosion and runoff of a given soil. In the RUSLE model, the S factor accounts for the steepness of slope, and the L factor accounts for the length, or distance of slope. These factors are often considered together, as the LS factor.

Slope length represents the distance from the top of a slope to point at which concentrated flow begins. This may occur at the point where the hillslope becomes level, or it may occur at a flow channel that represents flow concentration. The NRCS provides guidelines on measurement of slope length and steepness to reduce the subjectivity of this measurement, however subjectivity is not eliminated. Selection of the most representative hill slope for an entire field relies on the judgment of the operator. Determining at what point flow becomes concentrated is also not always obvious. While measuring steepness and length are simple measures, the exact placement of these measurements in the field will lead to some variability in estimating LS.

The LS factor is calculated as follows:

$$LS = (\lambda/22.13)^m(65.4 \sin^2 \theta + 4.56 \sin \theta + 0.0654)$$

where λ is the slope length in feet, θ is the angle of slope (%), and m is a constant based on the range of slope percent (Wischmeier and Smith, 1978).

GIS estimation methods

Calculating the LS Factor in a GIS requires continuous elevation data of an acceptable resolution. The National Elevation Dataset (NED) is a seamless raster dataset compiled by the United States Geological Survey (USGS). It is compiled from several sources of elevation data, including USGS cartographic contour maps, digital photogrammetry, and LIDAR measurements. NED data are available for the most of the US at 1 arc-second (30 meter) and 1/3 arc-second (10 meter) resolution. Limited areas are available at the higher 1/9 arc-second (3 meter) resolution,.

There are several complications encountered when calculating LS within a GIS framework. The main difficulty comes from the fact that the RUSLE model is designed to use 2-dimensional topographic information to calculate LS, rather than 3-dimensional data that is provided by a DEM. Slope percent can easily be calculated for every pixel in a raster. Determining slope length is a little more ambiguous.

The simplest way to estimate slope length is to assume a constant value representative of the watershed. Molnar and Julien (1998) used a value of 100 meters to approximate the slope length for their watershed. Slope was calculated from the DEM. They then used the equation given by Wischmeier and Smith to calculate the LS factor.

Another way to estimate slope length is to assume a generalized relationship between slope percentage and slope length. In a given landscape, steeper slopes will generally have shorter slope length because surface runoff will become concentrated flow in a shorter distance.

There are several formulas and algorithms of varying complexity that calculate the LS factor for every pixel in a raster based on an input DEM. One such formula is described by (Mitasova and Mitas, 1999). The ArcGIS toolbox functions are used to create slope and flow accumulation rasters from the DEM. These rasters are then used with the following raster calculation to determine the LS value for each cell:

$$([\text{flow accumulation}] * 25/22.13)^{0.6} * (\text{Sin}([\text{slope of DEM}] * 0.01745/0.0896)^{1.3}$$

Simms et al. (2003) used this method to determine the LS factor in their watershed.

Employed method

The LS factor was initially determined by several different methods in order to determine which would be most appropriate for this study. This selection process and validation are further described in Appendix 1.

The method used for this project was developed by (Van Remortel et al., 2004). The Arc Markup Language (AML) script, that performs the calculation, was downloaded from http://www.onlinegeographer.com/slope/slope.html and executed using the ArcInfo command line interface. The National Elevation Dataset (NED) with a 10-meter resolution was used as the elevation data source for the LS computation (Gesch et al., 2002; Gesch and Maune, 2007).

C Factor – Cover-management

The C factor accounts for these effects of vegetative land cover and various management practices on soil erosion. In an agronomic setting, the year-to-year decisions on cropping rotation and tillage have a great impact on the C factor, and consequently impact the total estimated soil erosion. The subfactors that influence this factor include canopy cover, surface residue cover, and surface roughness.

Increases in plant growth and soil cover reduce erosion. The energy with which raindrops hit the soil surface contributes greatly to soil particle detachment. Rain that is intercepted by canopy cover loses much of its energy, and thus erosion potential. Canopy cover is dependent on what vegetation has been planted, or is naturally growing. Generally, the increased plant growth throughout the summer months will lead to a gradual decrease in the C factor from late spring until fall. The timing of crop growth, which is dependent on the intensity of the rotation, will determine whether or not a significant canopy-cover is present for a given time of year. Fallow periods will have little or no canopy cover, while the use of cover crops or multi-crop rotations will maximize the canopy cover throughout the year.

Surface residue follows a similar mechanism for reducing soil erosion. Plant residue that is in direct contact with the soil provides protection from raindrop impact as well as acts to promote soil structure and slow surface flow. Unlike canopy cover, surface residue is often primarily composed of dead plant matter that is in the process of decay, rather than growth. In agronomic situations, the primary source of surface residue comes from the unharvested portion of the crop, which is either re-applied to the field or left standing after harvest. The effect will generally be greatest immediately following harvest, and decrease slowly due to decay, or quickly due to tillage events. While the total biomass of a crop provides a source of surface residue, the frequency and intensity of tillage events has the greatest effect on the amount of surface residue, as well as the over-all annual C factor.

Surface roughness and antecedent soil moisture also play a role in the C factor. The surface roughness describes the micro-topography, which affects the flow of water over the soil surface. Bumps and depressions in the soil surface slow the flow of water, as well as provide a catch for sediment. Antecedent soil moisture is affected by surface conditions that promote or retard the loss of moisture from evapo-transpiration. Rainfall events will produce more surface runoff on soils that are already moist.

GIS estimation methods

The management factors influencing the C factor are not readily available in GIS format. The vegetative landcover of an area can be determined from aerial or satellite photography. Many important management factors, such as tillage, cannot be determined using currently available GIS datasets. Therefore, previous studies have employed techniques of various precision to estimate the C factor for their study areas, usually by generalizing management practices across entire vegetation or crop types.

The precision used in determining the C factor is based on the goals of the study as well as the available data. Chandramohan and Durbude (2002) didn't need to differentiate between specific agricultural practices, so all of the agricultural land in the watershed was given the same C factor value. The other possible C factors were assigned to land that was classified as barren, stony, or open water. Molnar and Julien (1998) also simplified C factors into only four categories.

Other researchers have used much more intensive methods for determining C factors. Fu et al. (2005b) and Yue-Qing et al. (2008) both took the time to experimentally determine the C factor at individual sites with their watersheds and then extrapolated these C factors to the rest of the watershed based on aerial imagery classifications.

If the management practices are known, the C factor can be estimated throughout the year by inputting the field operations into the RUSLE1.06 or RUSLE2.0 programs. Tables of C factors based on crop type and residue percentage are available for fast, if crude, estimations. Once the spatial distribution of landuse and cropping systems is known, it is possible to link these areas to C factor values that have been calculated outside of the GIS environment. Fu et al (2004)used the RUSLE 1.06b model to determine the C factor of various crop management schemes, and then used these values as inputs for their GIS model.

Collecting cropping system information through field visits and manually entering it into a GIS would be time and cost prohibitive for large watersheds. It also risks introducing errors that occur during manual data collection and input. Instead, it is necessary to obtain this spatial information using existing sources such as aerial imagery or landcover data.

The National Agricultural Statistics Service (NASS) currently uses multi-temporal imagery from the Advanced Wide Field Sensor (AWiFS) satellite sensor to create the Cropland Data Layer (CDL), which is a classification of crop-type landcover. Before 2006, they used LANDSAT data and only analyzed select states, but their most recent classification includes the continental U.S. The CDL has a resolution of 56 meters and has an accuracy ranging from about 80 to 90 percent, depending on crop type. (Johnson and Mueller 2009.) Data for Kansas is available beginning in 2006.

Employed method

The CDL data were used to determine the crop rotations in the watershed. In brief, the 2006, 2007, 2008, and 2009 CDL datasets were aggregated to develop a final dataset with landuse classified as one of 12 rotations. Because the Conservation reserve program data were not part of the CDL, 2006 CRP contract data were acquired from Cheney Lake Watershed. These data were added to the 12 rotations, creating a landuse datalayer that classified all landuse into one of 13 possible rotations (Table B-2). Additional details on the landuse reclassification process are provided in Appendix A - Landuse Reclassification.

This raster-format classification of landuse was aggregated to digitized field boundaries. This allowed for the layer to be up-scaled to a higher resolution, since the original CDL layer was in a courser resolution than the rest of the model, and it removed artifacts and aberrations from within areas of a consistent landuse.

The CDL data lacks tillage information, so a survey of the watershed conducted by Lisa French and Howard Miller was used to determine the spatial location of tillage practices in the watershed. This data consists of input by local producers and farm managers who are familiar with their respective areas. Producers were given PLATT maps of their respective locations, and asked to verify which parcels were being managed as forage or grazing, conventional-tillage cropping, reduced-tillage cropping, and no-tillage cropping systems. While crop rotations vary over time, producers who have committed a field to no-till will typically continue this practice into the future. This provided data for much, but not all of the watershed.

The crop rotation layer and tillage layer were overlain to produce a combination of tillage/crop rotation layer. This layer was used to determine which practices were most common within the watershed. Generalized management schemes were created for these management types using the RUSLE2.0 computer interface so that representative C factors could be assigned to each field in the watershed. These management schemes used for this project were based on input data reviewed by the CMC for an economic analysis being performed for the watershed. Table 3-1 shows the management types and their monthly average C factors. See Appendix B - Cropping Systems Used to Calculate C-Factors in RUSLE 2.0 for the field operations and soil conditions used as input to build each of these management schemes.

Monthly C, R, and Yearly CR

Because the C and R factors vary greatly throughout the course of the year, it was decided to use the monthly values for these factors when calculating RUSLE for the watershed. Figure 3-1 demonstrates how two different landcover types, sorghum and winter wheat, have peak C factors at different times of the year and therefore coincide with different rainfall erosivity. This difference in temporal distribution would not be taken into account if a single, annual C factor is used for each crop rotation. Table 3-1 lists the monthly average for each combination of crop rotation and tillage practice.

Rather than finding the yearly average C factor and the yearly average R factor and multiplying them by the other yearly average factor values, erosion was instead calculated for each month and then summed to produce the total yearly erosion. This is similar to the RUSLE1.06, which breaks down the factors into monthly values. This is in contrast to older versions of the USLE that use a single year-long value for each factor, or the RUSLE2.0 that actually breaks down each factor into a daily value before aggregating the annual results.

P Factor – Support Practice

The USLE model was originally created to estimate soil erosion due to the non-concentrated flow of water from rainfall events. It did not take into account the transportation or deposition of soil sediments once they had been eroded.

The P factor is used to represent the impact that various support practices have on soil erosion. It takes into account soil conservation practices that otherwise would not impact the other RUSLE factors, but have a demonstrated impact on reducing soil erosion loss from the field. The P factor used for a given field is generally found by using one of the published tables that lists which conservation practices correspond to which P factors.

GIS estimation methods

Spatial data to determine the P factor can be difficult to collect or generate. Most studies assume the P factor to be 1, (no conservation practices,) for the extent of the study area. (Fu et al., 2004; Kouli et al., 2009; Molnar and Julien, 1998; Simms et al., 2003) all set the P factor to 1 for their erosion estimates. Some studies, such as (Chandramohan and Durbude, 2002; Prasad et al., 2005; Yue-Qing et al., 2008) use an approximate P factor value for each land use, rather than separately determining it.

Employed method

In order to assign P factor values to the watershed, it was necessary to know the location of practices that would affect the P factor. In this watershed, the only widespread practice that affects the P factor is terracing, and the contour tillage that is assumed to be practiced on terraced land. The NRCS provided a polygon layer indicating fields that have been terraced up until the year 1997. Cheney Lake Watershed Inc. provided additional data by digitizing the boundaries of fields that have been terraced up until present (1996).

A raster layer was created using the terraced field data. The fields that had terraces, and the associated contour tillage, were given a P factor of 0.4, while the rest of the watershed was given a P factor of 1.0 (no support practices.) The value of 0.4 was chosen to be an appropriate average of the effectiveness of the terraces and contour tillage in this watershed. While the P factor describes conservation practices, it is also affected by the slope gradient, soil runoff classification, and other environmental variables, meaning that the generalized P factor value for one watershed may not be appropriate for another. The RUSLE 1.06 and RUSLE 2.0 computer interfaces were used to enter soil and landscape conditions representative to this watershed. When terraces and contour tillage were added to the field profiles, the total soil loss was reduced by about 60%, meaning that a value of 0.4 for these support factors would be the most appropriate in this watershed.

Common parameters for all factors

Area of study

The area of study used in this project is the total watershed of the Cheney Reservoir, as delineated by HUC 14 watershed delineation. Some publications, such as (Stone et al., 2009), describe the western portion of the watershed as not contributing to surface water flow. This distinction was not made for the purpose of this project. Data sources that extended beyond the borders of the watershed were clipped to the watershed boundaries. The entirety of the range and cropland in the watershed was included in the calculation of RUSLE. Land that is not pasture, native vegetation, forage, or cropland was omitted from the analysis.

Data raster format

The spatial data used to calculate the RUSLE factors were available in a number of different spatial patterns that did not necessarily line up with individual field boundaries. The simplest way to handle the data used to calculate RUSLE is to create a separate raster for each RUSLE factor. Once these rasters are converted to the same grid size and projection, they can be multiplied to calculate estimated soil erosion. This resulting raster can be aggregated to field boundaries in order to rank field erosion risk.

The raster format used in this study was a ten meter by ten meter grid, projected to UTM Zone 14 North. The UTM projection is useful for handling GIS projects that fall within a single UTM zone, and is convenient for calculating areas and distances based on metric units. Much of the publicly available GIS data used for this project was available for download in the UTM projection.

The grid resolution used for calculating RUSLE in a GIS system is important for two main reasons. First, the resolution must be fine enough to capture the change in value for the different factors that will be aggregated to the field polygon. The ten meter grid provided sufficient resolution to represent the spatial variability of the RUSLE factors across fields. Secondly, the grid resolution of the elevation raster can have a direct impact on the calculation of LS.

Field Validation

Twenty five locations were selected from the Red Rock Creek and Goose Creek subwatersheds for validation (Figure 3-2). Prior to calculation of soil loss with the GIS method, fields displaying a variety of topographies, soil types, landuse, and management types were selected from the GIS data. Directly measuring erosion across these fields was not practical, given the scope of this project. Instead, erosion was estimated for each field by manually using the RUSLE 2.0 model.

Erosion estimates were based on several sources of data. Hillslopes were measured at each field site using a handheld survey level and rod. Slope lengths were determined by pacing, and were measured from the beginning of a hillslope to the point of concentrated surface flow. Past field operations for each site were determined by brief phone conversations with landowners or producers at the time that permission was being requested to survey the sites. Soil types for each field were determined using SURRGO data. This information about each site, along with watershed location, was used as inputs data in the RUSLE 2.0 windows interface. Each field location received an annual average soil erosion estimate using this time and data intensive method.

These manually determined erosion estimates were then compared to the GIS-model results by finding the Nash Sutcliffe model efficiency coefficient (Nash and Sutcliffe, 1970). The Nash Sutcliffe coefficient is commonly used to assess the predictive power of hydrological models. It is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance (Moriasi et al., 2007).

Estimating Erosion for Current and Past Conditions

Erosion was estimated for three different scenarios: A, B, and C (Table 3-2). Scenario A represents the most current watershed conditions, which were used to prioritize fields for future BMP implementation and to identify current erosion trends. Scenarios B and C are based on past watershed conditions. To estimate scenarios B and C, modifications were made to some of the RUSLE factors. The R, K, and LS factors were left unchanged, as those factors are not directly influenced by short-term land management changes.

Scenario B represents the watershed before tillage changes and BMP implementations took place. This scenario is used to evaluate the placement of BMPs and CRP enrollment in the watershed since that time.

The C factor changed in two ways. First, all fields were considered to have conventional tillage. Feedback from local producers revealed that very few fields were under no-till management as of 1997. This was accomplished by reclassifying the crop/tillage layer to reflect conventional-till C factors.

Secondly, the distribution of CRP land within the watershed was changed to reflect past conditions. The data used to determine current crop rotations are not available for these past conditions. Any newly-established CRP land was instead assumed to be conventional-till wheat, because that is the most common crop rotation in the watershed.

Scenario C represents the watershed with no land in CRP. This scenario is useful in evaluating the placement of all CRP in the watershed.

CRP, BMP, and Tillage

One goal of this project was to evaluate the past placement of various BMPs within the watershed. Three different types of BMPs were considered: Fields where financially incentivized BMPs have been implemented, fields that have been added to the Conservation Reserve Program, and fields where less intensive tillage practices have been implemented.

Financially incentivized BMPs include nutrient management planning, tillage reduction, and erosion control structures that would influence the runoff of phosphorus or sediment. The location of BMPs that had been financially incentivized by the NRCS was collected from NRCS records and linked to CLU field polygons in the watershed.

