Landscape processes and management practices affecting phosphorous loss

by

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Abstract

Phosphorous (P) loss from non-point agricultural sources is an important factor that affects the deterioration of surface water quality. Excessive P inputs can exacerbate eutrophication and toxic algal blooms, thus leading to greater water treatment costs and reduced recreational value of water bodies. To reduce non-point source P loss, we need to go back to the source and help farmers and ranchers make better land management decisions. One tool that can help is the P index. The P Index rating can provide information on major P loss pathways and help producers adjust land management decisions to minimize P loss from a specific field. Currently, the Kansas P index does not meet USDA-NRCS standards as listed in Title 190, which was updated in 2017. Among other items, updating the P index will require estimates of long-term annual runoff for soils and cropping systems across Kansas. Additional research is needed to identify a method of estimating runoff volume and to update the P index to current standards.

Soil erosion presents one of the greatest concerns to most P mitigation programs worldwide because the majority of P loss occurs with eroded sediments. Ephemeral gully erosion is a type of erosion that can remove large quantities of sediment and is particularly difficult to control in no-till agriculture. Ephemeral gullies can develop in areas of concentrated flow within cultivated crop fields. Additional research is needed to identify best management practices that can reduce ephemeral gully erosion in no-till systems.

The objectives of this research are to i) develop and evaluate a new approach to estimate long-term average annual runoff from agricultural fields, ii) develop a revised P index, and iii) investigate the effect of cover crops on ephemeral gully erosion.

Two methods were evaluated to estimate long-term average annual runoff: use of the standard curve number (CN) approach with a daily time-step on long-term historical datasets (method 1) or a modified CN approach that uses long-term average annual rainfall and assumes an exponential distribution of rainfall (method 2). Both methods were calibrated and evaluated with edge-of-field monitoring data. The calibrated method 2 results revealed an $R^2 = 0.88$, NSE = 0.56 and when validating this method $R^2 = 0.66$, NSE = 0.54 indicating that this model had good model performance and that no further calibration was needed.

The proposed P index is structured as a component P-index. Inputs were updated to include estimated average annual runoff calculated with the previously described modified CN approach. The coefficients for the P index components were developed through multiple linear regression with SAS proc mixed using a database of P loss estimates for 1360 cropping scenarios. Validation of the revised P index was conducted by relating the P index values to measured P loss data using both annual and summarized data from edge-of-field runoff experiments located in Riley, Crawford, Franklin, and Geary County. Coefficients to the revised P index were all significant at $p<0.0001$. Results showed that the proposed P index improved the relationship between the P index and P loss from $R^2= 0.41$ to $R^2= 0.82$ and validation of revised P index to the current index improved relationship between the P index and P loss from $R^2= 0.09$ to $R^2= 0.71$ using annual data and from $R^2= 0.73$ to $R^2= 0.85$ using average annual P loss data. The revised P index had improved model performance and would be a sufficient model to use for the Kansas P index.

The final portion of this research was conducted in the summers of 2021 and 2022 at the Kansas Agricultural Watershed (KAW) field laboratory located near Manhattan, KS, USA. Ephemeral gully length, depth and width were measured and used to determine the volume of sediment lost through ephemeral gully erosion. Elevation data from an unmanned aerial vehicle (UAV) was collected in fall of 2016, 2020, and 2022 to determine ephemeral gully formations using ArcGIS Pro to compare elevation data. Results did not identify a significant effect of cover crops on ephemeral gully erosion. This could be due to insufficient ephemeral gully erosion in the watersheds at the KAW field lab. Furthermore, Elevation data collected by aerial imagery did not prove useful in quantifying the soil loss from ephemeral gullies.

Results from this research will help producers and land managers more accurately evaluate effects of agricultural management systems on the risk of P loss to surface water using a revised P-index. The revised P index will also help producers identify the mechanisms responsible for P loss from their fields and thereby select conservation practice systems that can most effectively reduce those P losses.

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Obtaining my masters has been a unique experience and something I will always look back on. I am very grateful to be given the opportunity to work on the Phosphorus Index and look forward to how my research can be used in the future.

I want to give a shout out to Dr. Michel Ransom and his immense support throughout my undergraduate and graduate career. The knowledge and wisdom I learned from him will always be ingrained in my head. As Mickey always said, “Its complex”, I apply this to most things when dealing with academia. Next, I want to give a huge thank you to Dr. Clenton Owensby and Lisa Auen for their support throughout my time at Kansas State University. I had the privilege of working cattle and burning pastures with them out at Rannells Ranch, experiences I will never forget. I will always remember the fun times I had out at the Rennels as it gave me an escape from school, a place I could hike and take my dogs and listen to amazing stories from Dr. Owensby. Truly some of my best memories with K-State are with Dr. Owensby, so thank you!

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Dedication

I would like to dedicate my research and thesis to my dad (Kurt), mom (Laura) and my brother (Jack Kortokrax). I would not have been able to complete my thesis without their support. Finally, I want to dedicate this to my two dogs (Junebug and Olive). Without them I would not have been able to finish my thesis. They are my world and I do not know where I would be today without them.

He said, "Write it on your heart that every day is the best day in the year. He is rich who owns the day, and no one owns the day who allows it to be invaded with fret and anxiety. Finish every day and be done with it. You have done what you could. Some blunders and absurdities, no doubt crept in. Forget them as soon as you can, tomorrow is a new day; begin it well and serenely, with too high a spirit to be cumbered with your old nonsense. This new day is too dear, with its hopes and invitations, to waste a moment on the yesterdays."

- *Ralph Waldo Emerson*

"Do not go where the path may lead, go instead where there is not a path and leave a trail."

- *Ralph Waldo Emerson*

Chapter 1 - Literature Review on Landscapes Processes and Management Practices Affecting P Loss from Agriculture.

Introduction

Phosphorus (P), an important nutrient for crop and livestock production, may be transported off agricultural fields and increase the eutrophication of fresh water, which is currently one of the most serious water quality issues in the United States (Sharpley et al., 2003). For example, in August 2014 Toledo's drinking water supply was shut down for many days due to hazardous algal blooms in Lake Erie, highlighting the relationship between nutrient enrichment (especially P) and water quality impairment (Stow et al., 2015). Nutrients can occur naturally in water, but elevated concentrations are usually due to human activities, such as land use and associated fertilizer applications, as well as animal manure in upstream watersheds, all of which can contribute to increased P concentrations in runoff from agricultural settings (Dubrovsky, N.M., &Hamilton, P.A., 2010). Several management approaches at the source and during transport into downstream water resources are necessary to decrease agricultural nutrient input to surface waterways (Osmond et al., 2017). Many states have developed guidelines for P application and watershed management in response to rising water quality issues based on tools that rate the potential for P loss in agriculture runoff (Sharpley et al., 2003). These tools are known as P Indices and many states have invested significant resources to identify the components influencing P loss in order to reliably estimate the relative risk of P loss and incentivize conservation management (Sharpley et al., 2012). Certain inputs to the Kansas P-Index are categorical and do not zero out potential affect the overall P Risk loss value. Revising the Kansas P index would improve our ability to identify fields at high risk for P loss.

One challenging P transport process that has been difficult to correctly estimate and manage is erosion associated with ephemeral gullies in no-till crop fields. Identifying additional best management practices to control ephemeral gully erosion in no-till fields will help producers decrease P loss through erosion. Cover crops have the potential to help decrease gullies from forming, thereby reducing sediment and P loss from crop fields. Producers will benefit from improved tools and methods to help identify water quality problems and identify the best management practices to reduce these risks and issues.

Background

P Index History

The USDA–NRCS revised the Nutrient Management Conservation Practice Standard (590 standard) in 2011, in part to address the major disparities in P Index ratings and recommendations across state lines, as well as the concern that soil-test P concentrations and runoff P losses had remained unchanged (Bolster et al., 2012; Osmond et al., 2017; Sharpley et al., 2003). There are three different structures for P indices: additive, multiplicative, and component (Osmond et al., 2017). For additive P indices, the weighted transport and source factors are summed together (Osmond et al., 2017). The Multiplicative P indices sum source and transport components separately then multiply the sum of source components with the sum of transport components to get the final P Index value (Osmond et al., 2017). Finally, component indices are constructed as a series of P loss components, where each component is computed as the product of transport and source factors. Components are multiplied by weighting coefficients and summed to produce the final P-Index rating. (Osmond et al., 2017).

Currently, the Kansas P index is multiplicative, but there is interest in developing a component index for Kansas (Nelson & Shober, 2012). The general multiplicative P index equation is written, where the P-index is the product of P source factors (*S*) and P transport factors (*T*) (Eq. [1.1]), with *n* source factors and *m* transport factors, βi is the weighting factor for the *ith* source factor (*S*), and χj is the weighting factor for the *jth* transport factor (*T*) (Nelson & Shober, 2012).