A significant proportion of the Cheney Lake watershed has been enrolled in the CRP program. CRP land was identified based on records of CRP contracts. These records were obtained from the NRCS through a freedom of information request made by Cheney Lake Inc. and digitized to the watershed. The changes in CRP land from 1997 to 2006 were evaluated by comparing the new CRP land to potential field-scale erosion.

Prioritization and Comparison

The RUSLE-based GIS method previously described creates a 10 m grid raster of estimated annual erosion across the watershed. This data was aggregated to the field boundaries within the watershed, which represent Common Land Units (CLU)s, or changes in landcover or crop type. This provided average annual erosion estimation for each field within the watershed. Fields were ranked in order of average erosion estimate, and the top 20% of the watershed (by area) was identified as “high-eroding” land. This was done for each of the watershed erosion scenarios.

Results and Discussion

Field Validation

The correlation between the manual soil erosion estimate and the model erosion estimate can be seen in Figure 3-3. The R^2 value for the linear relationship is 0.5513. The Nash Sutcliffe model efficiency coefficient is 0.44. Despite these relatively low correlation coefficients, the GIS model and RUSLE identified 4 out of 5 of the same fields when identifying the top eroding areas. The slope of the best fit line is approximately 0.4, indicating that the GIS model tends to under predict soil erosion when compared to RUSLE 2.0 erosion estimates. This discrepancy may be due to the GIS model predicting a lower LS factor value than the manual field measurement of LS. The correlation between the model predicted LS values and the manual field measurements of LS taken for the validation fields has a slope of 0.452 (Figure 3-4).

Result summaries of individual RUSLE factors

Before considering the model results as a whole, it is important to consider the RUSLE factors individually. The spatial distribution, range of values, and real-world implications of each factor can be considered. Figure 3-5 illustrates the spatial distribution of each factor as a form of comparison. A small subset of the watershed has been enlarged to make it possible to see how the factor values vary across and between fields. This figure is not meant to quantify the data, but to provide a qualitative perspective on the overall method.

The rainfall factor can be described as a smooth, east-west gradient across this watershed, as seen in Figure 3-5. There is very little difference in R factor between neighboring fields. The R factor does change significantly from higher values in the eastern portion of the watershed to lower values in the west, as well as changing in magnitude over the course of a year. Figure 3-6 and Figure 3-7 show how the spatial distribution of the R factor and, more importantly, that the overall magnitude changes significantly between the winter and summer months. This fact led to the decision to calculate the R factor on a monthly basis, rather than using an annual average value.

The K factor varies with the changing soils due to landscape position (on a smaller scale) and other soil formation factors (on a larger scale) (Figure 3-5) . The relatively high K factor values found in the western half of the watershed (Figure 3-9) is due to a change in dominant soil texture from the silt loams of the eastern half of the watershed to the sandier loams of the western half.

It can be seen that LS has great variability on a small scale (Figure 3-5) as well as on a larger scale (Figure 3-11). Unlike the R and K factors, the distribution of LS values shows that most of the watershed has relatively low values, while a small percentage of land area contains exponentially higher LS factor values (Figure 3-8). Because RUSLE is a simple multiplicative model, a single factor with a range of values spanning nearly two orders of magnitude could dominate the final model results. The dominating effect of LS on final erosion estimates was assessed by plotting the average LS value of field versus its average erosion value. The LS value shows two different linear correlations with total soil erosion, due to different landcover types (Figure 3-11). Many of the fields with the highest LS factors are under perennial grass cover, which dramatically lowers their final erosion estimate. If one were to select twenty percent of the watershed with the highest LS factor, it would only overlap 19% of the similarly selected area containing the highest erosion (Table 3-3). This is a lower overlap than was found for the other RUSLE factors.

The cover factor clearly delineates field boundaries in the watershed, which contain different crop rotations or landcovers (Figure 3-2). On a watershed-wide scale it is noticeable that the western side of the watershed contains a higher percentage of grass cover and thus a lower C factor (Figure 3-13). The C factor can vary greatly from field to field in this watershed, ranging over two orders of magnitude from 0.00181 to 0.287. In general, the C factor falls into four general categories: pasture/grass, no-till, reduced tillage, and conventional tillage (Figure 3-14).

The P factor generally falls between two values for this watershed, based on the presence, partial presence, or absence of terraces in a given field. The eastern portion of the watershed contains the majority of terraced fields, due to the presence of steeper topography. The P factor affects relatively few fields, as only 8.5 percent of the watershed is terraced.

Watershed Classification

The amount of each landuse classification in the watershed is given by Table 3-4. Continuous wheat makes up about 60,000 ha of the watershed, and is the most common crop rotation. A majority of the crop fields in the watershed are practicing conventional tillage, covering 79,000 ha (Table 3-5).

Table 3-6 shows the coverage of each BMP that was analyzed for placement in the watershed. 29,000 ha received some financial incentive for BMP placement, while a total of 14,000 ha converted to no-till management. A total of 48,000 ha are enrolled in the CRP program, with 17,000 ha being newly enrolled since 1997.

Watershed-wide erosion estimates

The erosion estimate for the entire watershed given current conditions is shown in Figure 3-16. The total watershed-wide erosion was estimated to be 288,000 Mg year^{-1}. When adjustments were made to the CRP coverage and estimated tillage practices of 1997, the total watershed-wide erosion is estimated to be 338,000 Mg year^{-1}. This would indicate a 15% decrease in RUSLE erosion from the 1997 until present.

These values are not directly comparable to sediment loading data. The RUSLE erosion estimate is meant to calculate field-scale erosion, and doesn't take into account the transport and deposition that may take place between a given field and water body. When transport factors and sediment deposition are taken into account, the actual stream load would be less than these values.

The RUSLE-based GIS model may, on the other hand, be under predicting the effect of erosion in the watershed. RUSLE is meant to estimate erosion caused by the non-concentrated flow of rainfall. Areas such as ditches and gullies are not accounted for by the RUSLE model nor, by extension, our GIS model. While the GIS model is useful in comparing erosion between fields, it is not designed to directly estimate stream quality. (Wischmeier and Smith, 1978)

Factor importance

Table 3-3 shows the overlap between land identified as high-eroding using the final erosion estimate, and land identified as high-eroding using only a single factor. No single-factor targeting overlapped the total erosion targeting by more than 70 percent. If one factor had overlapped by 80 or 90 percent, then it would have indicated that the model was being driven by a single factor.Instead, each factor was important in determining the ranking of fields by estimated erosion.

Landcover/Management analysis

There are several ways to present field-level erosion with regard to landscape or management trends within the watershed. One simple way to look at the effect and placement of crop rotations is given in Table 3-7, which shows the percentage of each landcover type that is classified as the top 20% prioritized erosion area in scenario A. This tells us how likely it is for a random field to be identified as high-eroding, given its current crop rotation. The rotations with the highest percentage of their area identified as high-eroding by our model are the wheat-sorghum-soybean, wheat-sorghum, and continuous sorghum rotations. These crop rotations combined cover 32 percent of the watershed.

Another way to approach the data by viewing the total placement of high-erosion land within each cover type, as seen in Table 3-8. This tells us how likely a randomly selected, erosion prioritized field is to be a given landcover type. Here we can see that continuous wheat, wheat-sorghum, and corn-soybean rotations combined contain 85% of the prioritized land. The continuous wheat rotation, which makes up 25% of the total watershed area (Table 3-7), accounts for over half (51%) of the total area identified as high-eroding (Table 3-8). This is due in large part to the fact that this rotation scheme was programmed with an assumption of intensive tillage, as is observed within the watershed.

Virtually none of the land classified as pasture/range or CRP by the land-classification system was identified as high-eroding. The C factor of grassed vegetation is several orders of magnitude lower than the C factor of other land uses (Table 3-1), which greatly reduces the erosion estimates for those areas.

Conventionally tilled land is more likely to be prioritized than reduced or no-till land (Table 3-9). A total of 86% of the prioritized land is conventionally-tilled. Tillage operations greatly affect the C factor of a given crop rotation, sometimes by an order of magnitude (Table 3-1). In a multiplicative model, this great of difference in a single factor value has a proportionally great impact on the final erosion estimate. Fu et al. (2004) found similarly extreme impacts of tillage in their erosion estimates using RUSLE.

Placement analyses

The placement of various conservation efforts in relation to high-eroding land is shown in Table 3-3. In this case the high eroding land has been prioritized based on 1997 watershed conditions, in order to evaluate the placement of CRP enrollment, subsidized BMPs, and transition to no-till in the subsequent years.

The land identified as high-eroding in Scenario B had a proportionally higher amount of new CRP placement between 1997 and 2006 than the rest of the watershed as a whole. Unlike other BMP placement in the watershed, the FSA has taken into account the vulnerability of individual fields when enrolling them in the CRP program. The weighted average erosion index of the field is one of the factors that is considered (USDA 2011).

The overlap of CRP placement and vulnerable locations may also be explained by the tendency of producers to enroll marginal cropland into CRP, rather than fields that are producing a high profit. The factors that make a field marginally productive are often the same factors that lead to a high soil erosion estimate, such as easily eroded soil types and high slope.

Previous BMP efforts in the watershed, other than CRP placement, have not used erosion estimates or surface water risk assessments as criteria for specific fields to participate in cost-share programs. Our model shows that incentivized BMP placements were not influenced by the erosion risk of the fields they were implemented on (Table 3-11).

Voluntary no-till implementation, as measured by our producer survey, actually follows the opposite trend as seen with CRP enrollment. Fields that were low-eroding were more likely to have no-till implemented than fields identified as high-eroding. One possible explanation is that ephemeral gullies form in many fields within this watershed. Tillage operations are often required to remove the gullies and allow field operations to continue. Thus, steeper sloped fields, which have higher erosion, may be difficult to transition into no-till because tillage is necessary to remove the ephemeral gullies. The average LS factor for no-till fields in the watershed is 0.164, while the average LS factor for other cultivated cropland is 0.194. This indicates that no-till fields are on average flatter than fields receiving tillage in this watershed. However, there was not a significant correlation between the LS and C factors on a per-field basis across the watershed (Figure 3-21).

Erosion risk from management and location

Erosion in the Cheney watershed can be further characterized by viewing the model results with respect to the factors that can or cannot be altered by the management decisions of a producer or landowner. The C and P factors in the RUSLE model can be altered year-to-year by the choice of cropping system and BMP implementation. If erosion risk is driven by these factors, then it is possible to reduce the risk of erosion for a given field. The R, K, and LS factors, on the other hand, are inherent to the location of a given field, and cannot be feasibly improved by the producer. If erosion is driven by these factors, then any agricultural use of this land is likely to result in undesirable erosion rates.

Land area was classified as either high or low risk based on management, where high risk is the top 20% of the land area with the highest CP factor. Land area was also classified as either high or low risk based on location, where high risk is the top 20% of the land area with the highest RKLS factor. These two classification schemes were intersected to create a matrix of four unique categories based on management and location (Table 3-12).

Two percent of the watershed was classified as high risk based on both location and management, all of which was included in the prioritized area (Table 2-8). Seventeen percent of the watershed was high risk based on management and low risk based on location. Over 75% of this area was classified as high risk in the final analysis. The majority of the land in the other two risk classifications were low priority in the final analysis (Table 2-8).

While all of the RUSLE factors were observed to impact the erosion predictions across the watershed, 62% of the fields prioritized as high erosion risk were considered to have a high management-related risk but low location-related risk (Table 3-13). This indicates that management factors are driving the prioritization of fields as high-eroding or low-eroding. This also implies that the areas of greatest erosion risk within the watershed can be addressed through management decisions and BMP implementation. While this means that current practices are not ideal in their impact on erosion, it also provides evidence that changes can be made to greatly reduce the amount of erosion within the watershed.

Conclusions

The GIS-based RUSLE model proved to be a valid method of estimating field-scale soil erosion. It showed a definite correlation with the results of manually estimating soil erosion for individual fields using the traditional RUSLE2.0 computations.

Although, CRP placement favored high-eroding fields, other BMPs were not selective towards fields most at risk for erosion. Over-all adoption of no-till practices actually favored the areas that needed it the least.

Continuous wheat and rotations containing sorghum were especially likely to be classified as high-eroding areas. No-till and pasture land were hardly ever prioritized as high risk of erosion, while conventionally tilled land comprised the majority of all prioritized area.

When the RUSLE factors are classified into management or location effects, the majority of high-eroding areas are driven by management factors, rather than inherent properties of those landscapes.

The GIS-based method of calculating RUSLE facilitated the evaluation of BMP placement, provided insight into the primary factors causing erosion across the watershed, and prioritized fields within the watershed for the future placement of BMPs. This allows for a more efficient reduction of erosion within the watershed, leading ultimately to improved water quality in the streams and the reservoir.

Advice for erosion management in the Cheney Watershed

The results of this project are useful on three different levels. First, this project provides an example method for estimating field-scale soil loss in a watershed. It is comprehensive enough to be accurate, but simple enough to be practical.

Secondly, it reveals interesting trends across the Cheney watershed, as previously discussed. The impacts of land use and management decisions on a watershed-scale are useful for evaluating large-scale goals and progress. This aggregate data is useful when considering the watershed as a whole.

Finally, this study provides a field-scale soil erosion estimate for the entire watershed. It is possible for watershed managers, individual producers, or anyone with the map to find the estimate for a given parcel of land. As with any predictive model, this information should be used appropriately, and with the right perspective.

The Revised Universal Soil Loss Equation is meant to be used as a long-term predictive tool. Certain factors, especially involving rainfall or plant growth, are likely to change from year-to year. This means that even the most precise and accurate implementation of the model may not directly represent the soil loss or water quality of any single year.

Besides the inherent uncertainties of nature, there is also the possibility of overlooked variables that may have a significant impact on the water quality impact of a field. Flow paths and rates are confounded by small-scale terrain, roads, ditches, and drainage structures. This means that an accurate delivery estimate is beyond the scope of this project. Some of these variables cannot be detected without a ground-scale survey of the entire watershed.

These caveats are not meant to undermine the importance of the project, but to place the results in the proper perspective. The field-scale erosion map of the watershed is a useful tool for identifying high-priority fields in the watershed, but shouldn’t be used as the sole determinant for regulatory or incentive decisions. It can, however, serve alongside other criteria to inform eligibility in programs that are seeking to get the most water quality improvement for the least amount of funding.

The model may also provide watershed managers with a place to start when deciding where to focus their time, and may indicate problem areas that had been previously undetected. Areas of the watershed that are not accessible by public roads, or hidden by terrain, may have significant contributions to soil erosion in the watershed but go otherwise undetected. The map is not affected by any inherent visual bias that may affect a ground-level survey. A large part of the conservation efforts in the Cheney Watershed is the personal contact and education of local producers. This field-scale map can help watershed managers decide where to focus their time with personal outreach.

Tables and Figures

Table 3-1. Monthly cover factors of each landcover and tillage used in the erosion model for the Cheney Watershed. Colors highlight values ranging from low (green) to high (red.)

		Month											
Crop†	Tillage‡	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
W-G-S	NT	0.070	0.067	0.065	0.068	0.077	0.089	0.075	0.065	0.065	0.068	0.077	0.072
W-G-S	RT	0.137	0.133	0.127	0.134	0.218	0.274	0.186	0.114	0.123	0.130	0.151	0.144
W-G-S	CT	0.286	0.283	0.289	0.312	0.375	0.392	0.271	0.194	0.218	0.254	0.284	0.287
C-S	NT	0.100	0.095	0.113	0.153	0.149	0.128	0.121	0.127	0.108	0.084	0.090	0.094
C-S	CT	0.180	0.165	0.303	0.333	0.330	0.253	0.196	0.186	0.171	0.136	0.155	0.159
W-G	NT	0.074	0.067	0.066	0.068	0.072	0.077	0.074	0.078	0.110	0.118	0.106	0.094
W-G	CT	0.123	0.123	0.124	0.132	0.164	0.222	0.230	0.255	0.282	0.245	0.212	0.184
W-S	NT	0.046	0.044	0.040	0.043	0.049	0.051	0.048	0.048	0.048	0.046	0.050	0.048
W-S	RT	0.135	0.111	0.085	0.091	0.103	0.117	0.124	0.095	0.098	0.171	0.182	0.158
C	NT	0.080	0.079	0.088	0.109	0.105	0.096	0.105	0.120	0.095	0.077	0.079	0.080
C	RT	0.110	0.111	0.166	0.216	0.181	0.127	0.138	0.163	0.129	0.100	0.110	0.110
G	NT	0.041	0.041	0.040	0.040	0.052	0.062	0.054	0.050	0.052	0.046	0.043	0.042
G	RT	0.150	0.150	0.173	0.218	0.322	0.313	0.204	0.159	0.150	0.141	0.148	0.150
G	CT	0.150	0.150	0.174	0.268	0.355	0.336	0.214	0.163	0.150	0.141	0.150	0.150
W	NT	0.096	0.069	0.055	0.057	0.060	0.065	0.088	0.129	0.157	0.177	0.141	0.117
W	RT	0.176	0.114	0.082	0.085	0.088	0.091	0.148	0.216	0.323	0.368	0.281	0.223
W	CT	0.184	0.117	0.084	0.087	0.090	0.092	0.148	0.216	0.330	0.390	0.294	0.233
A		0.110	0.111	0.112	0.092	0.074	0.073	0.074	0.098	0.097	0.112	0.103	0.107
P		0.015	0.015	0.015	0.006	0.006	0.014	0.016	0.026	0.029	0.017	0.018	0.014
CRP		0.005	0.004	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.003	0.005

† Landcover rotations contain one or more of the crops corn (C), wheat (W), grain sorghum (G), soybean (S), alfalfa (A), pasture (P), and Conservation Reserve Program (CRP).

‡ Tillage types, when applicable, are no-till (NT), reduced tillage (RT), and conventional tillage (CT).

Table 3-2. Dates of CRP, terrace, and tillage data used for erosion estimate scenarios.

Scenario	CRP coverage	Terraces	Tillage
A	2006	2006	2009
B	1997	1997	All conventional till
C	none	1997	

Table 3-3. Watershed area identified as top 20% of overall erosion compared to land in the top 20% of each individual RUSLE factor.

RUSLE Factor	**Percent overlap**
LS	19
P	70
K	41
CR	63
C	69

Table 3-4. Landcover classification of the Cheney Watershed, delineated by HUC 14 boundaries.

Landcover classification†	Coverage Area (ha)
Wheat-Sorghum-Soybean	6,000
Corn-Soybean	13,000
Wheat-Sorghum	17,000
Wheat-soybean	6,000
Continuous Corn	17,000
Continuous Sorghum	3,000
Continuous Wheat	60,000
Continuous Alfalfa	4,000
Pasture/Range	65,000
CRP	48,000
Non-arable land	7,000
Total	243,000

† Landcover classification determined by processing NASS Crop Data Layer (CDL) into multi-year crop rotations.

Table 3-5. Tillage classification of the Cheney Watershed, delineated by HUC 14 boundaries.

Tillage Type†	Coverage Area (ha)
Conventional till	79,000
Reduced Till	24,000
no-till	13,000
Pasture	111,000
non-arable	16,000
Total	243,000

† Tillage areas determined by producer input, roadside watershed survey, aerial imagery, and assumptions about common management practices. (See Figure 3-20)

Table 3-6. Best Management Practices (BMP) classification of the total Cheney Watershed, delineated by HUC 14 boundaries.

Change in land management	Coverage Area (ha)
Financially-Incentivized BMP implemented†	29,000
Voluntary No-till implementation‡	14,000
Newly enlisted fields in the Conservation Reserve Program (CRP) §	17,000
Total enlistment of fields in CRP¶	48,000

† Participation in one or more BMP cost-sharing contracts.
‡ Area is under no-till management practices, as determined by producer input and roadside watershed survey.
§ Fields enlisted in CRP from 1997 to 2006.
¶ All fields enlisted in CRP as of 2006.

Table 3-7. Watershed coverage and percent of landcover classification that contains prioritized and non-prioritized area in the Cheney Watershed.

Landcover classification†	Percent of total watershed area	Landcover classification identified as prioritized‡	Landcover classification identified as non-prioritized§
Wheat-Sorghum-Soybean	4	62	38
Corn-Soybean	16	52	48
Wheat-Sorghum	24	64	36
Wheat-soybean	5	15	85
Continuous Corn	13	17	83
Continuous Sorghum	4	61	39
Continuous Wheat	69	44	56
Continuous Alfalfa	2	4	96
Pasture/Range	34	0	100
CRP	25	0	100
Non-arable land	3	0	100

† Landcover classification determined by processing NASS Crop Data Layer (CDL) into multi-year crop rotations.
‡ Prioritized area identified as 20% of the watershed with the highest erosion, as determined by the GIS-based RUSLE model.
§ Non-prioritized area identified as 80% of the watershed with the lowest erosion, as determined by the GIS-based RUSLE model.

Table 3-8. Percent of prioritized area (top 20% erosion) and non-prioritized area (bottom 80% erosion) by tillage type in the Cheney Watershed.

Landcover classification†	Prioritized area in each landcover classification‡	Non-prioritized area in each landcover classification§
Wheat-Sorghum-Soybean	3	1
Corn-Soybean	13	3
Wheat-Sorghum	21	3
Wheat-soybean	2	3
Continuous Corn	6	7
Continuous Sorghum	4	1
Continuous Wheat	51	18
Continuous Alfalfa	0	2
Pasture/Range	0	34
CRP	0	25
Non-arable land	0	3

† Landcover classification determined by processing NASS Crop Data Layer (CDL) into multi-year crop rotations.
‡ Prioritized area identified as 20% of the watershed with the highest erosion, as determined by the GIS-based RUSLE model.
§ Non-prioritized area identified as 80% of the watershed with the lowest erosion, as determined by the GIS-based RUSLE model.

Table 3-9. Watershed coverage and percent of tillage type that contains prioritized and non-prioritized area in the Cheney Watershed.

Tillage Type†	Percent of total watershed area	Tillage type identified as prioritized‡	Tillage type identified as non-prioritized§
Conventional till	33	53	47
Reduced Till	10	24	76
no-till	5	6	94
Pasture	46	0	100
non-arable	6	0	100

† Tillage areas determined by producer input, roadside watershed survey, aerial imagery, and assumptions about common management practices. (See Figure 3-20)
‡ Prioritized area identified as 20% of the watershed with the highest erosion, as determined by the GIS-based RUSLE model.
§ Non-prioritized area identified as 80% of the watershed with the lowest erosion, as determined by the GIS-based RUSLE model.

Table 3-10. Percent of prioritized area (top 20% erosion) and non-prioritized area (bottom 80% erosion) by tillage type in the Cheney Watershed.

Tillage Type†	Prioritized area in each tillage type‡	Non-prioritized area in each tillage type§
Conventional till	86	19
Reduced Till	12	9
no-till	2	6
Pasture	0	57
non-arable	0	8

† Tillage areas determined by producer input, roadside watershed survey, aerial imagery, and assumptions about common management practices. (See Figure 3-20)
‡ Prioritized area identified as 20% of the watershed with the highest erosion, as determined by the GIS-based RUSLE model.
§ Non-prioritized area identified as 80% of the watershed with the lowest erosion, as determined by the GIS-based RUSLE model.

Table 3-11. Percent of prioritized area (top 20% erosion) and non-prioritized area (bottom 80% erosion) affected by Best Management Practice (BMP) implementation in the Cheney Watershed.

Change in land management	Prioritized area affected by change#	Non-prioritized area affected by change
Financially-Incentivized BMP implemented†	13	11
Voluntary No-till implementation‡	13	18
Newly enlisted fields in the Conservation Reserve Program (CRP) §	13	5
Total enlistment of fields in CRP¶	32	16

† Participation in one or more BMP cost-sharing contracts.
‡ Area is under no-till management practices, as determined by producer input and roadside watershed survey.
§ Fields enlisted in CRP from 1997 to 2006.
¶ All fields enlisted in CRP as of 2006.
# Prioritized watershed area is determined with model inputs that assume no current BMPs and/or substitutes CRP management with common crop cultivation practices.

Table 3-12. Percent total watershed area in each combination of management risk, location risk, and over-all erosion prioritization based on RUSLE factors and erosion estimate.

		High Management Risk†		Low Management Risk‡
High Location Risk§	Prioritized#	2	Prioritized	3
	Non-Prioritized††	0	Non-Prioritized	15
Low Location Risk¶	Prioritized	13	Prioritized	3
	Non-Prioritized	4	Non-Prioritized	60

† Twenty percent of the watershed with the highest product of the cover-management (C) and conservation practice (P) factors.
‡ Eighty percent of the watershed with the lowest product of the cover-management (C) and conservation practice (P) factors.
§ Twenty percent of the watershed with the highest product of the rainfall intensity (R), soil erosivity (K), and topographic (LS) factors.
¶ Eighty percent of the watershed with the lowest product of the rainfall intensity (R), soil erosivity (K), and topographic (LS) factors.
# Twenty percent of the watershed prioritized as high-eroding, based on overall RUSLE erosion estimate.
††Eighty percent of the watershed identified as low-eroding, based on overall RUSLE erosion estimate.

Table 3-13. Percent total prioritized area (top 20% erosion) within each risk classification category.

	High Management Risk§	Low Management Risk¶
High Location Risk†	12	13
Low Location Risk‡	62	13

† Twenty percent of the watershed with the highest product of the cover-management (C) and conservation practice (P) factors.
‡ Eighty percent of the watershed with the lowest product of the cover-management (C) and conservation practice (P) factors.
§ Twenty percent of the watershed with the highest product of the rainfall intensity (R), soil erosivity (K), and topographic (LS) factors.
¶ Eighty percent of the watershed with the lowest product of the rainfall intensity (R), soil erosivity (K), and topographic (LS) factors.

Table 3-14. Percent total watershed area in each risk classification category

	High Management Risk§	Low Management Risk¶
High Location Risk†	2	17
Low Location Risk‡	17	59

† Twenty percent of the watershed with the highest product of the cover-management (C) and conservation practice (P) factors.

‡ Eighty percent of the watershed with the lowest product of the cover-management (C) and conservation practice (P) factors.

§ Twenty percent of the watershed with the highest product of the rainfall intensity (R), soil erosivity (K), and topographic (LS) factors.

¶ Eighty percent of the watershed with the lowest product of the rainfall intensity (R), soil erosivity (K), and topographic (LS) factors.

Table 3-15. Percent in each risk classification category that was prioritized by the GIS-Based RUSLE method (top 20% erosion).

	High Management Risk§	Low Management Risk¶
High Location Risk†	100	15
Low Location Risk‡	75	4

† Twenty percent of the watershed with the highest product of the cover-management (C) and conservation practice (P) factors.

‡ Eighty percent of the watershed with the lowest product of the cover-management (C) and conservation practice (P) factors.

§ Twenty percent of the watershed with the highest product of the rainfall intensity (R), soil erosivity (K), and topographic (LS) factors.

¶ Eighty percent of the watershed with the lowest product of the rainfall intensity (R), soil erosivity (K), and topographic (LS) factors.

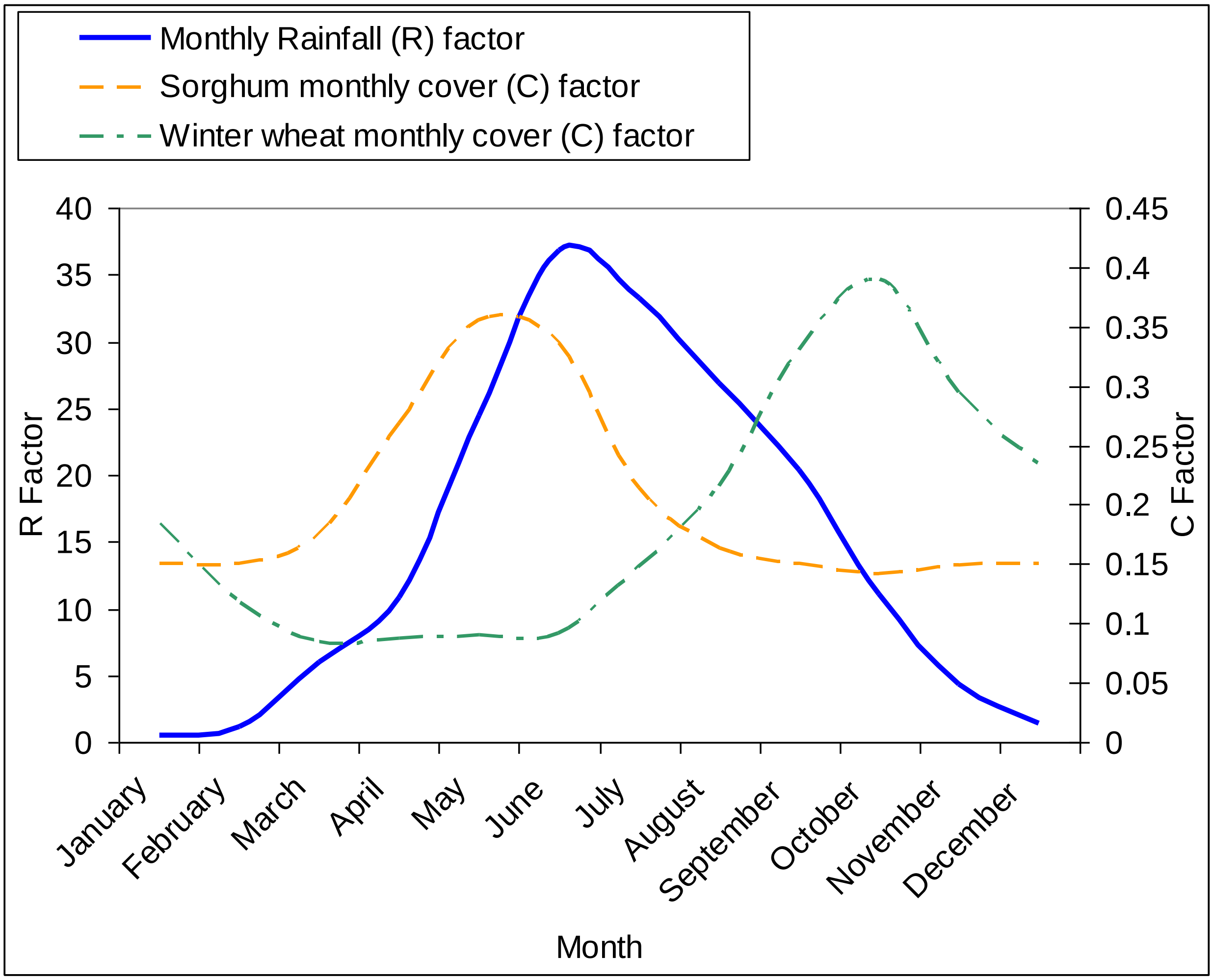


Figure 3-1. Average monthly Rainfall (R) factor for Reno County and average monthly cover (C) factor for continuous sorghum and continuous winter wheat crop rotations.