Equation 1.1: Multiplicative Phosphorus Index

$$\mathrm{PI}_m = \left(\sum_{i=1}^{n} \beta_i S_i\right)\left(\sum_{j=1}^{m} \chi_j T_j\right)$$

....[Eq. 1.1]

The multiplicative index used in Kansas has source characteristics of soil test P, annual average fertilizer P application rate, P fertilizer application method, annual average organic P application rate organic P source application method. The transport characteristics include soil erosion, soil runoff classification, proximity of fields to perennial streams (perennial surface water bodies or intermittent streams), furrow irrigation erosion, and sprinkler system erosion/runoff. The inputs for fertilizer P application rate (lb P_2O_5 ac^{-1}), organic P application rate (lb P_2O_5 ac^{-1}), and erosion (ton ac^{-1}) are continuous variables with coefficients of 0.1, 0.1, and 2 respectively. All other inputs are categorical variables with coefficients of 1.

The P-Index is used in two primary situations in Kansas. One example is farm programs like NRCS conservation practice 590 standards where farmers are required to submit a P-Index risk assessment yearly to prove they are maintaining their nutrient requirements allowing them to stay within that cost share program. Another example more impacted by the P-Index are concentrated animal feeding operations (CAFOs). CAFO's need to create and implement an authorized nutrient management plan (NMP) as a requirement for National Pollutant Discharge Elimination System (NPDES) Permit coverage and to comply with the Environmental Protection

Agency's (EPA's) 2008 Final Rule for CAFOs (USDA & NRCS, 2009). Both of these programs use the P-Index to help mitigate P loss in these systems.

The P index used in different agricultural sectors as talked about prior, also has implementation impacts that can cause cost and operation implications of many farms and CAFO's in the state of Kansas. For example, with crop operations, best management practices with proper use of the 4 R nutrient management and university soil fertility recommendation are compatible with establishing nutrient balance within a field (Pease, 2023). Cost can be saved on fertilizer input if P fertilizer application and crop absorption are balanced (Pease, 2023). On top of this if a farmer chooses not to participate in the farm programs and follow 590 standards then that farmer simply just does not have to join that program. Another example is animal operation which can cost a lot of extra money to maintain and implementing practices to lower the risk of P loss (Pease, 2023). CAFO's do not get a choice like farmers as if they chose not to comply with the EPA by following a NMP they will not receive a permit and will have to stop their operations. Therefore, alternative strategies will be necessary to maintain a phosphorus balance for animal activities (Pease, 2023). Examples of strategies include moving manure off the farm, securing more land for manure applications or reducing animal density on the farm (Pease, 2023). To reduce P loss risk at both farm and animal operations proper implementation of best management practices and nutrient management of manure will be required.

Deficiencies in the KS P Index

There are a few deficiencies in the current Kansas P-Index. The original authors of the P-index recognized that the weighting factors (stated above) were arbitrarily selected, and indicated that caution should be taken when developing ratings for these values (J. L. Lemunyon & R. G. Gilbert, 1993). Secondly, the Kansas P index uses soil runoff classes (very low, low, medium, high, very high) corresponding to categorical inputs (0, 2, 4, 8, and 16 respectively) to estimate the risk of P transport by runoff rather than using a quantitative estimate of runoff. Third, Soil Test P components are not continuous. Risk categories are assigned based on Bray P1 or Mehlich III Soil P Test (< 25 mg kg^{-1}, 26 – 50 mg kg^{-1}, 51 – 75 p mg kg^{-1}pm, 76 – 200 mg $kg^{-1}$and >200 mg kg^{-1}) or Olsen Soil P Test (< 16 mg kg^{-1}, 17 – 31 mg kg^{-1}, 32 – 47 mg kg^{-1}, 48 – 62 mg $kg^{-1}$and > 62 mg kg^{-1}) that correspond to categorical inputs of 1, 2, 4, 8, and 10 respectively. Because values are not continuous, increasing soil test P above 200 ppm Mehlich III or Bray I (or > 62 ppm Olsen) does not affect the P index result. This can be problematic because soils with dramatically increased soil test P (e.g., 2000 ppm), which may have increased environmental risk, have the same index rating as soils with 201 ppm soil test P.

New NRCS Standards

In 2017 The National Instruction for Nutrient Management Policy Implementation (Title 190) was amended to include minimum criteria for P indices, known as section D (Minimum Criteria for State P-Index Tools), which has six different criteria (NRCS & USDA, 2017). The current Kansas P index meets criteria *(i), (ii) (V)* if it was employed correctly by the staff. It is debatable whether the Kansas P-Index meets criteria *(iii),* which reads:

(iii) *"A P index tool must demonstrate that risk increases with increasing runoff, erosion, STP, application rate, and also depends on method of application (surface application versus injection/incorporation), and leaching (when leaching is applicable) factors"* (NRCS & USDA, 2017).

Increased runoff would not be directly reflected in the P index because runoff is not a direct factor. However, a runoff rating is used to indicate runoff, and increasing the runoff classification does raise the risk. Soil Test Phosphorous (STP) is also listed as a category variable. As a result, raising STP increases the P index up to the highest category (200 ppm), but after 200 ppm, increasing STP has no effect on the P index. We are unsure if the current Kansas P index meets criteria *(iv)*, which reads:

(iv) *"A P index tool must include the following risk categories:*

a. Low risk.—P can be applied at rates greater than crop removal not to exceed the nitrogen requirement for the succeeding crop.

b. Moderate risk.—P can be applied not to exceed the crop removal rate.

c. High risk.— P can be applied not to exceed the crop removal rate ***if*** *the following requirements are met: A soil P drawdown strategy has been implemented; A site assessment for nutrients and soil loss has been conducted to determine if mitigation practices are required to protect water quality"*(NRCS & USDA, 2017).

According to the Kansas index's description of the categories and the soil test interpretation table, P-based manure treatments are allowed for "high risk" sites without the need for a P removal strategy. However, we are unsure of how this is implemented in practice by the NRCS. The current Kansas P index does not meet criteria *(vi)*, which reads:

(vi) *"The P-Index must "zero-out" at some point (environmental threshold). There is a point above which the risk of P loss from a field is too great to warrant the application of P in any form. States must establish an upper limit of STP above which manure must not be applied regardless of the P-Index results"*(NRCS & USDA, 2017).

Since there is no regulation stopping farmers and ranchers from adding more P to the soil, as long as a producer can manage a field with a medium risk of P loss, they can continue to apply P regardless of the soil test, even if the soil test P continues to rise. Although producers would apply at crop P removal, due to variability in manure analysis and application equipment, the soil test P could increase if the yield goal were not met or if the application rate were higher than planned.

Kansas P Index Transition

Because of these deficiencies, the Kansas P index needs to be updated and this update is an opportunity to consider converting to a component index. The component index equation (PI_c) is a modification of the multiplicative index, each one of the components represents a specific combination of P sources and interconnected transport processes (Eq. [2]) (Bolster et al., 2012). This equation ultimately demonstrates the concept that P transport pathways may have different interactions with the P sources, where there are *n* source factors and *m* transport factors with βij as the weighting factor for the interaction of the *ith* source factor (*S*) and *jth* transport factor (*T*) (Nelson & Shober, 2012). Ultimately, our goal is to find a method that calculates a value for each input for each component for both our source (S) and transport (*T*) factors. Once we have these values, we will need to compare our P risk value with our P loss value to produce a coefficient value (βij) that will go along with each of our components (*S*) and (*T*).

Equation 1.2: Component Phosphorus Index

$$\mathrm{PI}_c = \sum_{i=1}^{n}\sum_{j=1}^{m}\beta_{ij}S_iT_j$$ .... [Eq. 1.2]

Benefits of a Component P-Index

The main benefit of a Component P-Index would be that the components are independent of each source and interconnecting transport value. If we take a simple example using two source inputs (phosphorous rate (*Prate*) and soil test phosphorous (*STP*)) and two transport sources (runoff (*R*) and sediment loss (*Sed.*)), the Kansas phosphorus index would look like Equation 1.3.

Equation 1.3: Example of the Multiplicative Phosphorus Index

$$Ploss = \beta_1 \times [\beta_2(Prate) + \beta_3(STP)] \times [\beta_4(R) + \beta_5(Sed.)]$$ ....[Eq. 1.3]

Equation 1.3 can be expanded to look much like a component P-Index by multiplying the source and transport factors (Equation 1.4).

Equation 1.4: Example of the Multiplicative Phosphorus Index Expanded

$$Ploss = \beta_1 \times \beta_2\beta_4(Prate \times R) + \beta_2\beta_5(Prate \times Sed.) + \beta_3\beta_4(STP \times R) + \beta_3\beta_5(STP \times Sed.)$$ ....[Eq. 1.4]

There are two main problems with Equation 1.4. One, (*Prate*) would not be multiplied by (*Sed.*) because the source of (Prate) is not affected by the transport source of (Sed.). (*Prate*) affects the amount of phosphorus being applied to the field. Phosphorus fertilizer is directly available for plant uptake, therefore it is not affected by sediment loss and would not affect overall P-loss in one's field. The second problem is that the coefficients are not independent. Therefore, by making one coefficient zero (example, β_5), it would effectively get rid of all the source by transport interactions that are affected by that specific coefficient. This is a problem as one set of source by transport interaction may need to be removed (like *Prate* X *Sed.*) but another may be needed in the equation (like *STP* X *Sed.*). This is the main difference between the Kansas p-index and the component p-index as all the coefficients in the component P-Index are independent only affecting one set of source by transport interaction like in Equation 1.5.