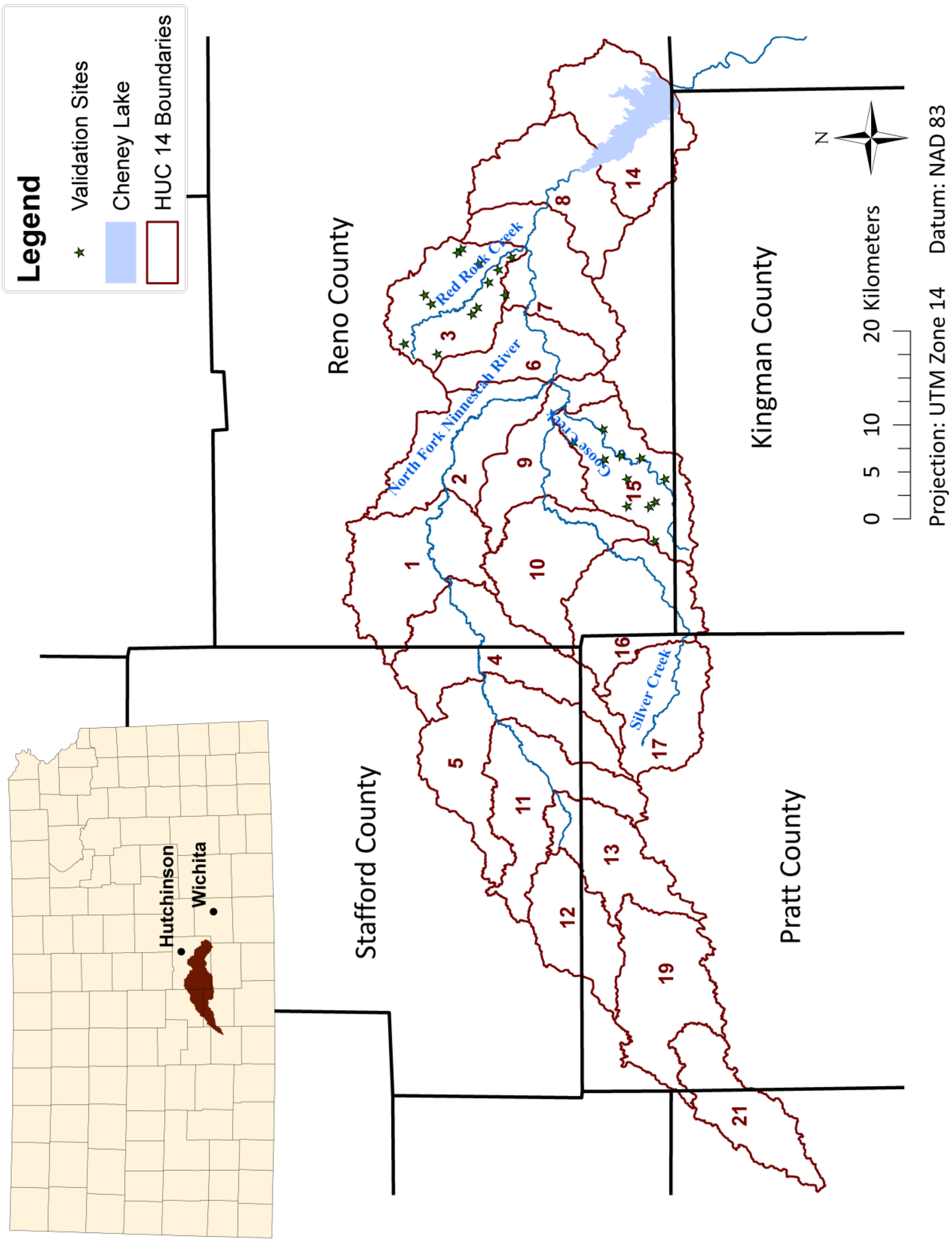


Figure 3-2. Cheney Watershed Overview

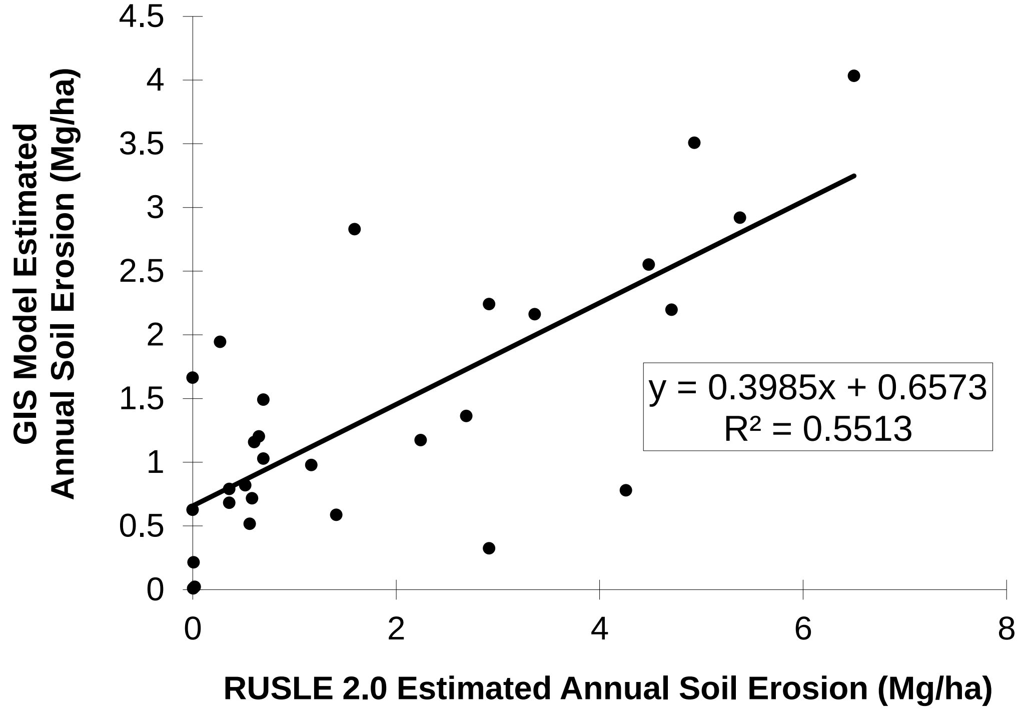


Figure 3-3. Model validation results comparing the annual soil erosion estimates of individual fields obtained by using the RUSLE2.0 program with the erosion estimates determined by the RUSLE-based GIS method described in this chapter.

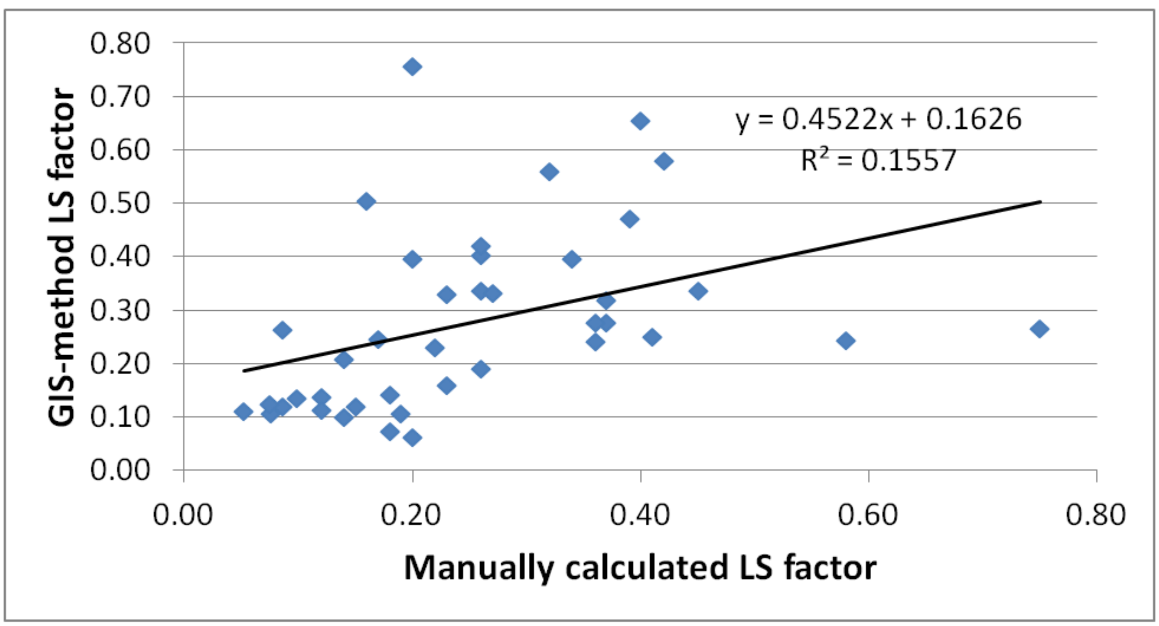
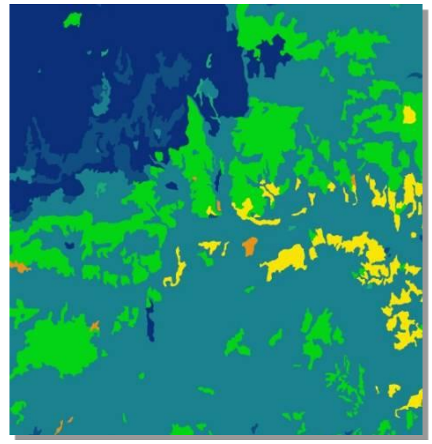
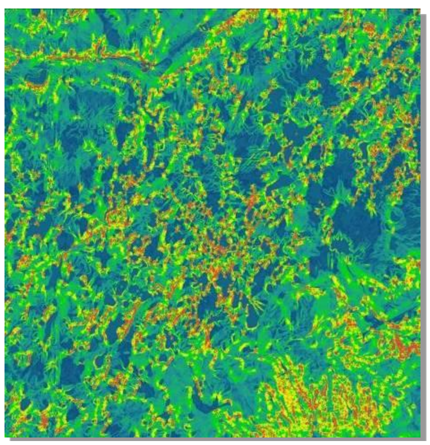


Figure 3-4. Manually calculated LS factor values compared to the LS factor calculated using the Van Remortel method for fields in the Cheney Watershed.

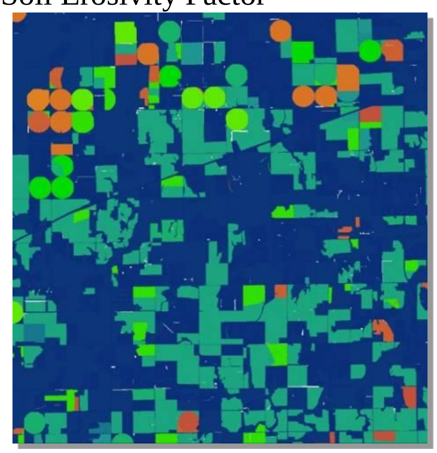
Rainfall Factor



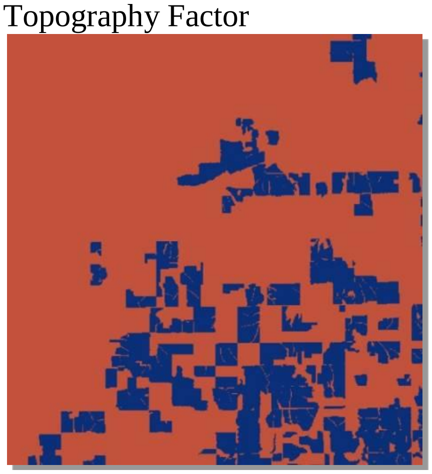
Soil Erosivity Factor



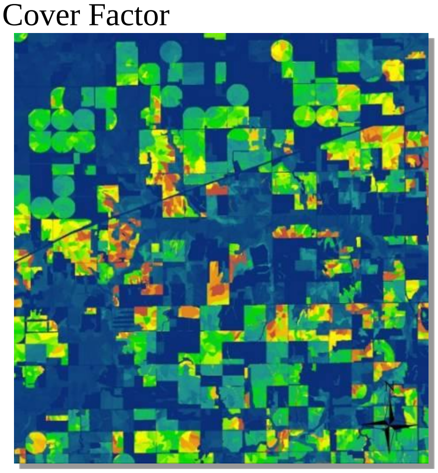
Topography Factor



Cover Factor



Conservation Practice Factor



Annual RUSLE Erosion

Figure 3-5. Qualitative examples of the variability and distribution of the RUSLE factors over a 25 square mile area.

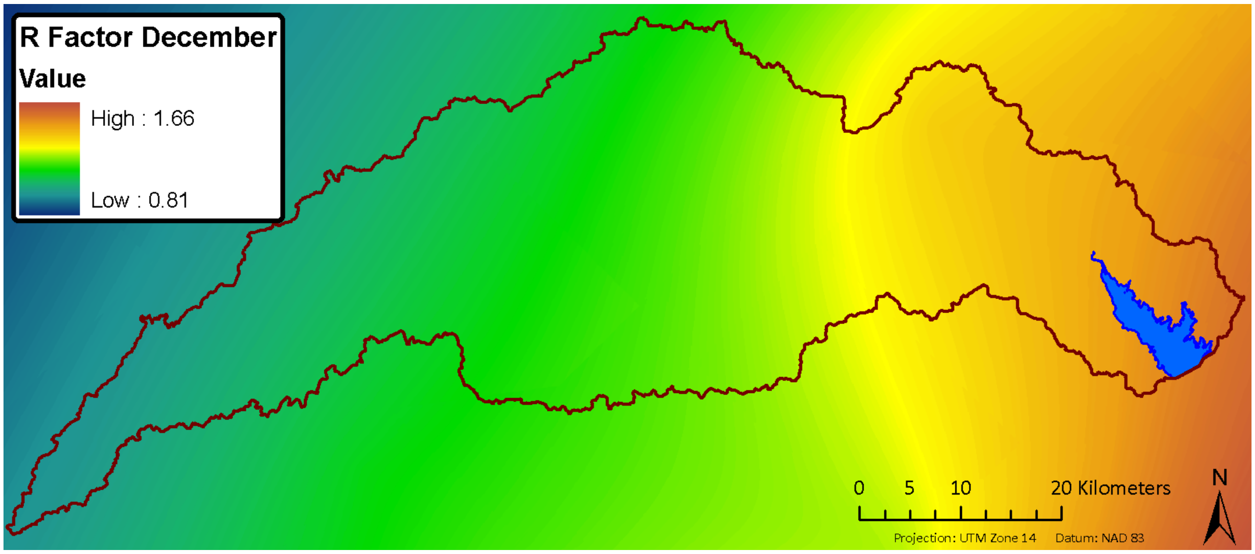


Figure 3-6. Rainfall intensity (R) factor for the Cheney Watershed in the month of December, interpolated from USDA-NRCS county R factor data.

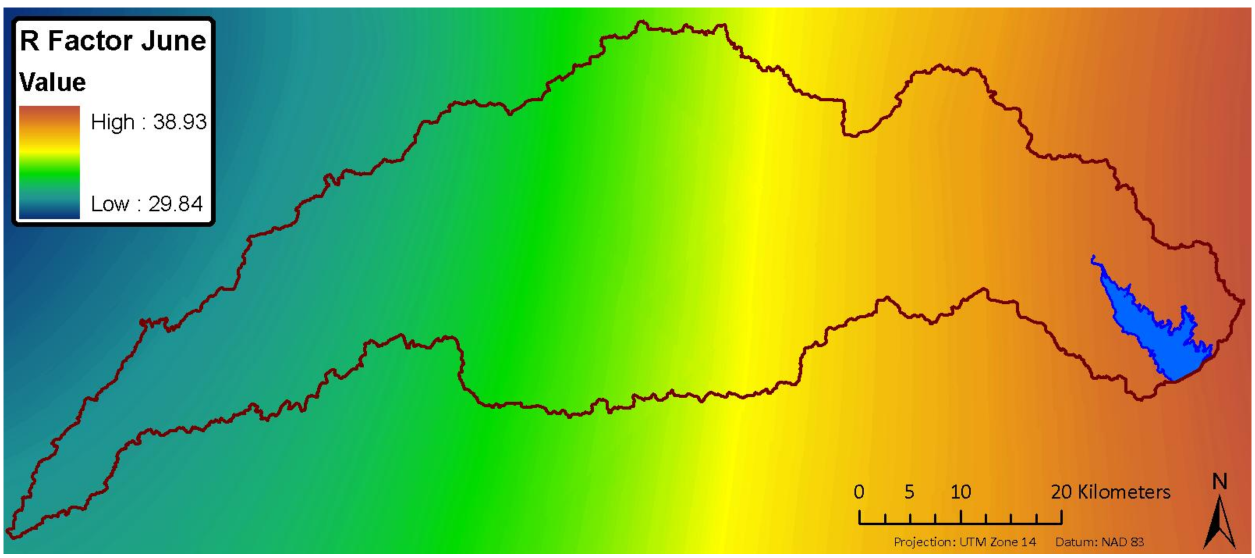


Figure 3-7. Rainfall intensity (R) factor for the Cheney Watershed in the month of June, interpolated from USDA-NRCS county R factor data.

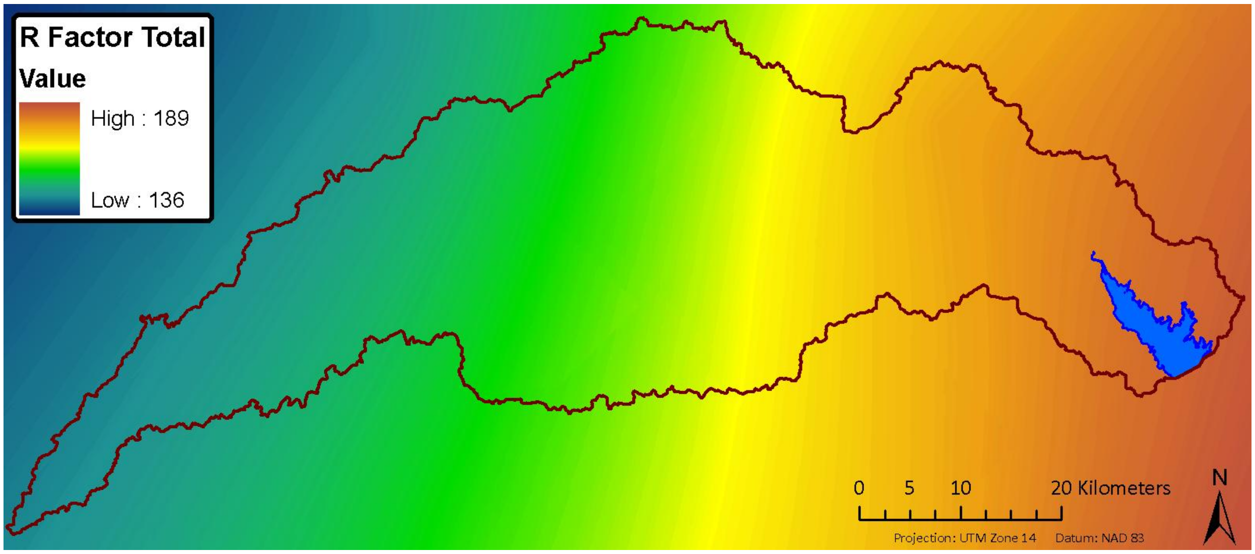


Figure 3-8. Annual rainfall intensity (R) factor for the Cheney Watershed, interpolated from USDA-NRCS county R factor data.