Equation 1.5: Example of the Component Phosphorus Index

$$Ploss = \beta_1 + \beta_2(Prate \times R) + \beta_3(Prate \times Sed.) + \beta_4(STP \times R) + \beta_5(STP \times Sed.) \text{[Eq. 1.5]}$$

Recent Research on Component P Indices in Other States

States that currently use component indices include Georgia, Kentucky and North Carolina (Osmond et al., 2017). Each state has their own equation that they use to estimate P loss. Kentucky, uses the (APLE) Annual P Loss Estimator model (Bolster et al., 2014). While, North Carolina uses the (PLAT) Phosphorus Loss Assessment Tool (Johnson et al., 2005). With each different model each state has their own way of estimating inputs to each component as well as the coefficients to go along with the components. However, there is lack of information on how states calculated their components and coefficient values, thus more research needs to be conducted.

Comparing Runoff Inputs within the Component P Indices of Other States

A literature review was done to determine how the above-mentioned states calculated a runoff value for their P-index inputs. Georgia's P index currently uses the curve number (CN) method to obtain estimation of the risk of runoff form a certain field (USDA & University of Georgia, 2013). In Kentucky, the Soil Conservation Service (SCS) CN method is also used in the revised Kentucky P index to estimate the average annual runoff from a particular field (Bolster et al., 2014). For North Carolina, estimates of surface runoff and subsurface drainage volumes are calculated differently based on the condition of drainage on a particular site (Johnson et al., 2005). On well-drained soils that do not require enhanced drainage, surface runoff is determined using a modification of the (SCS) CN method and long-term rainfall data from each county (Johnson et al., 2005). To estimate subsurface drainage volume on naturally drained soils a mass balance approach is used where the average subsurface drainage is the volume of water after accounting for precipitation, runoff and evapotranspiration (Johnson et al., 2005). Because of the heavy integration of sub-surface drainage into runoff estimation, we will not use North Carolina index when comparing component P indices.

Sediment Control and Erosion Associated with P-loss

Soil erosion presents one of the greatest concern to most P mitigation programs worldwide (Kleinman et al., 2011). The concentration of P attached to soil particles is typically greater than dissolved P concentrations in runoff. Furthermore erosional processes readily remove the finest soil particles, resulting in sediment P concentrations up to five times higher than those found in the bulk soil from which the sediment erodes (Kleinman et al., 2011). Other things that can affect soil detachment and sediment transport, including field hydrologic conditions, crop type, root structure, vegetation density, and antecedent soil moisture content (Tao et al., 2011). Agricultural management practices that influence these factors will influence the overall amount and bioavailability of P loss to surface waterways (Wallbrink et al., 2003). Greater rainfall intensities can result in an increase of erosive power in surface runoff, which increases the potential for gully erosion and ultimately P loss in agricultural fields (Karimov & Sheshukov, 2017; Wallbrink et al., 2003). One of the essential problems that limits agricultural productivity relates to soil degradation due to loss of topsoil and soil erosion processes (Foster, G.R, 1986; Karimov & Sheshukov, 2017). Soil erosion can be divided into three general types: sheet and rill erosion, ephemeral and classical gully erosion, and stream bank and bed erosion (Foster, G.R, 1986; Karimov & Sheshukov, 2017). Ephemeral gullies are usually present on cultivated crop fields and studies indicated that in the areas of significant agricultural production, contribution of ephemeral gully erosion could be substantial, close to or exceeding estimates of sheet and rill erosion (Sheshukov et al., 2018).

Ephemeral Gullies

An ephemeral gully (EG) is defined as small channels that can be eroded by concentrated flow within an agricultural field that can be easily filled by conventional tillage but can reappear in the same location by additional runoff events (Soil Science Society of America, 2008). An ephemeral gully can also be a small channel with an average cross-sectional area larger than 0.1 m^2 (or about 1 ft^2) that is shaped by concentrated surface runoff along certain drainage pathways on a hillslope or in the lower part of a cultivated field (Foster, G.R, 1986). Gully erosion is frequently triggered or accelerated by land use change or extreme climatic events, it can also result from a long preceding history of erosion patterns (Valentin et al., 2005). Gully erosion results not only from surface flow but also from subsurface flow (USDA, NRCS, ARS, 2007). Ephemeral gullies eventually grow into classical gullies if left untreated over long periods of time (Karimov & Sheshukov, 2017). Ephemeral gully development is affected by several factors include rainfall characteristics, soil properties, topographic features, and land use and management (Karimov & Sheshukov, 2017). Gullies can be the root cause of a lot of agricultural issues worldwide. One of the biggest concerns with gully erosion is extreme sediment and nutrient loss in agricultural fields (Foster, G.R, 1986; Karimov & Sheshukov, 2017). Another major issue is how to control EGs in crop fields.

Methods of Controlling Ephemeral Gullies

Ephemeral gully prevention and control is extremely important when talking about sediment control and erosion and many techniques have been proven to be effective depending on the severity of the case (Valentin et al., 2005). Ways to prevent EGs include vegetation cover, zero or reduced tillage, and terracing (Valentin et al., 2005). Conservation tillage can adequately control ephemeral erosion in less severe cases (Foster, G.R, 1986). In other situations, permanent channels like grassed waterways, terraces, and designed surface water disposal systems are needed to control EGs (Foster, G.R, 1986). In the severest cases, additional permanent structures, such as concrete, rock or stone bunds, enclosers, check dams and corrugated metal structures that "drop" water to a lower elevation without triggering erosion, may be needed to prevent an ephemeral gully from becoming a classic gully (Foster, G.R, 1986; Valentin et al., 2005). However, because their implementation is rarely connected with a rapid advantage for the farmers in terms of an improvement in land or labor productivity, these approaches are rarely adopted by farmers in the long run and at a larger spatial scale (Valentin et al., 2005).

Other ways to help control EG's in agriculture fields is through best management practices through cover crops, although it is important to point out that little research has been done to quantitatively prove if cover crops are an effective method for controlling or preventing EG formations in agricultural fields. Cover crops usually refers to plants cultivated in cropping systems to cover the soil when it is fallow (Reeves, 1994). One research article by (Knapen & Poesen, 2010) found that the use of cover crops will reduce soil erodibility. They also state that soil erodibility controls the cross-sectional dimensions of the concentrated flow paths in gullies proving that there is a direct relationship between cover crops and gully formations. On top of being utilized to decrease soil erosion in agricultural fields, the usage of cover crops has also been demonstrated to be a successful alternative that can directly build up soil surface residues (Kaye & Quemada, 2017).

Methods of Quantifying Sediment Loss and Erosion from EGs

Many different methods can be used to quantify the amount of soil and sediment lost from gullies in crop fields. One of the easiest methods of measuring a gully cross-sectional area and length is with a pole and tape measure to determine the soil volume lost within the gully (Karimov & Sheshukov, 2017). More complex approaches require remote sensing and photogrammetry techniques (Karimov & Sheshukov, 2017). Another approach that can combine the accuracy of complex methods while allowing to still collect data with mature crop canopy is the use of micro-topographic profiler or a pin-frame (Karimov & Sheshukov, 2017). The pin-frame device was made so that rods were allowed to freely fall when the pin-frame was placed above the ground(Karimov & Sheshukov, 2017). When the rods touch the ground, their top ends formed a profile which is used to represent a gully cross-section, after this the rods can then be photographed from 2 meters away with a high-resolution digital camera aimed perpendicular to the face of the frame (Karimov & Sheshukov, 2017). The digital images can then be used to calculate sediment loss (Karimov & Sheshukov, 2017). This method will not be used in this research but is another method used to quantify sediment loss from EG's.

One of the more complex approaches is the Topographic index (TI) model which uses a topographic threshold concept to identify EG locations in agricultural fields (Sheshukov et al., 2018). A TI is calculated at each point in the field by using a list of site-specific characteristics, derived from topographic information like slope, contributing area, curvature, and flow length (Montgomery R. David and Dietrich E. William, 1992; Sheshukov et al., 2018; Torri et al., 2013). A geographical information system (GIS) is often used to calculate a TI, but the accuracy depends on the quality of input datasets (Sheshukov et al., 2018). A commonly used GIS system is GIS-based grid order (GORD) analysis of surface flow networks which may simplify the process for determining EG occurrence (Wang et al., 2021). Grid order can be defined as the ordered level of flow at each pixel generated by using Tau Digital Elevation Model (DEM) toolsets in ArcGIS based on LiDAR DEM raster using Strahler's stream order theory (Wang et al., 2021). The GORD approach is based on the hydrologic flow increase that occurs when flow paths join (Wang et al., 2021).