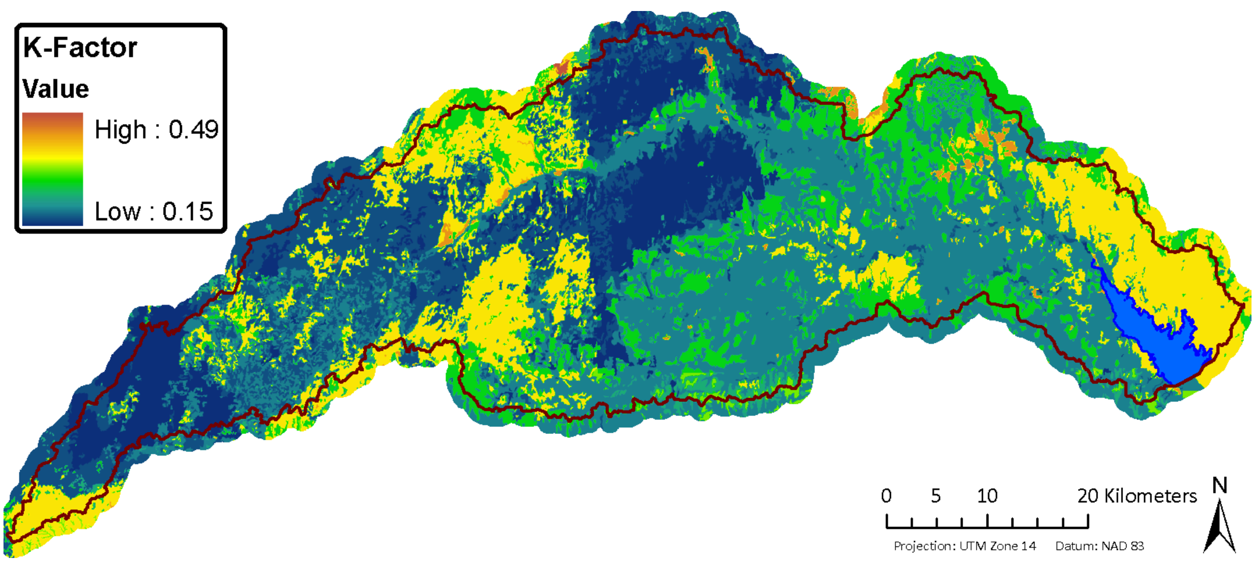


Figure 3-9. Soil Erosivity (K) Factor from the Soil Survey Geographic (SSURGO) database.

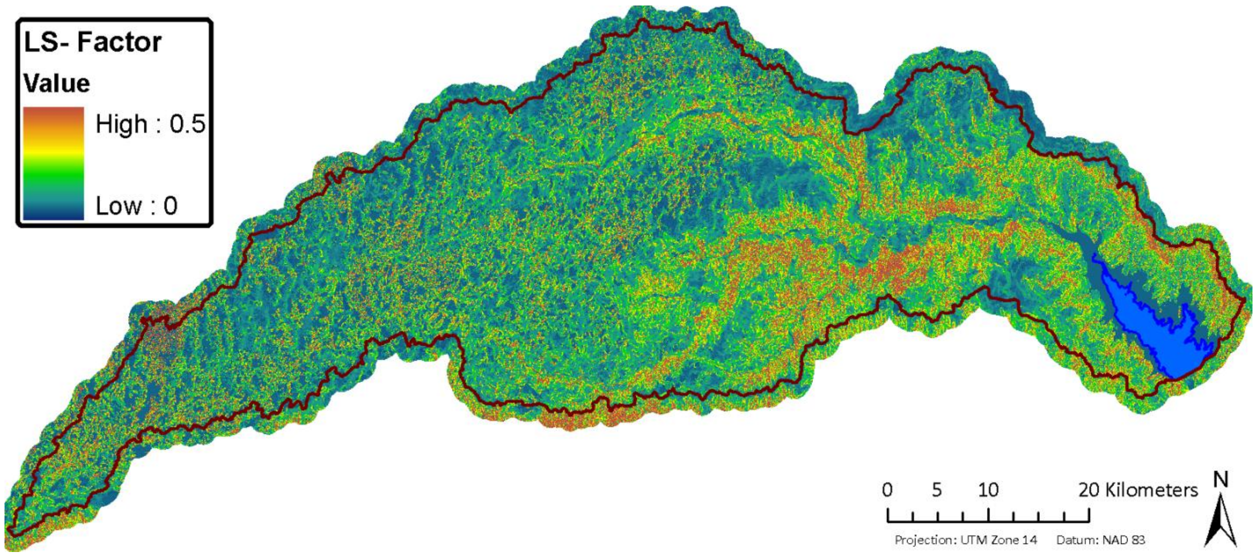


Figure 3-10. Topographic (LS) Factor generated by the Van Remortel (2004) **AML script with 10-meter Digital Elevation Model (DEM) from the National Elevation Dataset** (Gesch et al., 2002)**.**

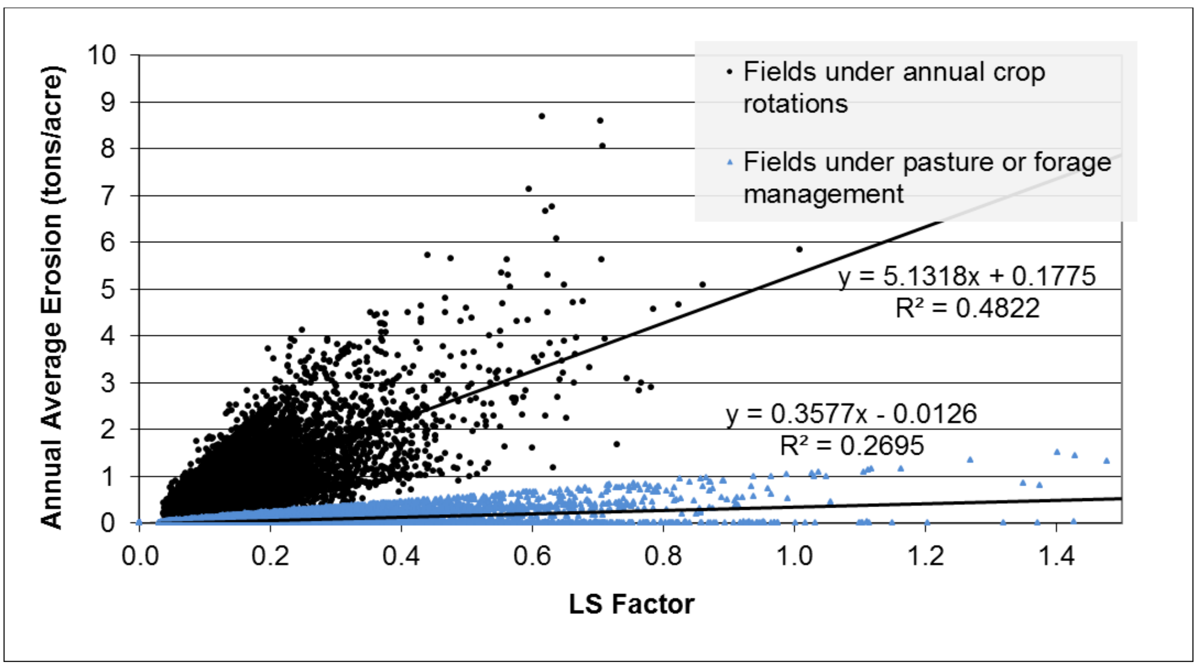


Figure 3-11. Landscape topography (LS) factor and the total erosion estimate for individual fields in the Cheney Watershed, categorized by landcover type.

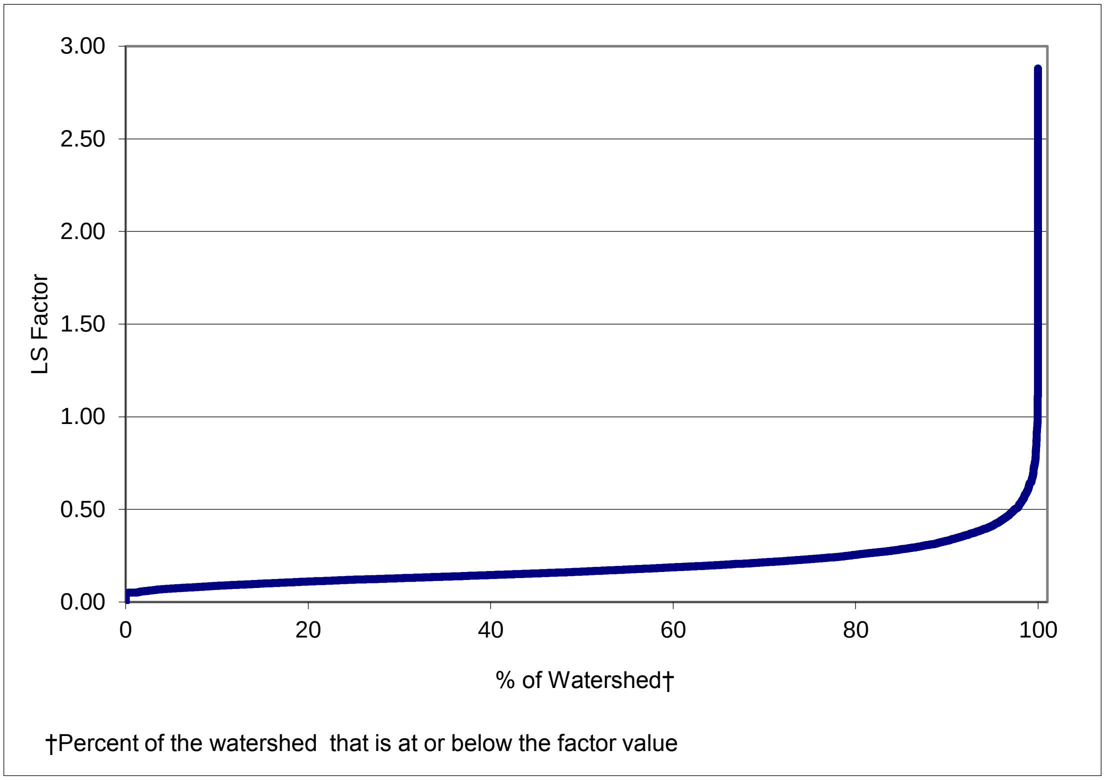


Figure 3-12. Topography (LS) Factor in the Cheney Watershed

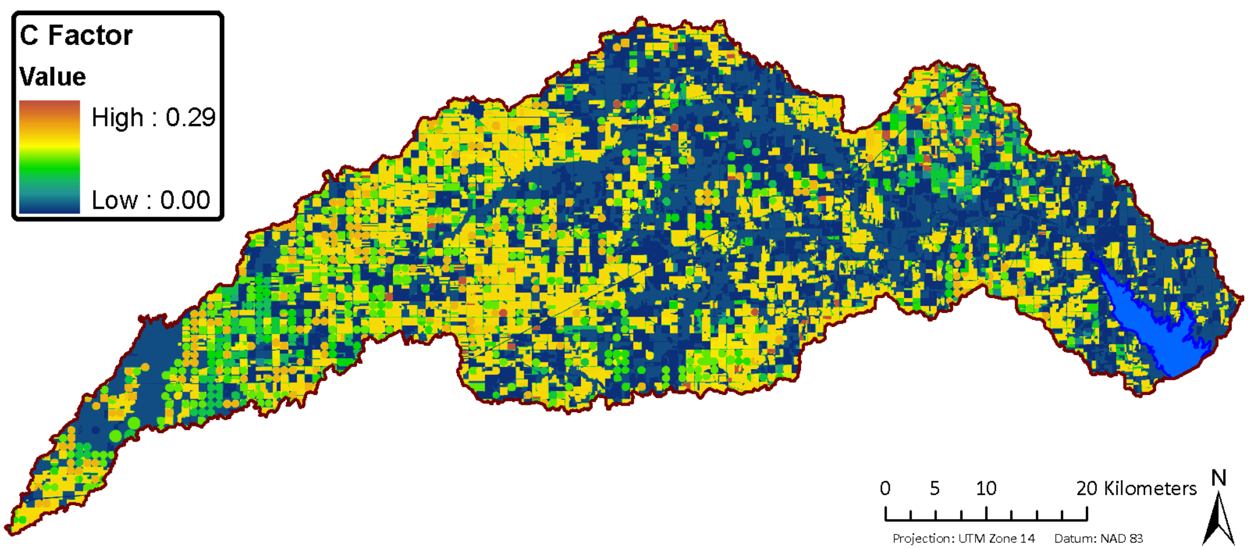


Figure 3-13. Cover-Management (C) Factor estimate. Landcover type determined from NASS Crop Data Layer, tillage practice determined by watershed survey, and annual factor values generated using RUSLE2.0 windows interface.

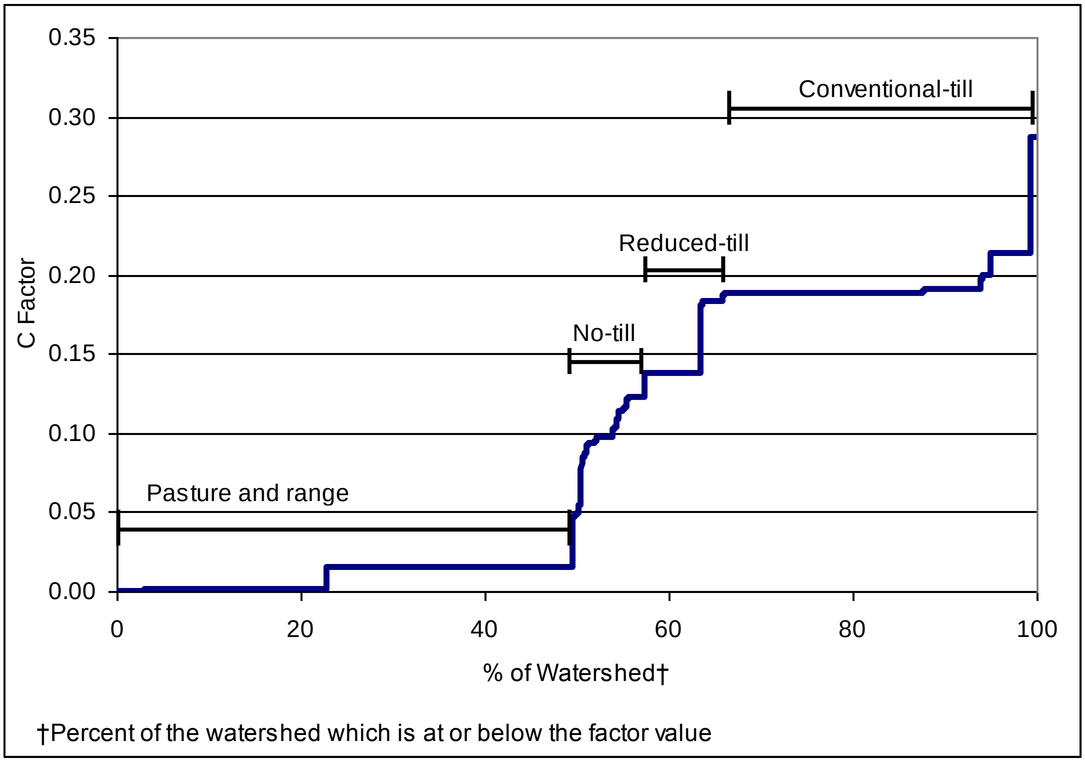


Figure 3-14. Cover (C) Factor in the Cheney Watershed

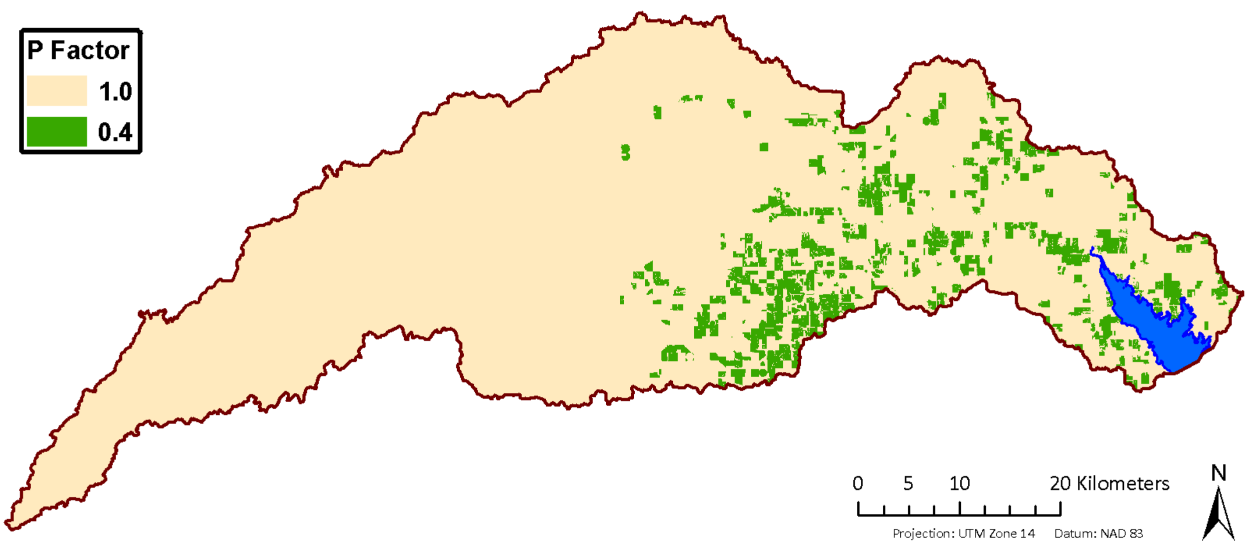


Figure 3-15. Conservation Practices (P) Factor determined by digitized locations of fields containing terraces and contour tillage as of 2006.