Objectives and Hypotheses

1. Develop and evaluate a new approach to the P-index. *Hypothesis: A component P index will improve the correlation between the Kansas P-index and estimated P loss.*
    a. Identify a method to estimate average annual runoff from agricultural fields. *Hypothesis: estimated runoff will be correlated to measured runoff*
    b. Determine coefficients to the components of the revised P index. *Hypothesis: Including each component with a non-zero coefficient will improve the correlation between the P-index and estimated P loss.*
2. The objective is to determine the effect of cover crops on ephemeral gully erosion. *Hypothesis: Cover crops decrease ephemeral gully erosion in crop fields.*
    a. Quantify ephemeral gully erosion in crop fields with and without cover crops. *Hypothesis: There will be an increase in ephemeral gully erosion in non-cover crop fields.*
    b. Measure and determine how crop residue will affect ephemeral gully erosion. *Hypothesis: Increased crop residue will decrease ephemeral gully erosion.*

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Chapter 2 - Estimation of Average Annual Runoff for Large Regions with Diverse Agricultural Systems and Climates Using Limited Data.

Introduction

Runoff can affect many things, including sediment loss, nutrient loss, downstream flooding, and downstream water quality. Therefore, it is desirable to estimate how land management would affect runoff. Many process-based models estimate runoff for individual runoff events or days, which can be complex. Some applications may only need general estimates of annual runoff. For example, annual runoff is an input to many P indices throughout the nation. Estimates of how annual runoff would be influenced by climate, crops, and soils could be helpful for estimating cropping system effects on downstream flood risk. There are many different uses for a method that estimates long term average annual runoff which can be used not only by farmers and ranchers but by government employees, private contractors, or even for university research.

Finding ways to estimate runoff can prove to be challenging due to the many model-based approaches out there today (Bariamis & Baltas, 2021). In a paper by (Ratzlaff, 1994) there is an Isoline map of mean annual runoff for the state of Kansas, 1971-1990. While this does give a runoff estimate for a specific location in Kansas, there are a few reasons we would not be able to use this directly for land management decisions. For one, a method that would include both management and soil type would be ideal, and this map does not use either. For this map regardless of what field you are in within a specific county and no matter what management the producer uses you would estimate the same runoff depending on your isolines. This meant that in

Cherokee county, a CRP field in native grass would have the same runoff value as a conventional tilled field planting up and down the slopes. While this map produces mean annual runoff, due to the fact that this map does not incorporate soil, management, or effects of cover, it would not meet the site-specific needs of a land manager.

Considering recent research specific to methods used to estimate runoff, many processed based models would not work well to predict long-term average annual runoff across the state of Kansas. The existing models take a fair amount of learning to use the program, taking hours to days and can be overly complicated. One example is the Soil and Water Assessment Tool (SWAT) developed by the USDA Agriculture research service as a large (thousands of acers) river basin scale model to assist in assessing the impact of management on water supplies and nonpoint source pollution in watersheds (Arnold et al., 1998; Bariamis & Baltas, 2021). In addition to the fact that there are many diverse inputs, users can often get overwhelmed by the application process leading to missed steps. This along with subjective inputs can impact the ability to obtain consistent results. A second example is the Agricultural Policy Environmental eXtender (APEX), which is a small scale water quality-based model used to predict surface runoff, erosion, sediment deposition and degradation, nutrient and pesticide transport, and subsurface flow (Osmond et al., 2017; Williams et al., 2012). Much like the previous model, important steps must be taken in model set up, sensitive analysis, and calibration / validation for the model to work properly (Bhandari, 2016). While both models are used to estimate runoff, due to the many shortcomings they would not work well to estimate long-term average annual runoff within Kansas. A model that is user friendly and incorporates different cropping scenarios, soils and climates should be researched.

The curve number (CN) method is used by the four models listed above and was developed to estimate the direct runoff that results from an individual rainfall event as a function of land-cover and soil characteristics (Guswa et al., 2018). The CN method is often used because it represents multiple variables such as land use, hydrologic cover conditions, soils, and antecedent runoff conditions (Guswa et al., 2018; USDA & NRCS, 2004). While this method is a simple approach, it has one downfall for our application in that the approach is for an individual storm event. One could overcome this by using actual precipitation data for every day of the year and estimate runoff for every single event over a 30-year period and then produce some average runoff for every year. While this is doable, one drawback to this is that it requires a lot of data and is time consuming. Another drawback of this approach is it requires some estimate of antecedent moisture. One of the major factors in determining CN that was mentioned prior, is the antecedent runoff condition (ARC) (USDA et al., 1986). One downside to ARC is that it would require knowledge of soil moisture and soil cover, which can be difficult to obtain or estimate for long periods of time. Contributions to CN variability include temperature, growth stage, cover density, total rainfall, rainfall intensity and duration, and soil moisture conditions (NEDS et al., 1989; USDA & NRCS, 2004). The ARC refers to all these factors of variability (USDA & NRCS, 2004). The ARC is split into three categories: CNII for average conditions, CNI for dry conditions, and CNIII for wetter conditions (USDA & NRCS, 2004).