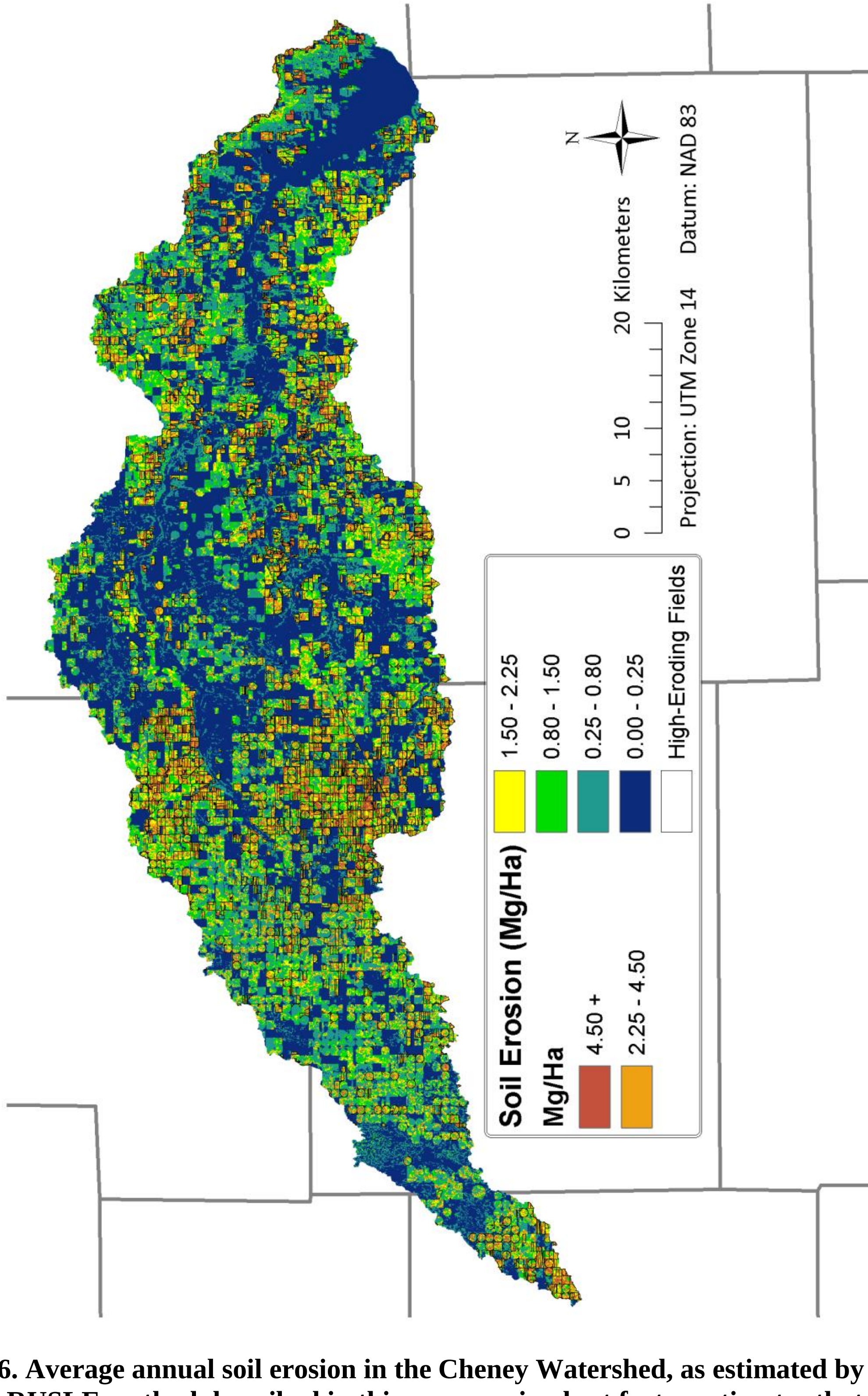


Figure 3-16. Average annual soil erosion in the Cheney Watershed, as estimated by the GIS-based RUSLE method described in this paper, using best factor estimates that represent current watershed conditions.

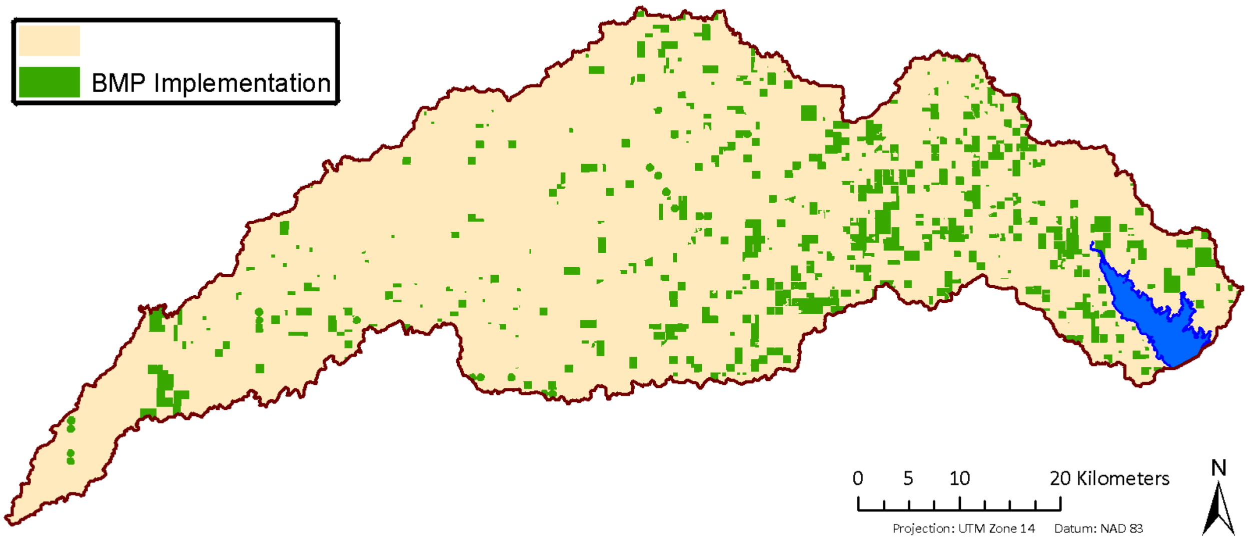


Figure 3-17. Known locations of Best Management Practices (BMPs) within the Cheney Watershed participating in one or more cost-sharing contracts.

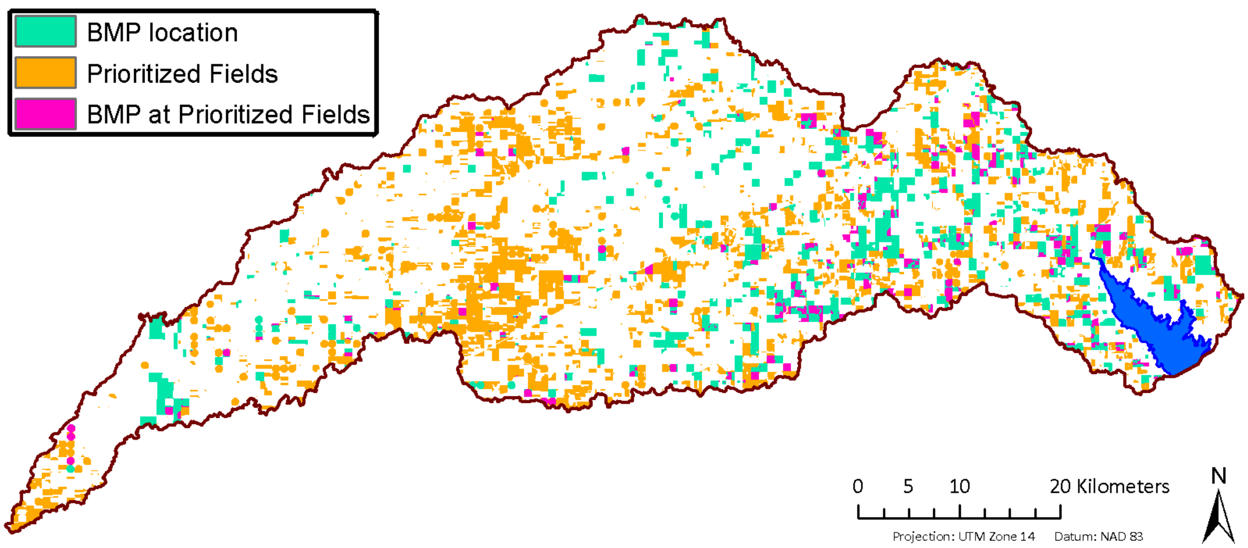


Figure 3-18. Overlap of BMP locations and prioritized high-erosion areas in the Cheney Watershed, with BMP locations from participating in one or more Environmental Quality Incentives Program (EQIP) cost-sharing contracts and fields prioritized by RUSLE model erosion estimates when approximating watershed conditions before BMPs were implemented.

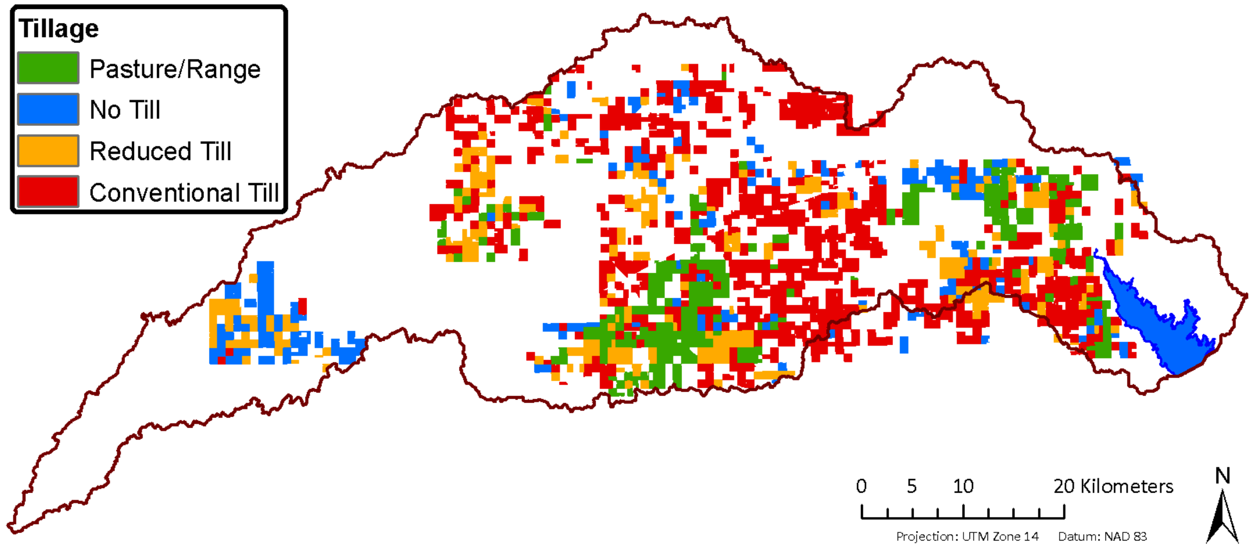


Figure 3-19. Tillage management by PLATT map parcel, as determined by input from local area producers.

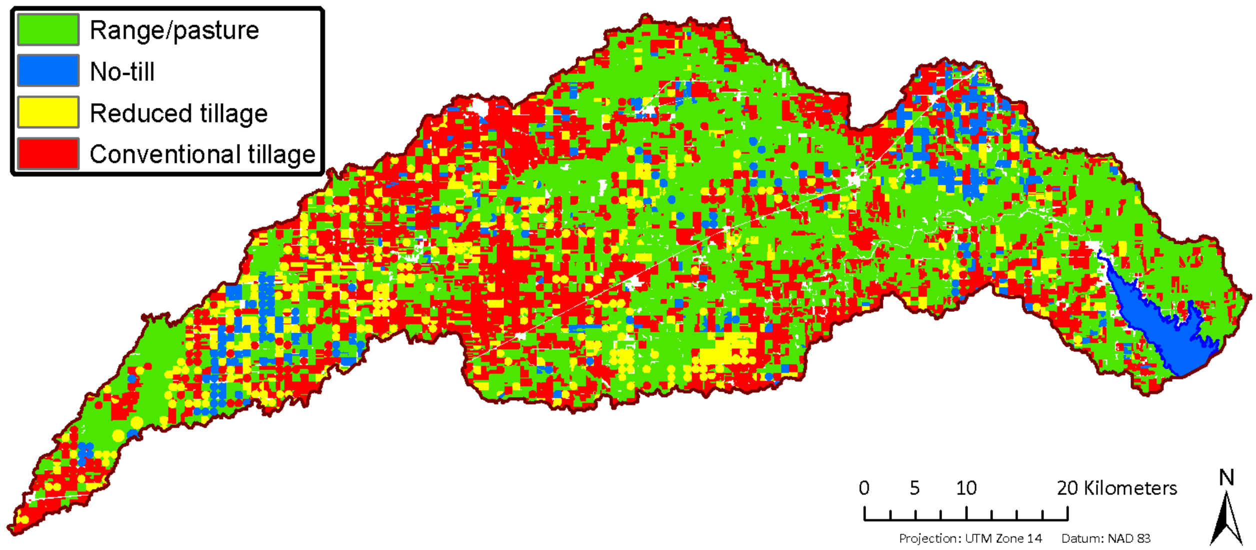


Figure 3-20. Tillage practices in the Cheney Watershed determined by producer input, roadside watershed survey, aerial imagery, and assumptions about common management practices.

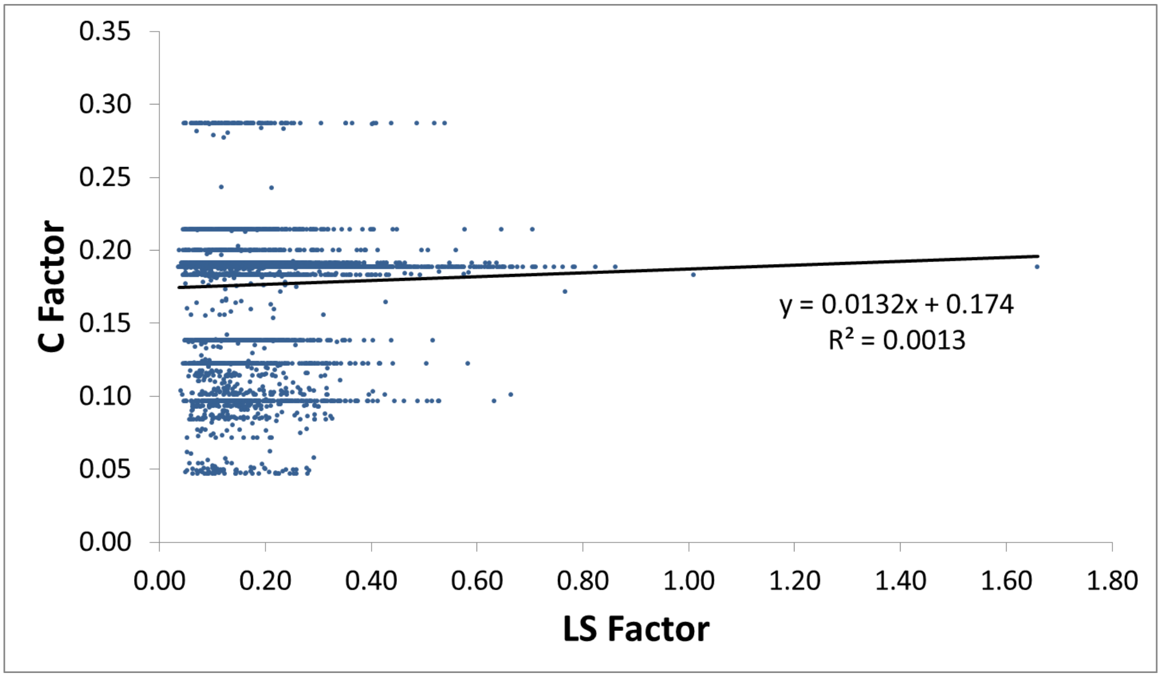


Figure 3-21. Per-field comparison of the topography (LS) and cover (C) Factors in the Cheney Watershed, excluding grassed areas.

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Appendix A - Landuse Reclassification

The 2006, 2007, 2008, and 2009 NRCS cropland data layers were used to determine the typical crops and crop rotations in CLW. This data was supplemented with a CRP data layer that was provided by the local watershed organization (Cheney Lake Watershed Inc.). The data processing steps for developing the final data layer are provided in detail in the following section.

Aggregating Landuse

Landuse data were extracted from an 8,100 km2 area in south central Kansas that encompassed Cheney Lake Watershed from each of the cropland data layers from 2006 through 2009. There were 42 different land uses defined for this region during the 4-yr time period (Table 1). These land uses were aggregated into the 11 primary land uses for the region (Table 2).

Identification of crop rotations

Crop rotations were identified by first multiplying the aggregated landuse classification values for 2007, 2008, and 2009 by 100, 10000, and 1000000 respectively. The four years of land use were then summed to create a unique 7 to 8 digit number that identified the 4-yr cropping sequence for each raster cell (56 m by 56 m). For example, if a cell was in a corn-soybean rotation beginning in 2006, then the cell value would start as 1 in 2006 and change to 3, 1, and 3 for 2007, 2008, and 2009 respectively. After the previously described calculations, that cell would have the value 3010301, where the two digits in the one and tens location indicate the crop in 2006, the digits in the hundreds and thousands location indicate the crop in 2007 and so forth. Because there were 11 aggregated landuses and 4 years, there were 11^4 (14,641) possible unique crop combinations, of which, 6,375 were represented in the final raster dataset.

The number of years that aggregate land uses appeared in each of the 6,375 crop combinations was used to classify each into one of 17 rotations according to a set of logical commands (Table 3). These commands were executed in the order listed in Table 3. Continuous soybean and wetlands represented less than 0.5% of the total land area (Table 3); therefore, these were combined with corn-soybean and forest rotations respectively. The other non-cultivated land (16) and the mixed cultivated land (17) were combined with forest and continuous wheat respectively. The Alfalfa-wheat rotation was dropped. Therefore, the resultant re-classification of the 6,375 crop combinations resulted in 12 rotations (Table 4).

Designation of CRP

Conservation Reserve Program (CRP) land was identified with a GIS layer identifying all fields within the Cheney Lake watershed boundaries under CRP contracts in 2006, which was provided by Cheney Lake Inc. The layer was converted into a raster format with either a 0 for non-CRP land or 201 for CRP land. This layer was added to the rotation grid. All cells with values above 200 were subsequently reclassified to 13. Therefore, the final landuse dataset consisted of 13 crop rotations and land uses (Table 5) with a very similar crop distribution to the average crop distributions from the 2006 to 2009 NRCS cropland data layers (Table 6).

Table 1. Land uses classified in the NRCS cropland data layers for the Cheney Lake Watershed and surrounding area for 2006, 2007, 2008, and 2009 with the accompanying reclassification. The area assessed is bounded by the UTM zone 14 coordinates 4216165, 476629, 615173, 4153333 for the top, left, right, and bottom respectively using the NAD83 projection.

Value†	NRCS landuse	Area 2006	Area 2007	Area 2008	Area 2009	Area 2006	Area 2007	Area 2008	Area 2009	ALU‡
		ha				%				
1	Corn	57914	62009	72535	69272	7.1	7.7	9.0	8.6	1
2	Cotton	1015	59	386	572	0.1	0.0	0.0	0.1	1
4	Sorghum	31205	25901	41280	44868	3.9	3.2	5.1	5.5	2
5	Soybean	31289	9915	27256	42087	3.9	1.2	3.4	5.2	3
6	Sunflower	143	19	101	188	0.0	0.0	0.0	0.0	2
21	Barley	3	75	17	35	0.0	0.0	0.0	0.0	4
23	Spring Wheat	70	41	0	0	0.0	0.0	0.0	0.0	4
24	Winter Wheat	247558	247669	256710	244079	30.6	30.6	31.7	30.1	4
25	Other	162	99	279	123	0.0	0.0	0.0	0.0	4
26	Wheat/DC Soybean	11049	5274	16243	12896	1.4	0.7	2.0	1.6	5
27	Rye	8001	3964	6088	5441	1.0	0.5	0.8	0.7	4
28	Oats	158	130	33	361	0.0	0.0	0.0	0.0	4
29	Millet	409	4	19	241	0.1	0.0	0.0	0.0	4
31	Canola	31	1	7	0	0.0	0.0	0.0	0.0	4
32	Flaxseed	0	0	0	0	0.0	0.0	0.0	0.0	4
36	Alfalfa	21784	16040	20365	17281	2.7	2.0	2.5	2.1	6
42	Dry Beans	4	0	0	0	0.0	0.0	0.0	0.0	3
43	Potatoes	6	0	0	0	0.0	0.0	0.0	0.0	3
44	Other Crops	1	0	8	3	0.0	0.0	0.0	0.0	4
53	Peas	0	0	1	3	0.0	0.0	0.0	0.0	3
57	Herbs	0	0	0	15	0.0	0.0	0.0	0.0	7
58	Clover/Wildflowers	0	0	1	0	0.0	0.0	0.0	0.0	7
59	Seed/Sod Grass	0	0	2	1	0.0	0.0	0.0	0.0	7
61	Fallow/CRP	104477	9782	13701	18508	12.9	1.2	1.7	2.3	7
62	Pasture/Range	28402	40167	263123	273206	3.5	5.0	32.5	33.7	7
63	Woodland	0	2	1	0	0.0	0.0	0.0	0.0	11
68	Apples	0	2	3	0	0.0	0.0	0.0	0.0	11
87	Wetlands	0	2	1	24	0.0	0.0	0.0	0.0	8
111	Open Water	7032	8123	10871	8038	0.9	1.0	1.3	1.0	9
121	Developed/Open Space	41076	44182	46534	45023	5.1	5.5	5.7	5.6	10
122	Developed/Low Intensity	6270	6337	6159	6759	0.8	0.8	0.8	0.8	10
123	Developed/Medium Intensity	1117	1118	1077	1101	0.1	0.1	0.1	0.1	10
124	Developed/High Intensity	489	451	517	432	0.1	0.1	0.1	0.1	10
131	Barren	19	47	75	29	0.0	0.0	0.0	0.0	10
141	Deciduous Forest	11293	9800	19865	13424	1.4	1.2	2.5	1.7	11
142	Evergreen Forest	10	2	2	1	0.0	0.0	0.0	0.0	11
143	Mixed Forest	15	1	1	2	0.0	0.0	0.0	0.0	11
152	Shrubland	11	2	8	13	0.0	0.0	0.0	0.0	11
171	Grassland Herbaceous	195949	314439	0	0	24.2	38.8	0.0	0.0	7
181	Pasture/Hay	403	0	0	391	0.0	0.0	0.0	0.0	7
190	Woody Wetlands	2589	4292	6526	5442	0.3	0.5	0.8	0.7	8
195	Herbaceous Wetlands	47	56	211	146	0.0	0.0	0.0	0.0	8

† raster value in the NRCS cropland data layer

‡ Aggregate landuse classification (Table 2)

Table 2. Primary land uses for aggregating the NRCS cropland data layers and the resultant landuse distributions.

Value[†]	Aggregate landuse	Area 2006	Area 2007	Area 2008	Area 2009	Area 2006	Area 2007	Area 2008	Area 2009	Area Average
		ha				%				
1	Corn	58929	62068	72921	69844	7.3	7.7	9.0	8.6	8.1
2	Sorghum	31349	25920	41380	45056	3.9	3.2	5.1	5.6	4.4
3	Soybean	31299	9915	27257	42090	3.9	1.2	3.4	5.2	3.4
4	Winter Wheat	256394	251983	263161	250284	31.7	31.1	32.5	30.9	31.5
5	Wheat/DC Soybean	11049	5274	16243	12896	1.4	0.7	2.0	1.6	1.4
6	Alfalfa	21784	16040	20365	17281	2.7	2.0	2.5	2.1	2.3
7	Pasture/Range	329231	364389	276827	292121	40.6	45.0	34.2	36.1	39.0
8	Wetlands	2636	4349	6737	5611	0.3	0.5	0.8	0.7	0.6
9	Open Water	7032	8123	10871	8038	0.9	1.0	1.3	1.0	1.1
10	Developed/Open Space	48971	52134	54362	53343	6.0	6.4	6.7	6.6	6.4
11	Deciduous Forest	11329	9808	19879	13440	1.4	1.2	2.5	1.7	1.7

† raster value used for reclassification

Table 3. Methods used to assign crop rotations to the Cheney Lake Watershed area based on aggregate land uses occurring during 2006 through 2009.

ID[†]	Rotation	Rule	Area (ha)	Area (%)
1	Wheat-Sorghum-Soybean	wheat, sorghum, and soybean are all present at least once	11448	1.4
2	Corn-Soybean	corn and soybean are both present and their sum is greater than any other single land use	43120	5.3
3	Wheat-Sorghum	wheat and sorghum are both present and their sum is greater than any other single land use	59471	7.3
4	Wheat-soybean	Wheat-double crop soybean is present in 2 or more years or wheat and soybean are both present and the sum of wheat-double-crop soybean, wheat, and soybean is greater than any other single land use	30325	3.7
5	Continuous Corn	corn is present in two or more years	46517	5.7
6	Continuous Sorghum	sorghum is present in two or more years	9089	1.1
7	Continuous Soybean	soybean is present in two or more years	1400	0.2
8	Continuous Wheat	wheat is present in two or more years	216912	26.8
9	Alfalfa-wheat	not used, not present in sufficient quantities	0	0.0
10	Continuous Alfalfa	alfalfa is present in two or more years	16395	2.0
11	Pasture/Range	Pasture/Range is > any other land use	291012	35.9
12	Wetlands	Wetlands > any other land use	2743	0.3
13	Open Water	Open water > any other land use	7429	0.9
14	Developed	Developed > any other land use	50971	6.3
15	Forest	Forest > any other land use	10173	1.3
16	Other non-cultivated land	non-cultivated landuse (7 through 11) occurs more often than cultivated land uses (1 through 6)	10867	1.3
17	Mixed Cultivation	everything else	2132	0.3

† Rotation ID, also the sequence in which reclassification rules were applied.

Table 4. Crop rotation and landuse reclassification based on NRCS cropland data layers

ID	Rotation	area (ha)	area (%)
1	Wheat-Sorghum-Soybean	11448	1.4
2	Corn-Soybean	44520	5.5
3	Wheat-Sorghum	59471	7.3
4	Wheat-soybean	30325	3.7
5	Continuous Corn	46517	5.7
6	Continuous Sorghum	9089	1.1
7	Continuous Wheat	219044	27.0
8	Continuous Alfalfa	16395	2.0
9	Pasture/Range	291012	35.9
10	Open Water	7429	0.9
11	Developed	50971	6.3
12	Forest	23782	2.9

Table 5. Final crop rotation landuse reclassification with CRP added as a landuse. Note, CRP land was only classified within the Cheney Lake boundaries.

ID	Rotation	area (ha)	area (%)
1	Wheat-Sorghum-Soybean	11424	1.4
2	Corn-Soybean	44383	5.5
3	Wheat-Sorghum	59362	7.3
4	Wheat-soybean	30277	3.7
5	Continuous Corn	46269	5.7
6	Continuous Sorghum	9023	1.1
7	Continuous Wheat	217876	26.9
8	Continuous Alfalfa	16365	2.0
9	Pasture/Range	247694	30.6
10	Open Water	7413	0.9
11	Developed	48911	6.0
12	Forest	22631	2.8
13	Conservation Reserve Program (CRP)	48374	6.0

Table 6. Crop distribution based on the final crop rotation landuse reclassification (Table 5).

Crop or Land use	Area (ha)	Area (%)	Initial crop distribution (%)†
Corn	68460	8.5	8.1
Sorghum	42474	5.2	4.4
Soybean	41100	5.1	3.4
Winter Wheat	266580	32.9	31.5
Wheat/DC Soybean	0	0.0	1.4
Alfalfa	16365	2.0	2.3
Pasture/Range	296069	36.6	39.0
Wetlands	0	0.0	0.6
Open Water	7413	0.9	1.1
Developed/Open Space	48911	6.0	6.4
Deciduous Forest	22631	2.8	1.7

† From Table 2

Appendix B - Cropping Systems Used to Calculate C-Factors in RUSLE 2.0

Add an explanation of what this Appendix contains…It can be brief. Refer to the Table if you use this explanation option

Table C.1 – Add a caption to this table. If you caption is complete enough, you will not need the previous explanation.

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
ID-01 Wheat Sorghum Soybean	10/17/2000	Cultivator, field 6-12 in sweeps				
	10/20/2000	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	2/20/2001	Fert applic. surface broadcast				
	6/29/2001	Harvest, killing crop 50pct standing stubble			2040	70
	7/10/2001	Plow, moldboard				
	7/25/2001	Disk, offset, heavy				
	8/25/2001	Chisel, st. pt.				
	9/20/2001	Cultivator, field 6-12 in sweeps				
	5/10/2002	Cultivator, field 6-12 in sweeps				
	5/22/2002	Cultivator, field 6-12 in sweeps				
	5/25/2002	Planter, double disk opnr	Sorghum, grain	60		
	10/20/2002	Harvest, killing crop 50pct standing stubble			1680	44
	10/30/2002	Disk, offset, heavy				
	11/15/2002	Chisel, st. pt.				
	4/20/2003	Disk, offset, heavy				
	5/17/2003	Cultivator, field 6-12 in sweeps				
	5/25/2003	Planter, double disk opnr	Soybean, group II, III and IV 30 in rows	30		
	10/10/2003	Harvest, killing crop 50pct standing stubble			554	28
ID-01 Wheat Sorghum Soybean (reduced till)	10/17/2000	Cultivator, field 6-12 in sweeps				
	10/20/2000	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	2/20/2001	Fert applic. surface broadcast				
	6/29/2001	Harvest, killing crop 50pct			2040	70

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
		standing stubble				
	5/10/2002	Disk, offset, heavy				
	5/22/2002	Cultivator, field 6-12 in sweeps				
	5/25/2002	Planter, double disk opnr	Sorghum, grain	60		
	10/20/2002	Harvest, killing crop 50pct standing stubble			1680	44
	4/20/2003	Disk, offset, heavy				
	5/17/2003	Cultivator, field 6-12 in sweeps				
	5/25/2003	Planter, double disk opnr	Soybean, group II, III and IV 30 in rows	30		
	10/10/2003	Harvest, killing crop 50pct standing stubble			554	28
ID-01 Wheat Sorghum Soybean (no till)	10/20/2000	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	2/20/2001	Fert applic. surface broadcast				
	6/29/2001	Harvest, killing crop 50pct standing stubble			2040	70
	5/25/2002	Planter, double disk opnr	Sorghum, grain	60		
	10/20/2002	Harvest, killing crop 50pct standing stubble			1680	44
	5/10/2003	Sprayer, pre-emergence				
	5/25/2003	Planter, double disk opnr	Soybean, group II, III and IV 30 in rows	30		
	10/10/2003	Harvest, killing crop 50pct standing stubble			554	28
ID-02 Corn Soybean	3/1/2001	Disk, tandem heavy primary op.				
	3/20/2001	Fert applic. anhyd knife 12 in				
	4/1/2001	Planter, double disk opnr	Corn, grain	112		
	9/10/2001	Harvest, killing crop 50pct standing stubble			3140	70
	5/1/2002	Disk, tandem heavy primary op.				
	5/10/2002	Cultivator, field 6-12 in sweeps				
	5/15/2002	Planter, double disk opnr	Soybean, southern 30 in rows	20		
	10/1/2002	Harvest, killing crop 50pct standing stubble			601	30
ID-02 Corn Soybean (no till)	3/20/2001	Fert applic. anhyd knife 12 in				
	4/1/2001	Planter, double disk opnr	Corn, grain	112		
	9/10/2001	Harvest, killing crop 50pct standing stubble			3140	70
	5/15/2002	Planter, double disk opnr	Soybean, southern 30 in	20		

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
			rows			
	10/1/2002	Harvest, killing crop 50pct standing stubble			601	30
ID-03 Wheat-Sorghum	7/15/2001	Sweep plow 20-40 in wide				
	8/15/2001	Sweep plow 20-40 in wide				
	9/15/2001	Sweep plow 20-40 in wide				
	5/1/2002	Sweep plow 20-40 in wide				
	5/15/2002	Cultivator, field 6-12 in sweeps				
	6/1/2002	Planter, double disk opnr w/fluted coulter	Sorghum, grain, South, shrt seasn hi density	60		
	10/10/2002	Harvest, killing crop 50pct standing stubble			7020	91
	6/1/2003	Disk, offset, heavy				
	7/15/2003	Sweep plow 20-40 in wide				
	8/15/2003	Sweep plow 20-40 in wide				
	9/15/2003	Cultivator, field 6-12 in sweeps				
	9/16/2003	Drill or air seeder, hoe opener in hvy residue	Wheat, winter, grain S.E.	40		
	6/15/2004	Harvest, killing crop 50pct standing stubble			3880	90
ID-03 Wheat-Sorghum (no till)	6/1/2002	Planter, double disk opnr w/fluted coulter	Sorghum, grain, South, shrt seasn hi density	60		
	10/10/2002	Harvest, killing crop 50pct standing stubble			2380	56
	9/16/2003	Drill or air seeder, hoe opener in hvy residue	Wheat, winter, grain S.E.	40		
	6/15/2004	Harvest, killing crop 50pct standing stubble			2040	70
ID-04 Wheat-Soybean (reduced till)	10/15/2001	Drill or airseeder, double disk, w/ fluted coulters	Wheat, winter, grain S.E.	30		
	6/15/2002	Harvest, killing crop 50pct standing stubble			1620	62
	6/15/2002	Disk, offset, heavy				
	6/15/2002	Cultivator, field 6-12 in sweeps				
	6/20/2002	Planter, double disk opnr w/fluted coulter	Soybean, southern 15-20 in rows	20		
	10/1/2002	Harvest, killing crop 50pct standing stubble			1000	45
	10/1/2002	Disk, offset, heavy				
	10/10/2002	Cultivator, field 6-12 in sweeps				
ID-04 Wheat-	10/15/2001	Drill or airseeder, double disk, w/ fluted coulters	Wheat, winter, grain S.E.	30		

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
Soybean (no till)	6/15/2002	Harvest, killing crop 50pct standing stubble			1620	62
	6/20/2002	Planter, double disk opnr w/fluted coulter	Soybean, southern 15-20 in rows	20		
	10/1/2002	Harvest, killing crop 50pct standing stubble			1000	45
ID-05 Continuous Corn	3/1/2001	Disk, tandem heavy primary op.				
	3/20/2001	Fert applic. anhyd knife 12 in				
	4/1/2001	Planter, double disk opnr	Corn, grain	112		
	9/10/2001	Harvest, killing crop 50pct standing stubble			3140	70
	3/1/2002	Disk, tandem heavy primary op.				
	3/20/2002	Fert applic. anhyd knife 12 in				
	4/1/2002	Planter, double disk opnr	Corn, grain	112		
	9/10/2002	Harvest, killing crop 50pct standing stubble			3140	70
	3/1/2003	Disk, tandem heavy primary op.				
	3/20/2003	Fert applic. anhyd knife 12 in				
	4/1/2003	Planter, double disk opnr	Corn, grain	112		
	9/10/2003	Harvest, killing crop 50pct standing stubble			3140	70
ID-05 Continuous Corn (no till)	3/20/2001	Fert applic. anhyd knife 12 in				
	4/1/2001	Planter, double disk opnr	Corn, grain	112		
	9/10/2001	Harvest, killing crop 50pct standing stubble			3140	70
	3/20/2002	Fert applic. anhyd knife 12 in				
	4/1/2002	Planter, double disk opnr	Corn, grain	112		
	9/10/2002	Harvest, killing crop 50pct standing stubble			3140	70
	3/20/2003	Fert applic. anhyd knife 12 in				
	4/1/2003	Planter, double disk opnr	Corn, grain	112		
	9/10/2003	Harvest, killing crop 50pct standing stubble			3140	70
ID-06 Continuous Sorghum	3/1/2001	Disk, offset, heavy				
	4/1/2001	Sweep plow 20-40 in wide				
	4/15/2001	Sweep plow 20-40 in wide				
	5/1/2001	Cultivator, field 6-12 in sweeps				
	5/10/2001	Planter, double disk opnr	Sorghum, grain South 135day	60		
	10/10/2001	Harvest, killing crop 50pct standing stubble			2390	56
	3/1/2002	Disk, offset, heavy				

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
	4/1/2002	Sweep plow 20-40 in wide				
	4/15/2002	Sweep plow 20-40 in wide				
	5/1/2002	Cultivator, field 6-12 in sweeps				
	5/10/2002	Planter, double disk opnr	Sorghum, grain South 135day	60		
	10/10/2002	Harvest, killing crop 50pct standing stubble			2390	56
	3/1/2003	Disk, offset, heavy				
	4/1/2003	Sweep plow 20-40 in wide				
	4/15/2003	Sweep plow 20-40 in wide				
	5/1/2003	Cultivator, field 6-12 in sweeps				
	5/10/2003	Planter, double disk opnr	Sorghum, grain South 135day	60		
	10/10/2003	Harvest, killing crop 50pct standing stubble			2390	56
ID-06 Continuous Sorghum (reduced till)	3/1/2001	Disk, offset, heavy				
	5/1/2001	Cultivator, field 6-12 in sweeps				
	5/10/2001	Planter, double disk opnr	Sorghum, grain South 135day	60		
	10/10/2001	Harvest, killing crop 50pct standing stubble			2390	56
	3/1/2002	Disk, offset, heavy				
	5/1/2002	Cultivator, field 6-12 in sweeps				
	5/10/2002	Planter, double disk opnr	Sorghum, grain South 135day	60		
	10/10/2002	Harvest, killing crop 50pct standing stubble			2390	56
	3/1/2003	Disk, offset, heavy				
	5/1/2003	Cultivator, field 6-12 in sweeps				
	5/10/2003	Planter, double disk opnr	Sorghum, grain South 135day	60		
	10/10/2003	Harvest, killing crop 50pct standing stubble			2390	56
ID-06 Continuous Sorghum (no till)	5/15/2001	Planter, double disk opnr w/fluted coulter	Sorghum, grain South 135day	65		
	10/10/2001	Harvest, killing crop 50pct standing stubble			2390	56
	5/15/2002	Planter, double disk opnr w/fluted coulter	Sorghum, grain South 135day	60		
	10/10/2002	Harvest, killing crop 50pct standing stubble			2390	56
	5/15/2003	Planter, double disk opnr w/fluted coulter	Sorghum, grain South 135day	60		
	10/10/2003	Harvest, killing crop 50pct standing stubble			2390	56

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
ID-07 Continuous Wheat	7/10/2000	Plow, moldboard				
	7/25/2000	Disk, offset, heavy				
	8/10/2000	Chisel, st. pt.				
	8/25/2000	Cultivator, field 6-12 in sweeps				
	9/12/2000	Cultivator, field 6-12 in sweeps				
	9/20/2000	Cultivator, field 6-12 in sweeps				
	9/25/2000	Cultivator, field 6-12 in sweeps				
	9/30/2000	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	12/15/2000	Sprayer, post emergence			0	0
	2/20/2001	Fert applic. surface broadcast				
	6/29/2001	Harvest, killing crop 50pct standing stubble			2040	70
	7/10/2001	Plow, moldboard				
	7/25/2001	Disk, offset, heavy				
	8/10/2001	Chisel, st. pt.				
	8/25/2001	Cultivator, field 6-12 in sweeps				
	9/12/2001	Cultivator, field 6-12 in sweeps				
	9/20/2001	Cultivator, field 6-12 in sweeps				
	9/25/2001	Cultivator, field 6-12 in sweeps				
	9/30/2001	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	12/15/2001	Sprayer, post emergence			0	0
	2/20/2002	Fert applic. surface broadcast				
	6/29/2002	Harvest, killing crop 50pct standing stubble			2040	70
	7/10/2002	Plow, moldboard				
	7/25/2002	Disk, offset, heavy				
	8/10/2002	Chisel, st. pt.				
	8/25/2002	Cultivator, field 6-12 in sweeps				
	9/12/2002	Cultivator, field 6-12 in sweeps				
	9/20/2002	Cultivator, field 6-12 in sweeps				
	9/25/2002	Cultivator, field 6-12 in sweeps				
	9/30/2002	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	12/15/2002	Sprayer, post emergence			0	0
	2/20/2003	Fert applic. surface broadcast				
	6/29/2003	Harvest, killing crop 50pct standing stubble			2040	70
ID-07 Continuous Wheat (reduced till)	7/10/2000	Plow, moldboard				
	7/25/2000	Disk, offset, heavy				
	8/10/2000	Chisel, st. pt.				
	8/25/2000	Cultivator, field 6-12 in sweeps				

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
	9/12/2000	Cultivator, field 6-12 in sweeps				
	9/30/2000	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	12/15/2000	Sprayer, post emergence			0	0
	2/20/2001	Fert applic. surface broadcast				
	6/29/2001	Harvest, killing crop 50pct standing stubble			2040	70
	7/10/2001	Plow, moldboard				
	7/25/2001	Disk, offset, heavy				
	8/10/2001	Chisel, st. pt.				
	8/25/2001	Cultivator, field 6-12 in sweeps				
	9/12/2001	Cultivator, field 6-12 in sweeps				
	9/30/2001	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	12/15/2001	Sprayer, post emergence			0	0
	2/20/2002	Fert applic. surface broadcast				
	6/29/2002	Harvest, killing crop 50pct standing stubble			2040	70
	7/10/2002	Plow, moldboard				
	7/25/2002	Disk, offset, heavy				
	8/10/2002	Chisel, st. pt.				
	8/25/2002	Cultivator, field 6-12 in sweeps				
	9/12/2002	Cultivator, field 6-12 in sweeps				
	9/30/2002	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	12/15/2002	Sprayer, post emergence			0	0
	2/20/2003	Fert applic. surface broadcast				
	6/29/2003	Harvest, killing crop 50pct standing stubble			2040	70
ID-07 Continuous Wheat (no till)	7/10/2000	Plow, moldboard				
	9/30/2000	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	12/15/2000	Sprayer, post emergence			0	0
	2/20/2001	Fert applic. surface broadcast				
	6/29/2001	Harvest, killing crop 50pct standing stubble			2040	70
	9/30/2001	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	12/15/2001	Sprayer, post emergence			0	0
	2/20/2002	Fert applic. surface broadcast				
	6/29/2002	Harvest, killing crop 50pct standing stubble			2040	70
	9/30/2002	Drill or airseeder, double disk	Wheat, winter, grain S.E.	40		
	12/15/2002	Sprayer, post emergence			0	0
	2/20/2003	Fert applic. surface broadcast				
	6/29/2003	Harvest, killing crop 50pct			2040	70

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
		standing stubble				
ID-08 Continuous Alfalfa	7/15/2001	Chisel, st. pt.			1800	63
	8/1/2001	Disk, tandem secondary op.				
	9/1/2001	Disk, tandem light finishing				
	9/10/2001	Harrow, spike tooth				
	9/14/2001	Cultipacker, roller				
	9/15/2001	Drill or airseeder, double disk	alfalfa, fall seed senes to yr2 regrowth	1		
	5/15/2002	Harvest, hay, legume	alfalfa, yr2 regrowth after cutting	1	83.5	4.5
	6/15/2002	Harvest, hay, legume	alfalfa, yr2 regrowth after cutting	1	213	11
	8/1/2002	Harvest, hay, legume	Alfalfa, yr2 regrowth after cutting	1	270	14
	9/15/2002	Harvest, hay, legume	Alfalfa, yr2 senes to yr3 regrowth	1.5	270	14
	5/15/2003	Harvest, hay, legume	alfalfa, yr3 regrowth after cutting	1	321	16
	6/15/2003	Harvest, hay, legume	Alfalfa, yr3 regrowth after cutting	1	213	11
	8/1/2003	Harvest, hay, legume	Alfalfa, yr3 regrowth after cutting	1	270	14
	9/15/2003	Harvest, hay, legume	Alfalfa, yr3 senes to yr4 regrowth	1.5	270	14
	5/15/2004	Harvest, hay, legume	Alfalfa, yr4 regrowth after cutting	1	321	16
	6/15/2004	Harvest, hay, legume	Alfalfa, yr4 regrowth after cutting	1	213	11
	8/1/2004	Harvest, hay, legume	Alfalfa, yr4 regrowth after cutting	1	270	14
	9/15/2004	Harvest, hay, legume	Alfalfa, yr4 senes to yr5 regrowth	1.5	270	14
	5/15/2005	Harvest, hay, legume	Alfalfa, yr4 regrowth after cutting	1	321	16
	6/15/2005	Harvest, hay, legume	Alfalfa, yr4 regrowth after cutting	1	213	11
	8/1/2005	Harvest, hay, legume	Alfalfa, yr4	1	270	14

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
			regrowth after cutting			
	9/15/2005	Harvest, hay, legume	Alfalfa, yr4 senes to yr5 regrowth	1.5	270	14
	5/15/2006	Harvest, hay, legume	Alfalfa, yr4 regrowth after cutting	1	321	16
	6/15/2006	Harvest, hay, legume	Alfalfa, yr4 regrowth after cutting	1	213	11
	8/1/2006	Harvest, hay, legume	Alfalfa, yr4 regrowth after cutting	1	270	14
	9/15/2006	Harvest, hay, legume	Alfalfa, yr4 senes to yr5 regrowth	1.5	270	14
ID-09 Pasture/range (continuous graze)	6/25/2000	Plow, moldboard			1000	43
	6/28/2000	Disk, tandem secondary op.				
	6/30/2000	Harrow, spike tooth				
	7/2/2000	Land plane				
	7/4/2000	Drill or airseeder, double disk	Tall fescue, spring seed 1st year	3000		
	4/1/2001	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	158	8.4
	5/1/2001	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	113	6.1
	6/1/2001	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	7/1/2001	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	8/1/2001	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	9/1/2001	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	10/1/2001	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	11/1/2001	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	4/1/2002	Graze, rotational	Tall fescue	1500	56.3	3.1

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
			pasture, regrowth after grazing			
	5/1/2002	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	113	6.1
	6/1/2002	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	113	6.1
	7/1/2002	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	8/1/2002	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	75	4.1
	9/1/2002	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	10/1/2002	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	56.3	3.1
	11/1/2002	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	4/1/2003	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	75	4.1
	5/1/2003	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	113	6.1
	6/1/2003	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	113	6.1
	7/1/2003	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	8/1/2003	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	75	4.1
	9/1/2003	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	10/1/2003	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	56.3	3.1
	11/1/2003	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	4/1/2004	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	75	4.1
	5/1/2004	Graze, rotational	Tall fescue pasture, regrowth	1500	113	6.1

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
			after grazing			
	6/1/2004	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	113	6.1
	7/1/2004	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	8/1/2004	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	75	4.1
	9/1/2004	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	10/1/2004	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	56.3	3.1
	11/1/2004	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	4/1/2005	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	75	4.1
	5/1/2005	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	113	6.1
	6/1/2005	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	113	6.1
	7/1/2005	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	8/1/2005	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	75	4.1
	9/1/2005	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	10/1/2005	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	56.3	3.1
	11/1/2005	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	4/1/2006	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	75	4.1
	5/1/2006	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	113	6.1
	6/1/2006	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	113	6.1

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
	7/1/2006	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	8/1/2006	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	75	4.1
	9/1/2006	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	10/1/2006	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	56.3	3.1
	11/1/2006	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	4/1/2007	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	75	4.1
	5/1/2007	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	113	6.1
	6/1/2007	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	113	6.1
	7/1/2007	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	8/1/2007	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	75	4.1
	9/1/2007	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	10/1/2007	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	56.3	3.1
	11/1/2007	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	4/1/2008	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	75	4.1
	5/1/2008	Graze, rotational	Tall fescue pasture, regrowth after grazing	1500	113	6.1
	6/1/2008	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	113	6.1
	7/1/2008	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
	8/1/2008	Graze, rotational	Tall fescue	750	75	4.1

Landcover/ tillage type	Date	Operation	Vegetation	Yield (# harv. Units)	Cover matl add/remove, lb/ac	Cover from addition, %
			pasture, regrowth after grazing			
	9/1/2008	Graze, rotational	Tall fescue pasture, regrowth after grazing	750	56.3	3.1
	10/1/2008	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	56.3	3.1
	11/1/2008	Graze, rotational	Tall fescue pasture, regrowth after grazing	1000	75	4.1
ID-13 CRP (warm season ungrazed)	1/1/2000	begin growth	Permanent cover not harvested\Grass, warm season permanent, not harvested	3		