Due to the shortcoming of using the CN method, it may not be the best approach to estimate long term average annual runoff for the state of Kansas, therefore further research should be conducted to evaluate other approaches to estimating runoff over multiple storm events. Guswa et al. (2018) presented a modified CN approach for estimating total precipitation for time periods of aa month to 6 months. In brief, this change substituted the average precipitation for an event in place of daily precipitation in the CN equation and assumed an exponential distribution of rainfall depths over the course of the year to estimate the average runoff per event. The output to this new method could allow the calculation of average long-term annual runoff based on the CN, average annual precipitation, and average number of rainfall events in a year runoff. This new method would give some advantages as it would be able to be applied to different weather gradients, something that could be applied over large geographic areas. Because one could use average annual precipitation, there is less time collecting data, therefore, this new approach would be simple to use, and a very broad spectrum of people could use this approach without having to go through excessive learning.

Further research needs to be done to determine the overall effectiveness of the modified CN method. This research is needed to gain a broad application for long term average annual runoff across the state of Kansas and how it is affected by general land management decisions. This study has three objectives: 1) Identify methods to overcome the gaps in data availability through calibration, 2) Compare the estimates of long-term average annual runoff with field data for both the CN method and modified CN method), and 3) Develop a database of runoff event for the state of Kansas.

Materials and Methods

Annual runoff estimates from two methods were compared to measured edge-of-field runoff to assess the most accurate method of estimating annual runoff. Method 1 used the curve number (CN) method from the NRCS Engineering Handbook to estimate daily runoff from daily precipitation and then summed it over the entire year to estimate annual runoff (USDA & NRCS, 2004). Method 2 used a modification of the CN method where daily precipitation was replaced with the average event precipitation and assumed an exponential distribution of precipitation amounts for the year (Guswa et al., 2018).

Method 1

Annual runoff was estimated by summing estimates of daily runoff for an entire year, where daily runoff was estimated with the curve number (CN) method as described in the NRCS Engineering Handbook (USDA & NRCS, 2004) using daily precipitation (Equation 2.1). The uncalibrated estimates were developed with a static CN representing hydrologic condition II (CNII) that was determined based on NRCS guidelines for the given cropping system and soil hydrologic group. Static inputs included CNII, daily precipitation.

Equation 2.1: Curve Number Method

$$Q = \frac{(P-I_a)^2}{(P+I_a)+S} \quad P > I_a \quad (Q = 0; P \leq I_a) \quad \text{........……...………………………[Eq. 2.1]}$$

Where Q equals the runoff depth (mm), *P* is rainfall (mm), *S* serves as the maximum potential retention (mm) and I_a functions as initial abstraction (mm) (USDA & NRCS, 2004). Where for Method 1 using this equation, the empirical relationship between I_a and *S* is expressed as $I_a = 0.2S$ because I_a is assumed a function of the maximum potential retention, *S*, as calculated by Equation 2.2 (USDA & NRCS, 2004).

Equation 2.2: Maximum Potential Retention (S)

$$S = \frac{25{,}400}{CN} - 254 \ (S \ in \ millimeters) \quad \text{…………………………………………[Eq. 2.2]}$$

Where *CN* is the curve number for a given soil and management practice as given in Table 9-1 of the NRCS National Engineering Handbook (USDA-NRCS, 2004).

The CN for a given field can change throughout the year due to crop or residue cover density and soil moisture conditions and these changes are generally characterized by the Antecedent Runoff Condition (ARC) (USDA & NRCS, 2004). The ARC is split into three categories: CNII for average conditions, CNI for dry conditions, and CNNIII for wetter conditions. Following standard practice, we selected the CNII based on the Hydrologic Soil Group and the cropping system as listed in Table 9-1 of the NRCS Engineering Handbook (USDA & NRCS, 2004). The CN for moisture conditions I or III were selected from Table 10-1 in the NRCS Engineering Handbook based on the CNII (USDA & NRCS, 2004).

Calibration of Method 1

Antecedent precipitation amounts have been used to estimate the appropriate Antecedent moisture condition (AMC); however, very little guidance is provided for this process (USDA & NRCS, 2004). Therefore, we developed the following process for selecting CNI or CNIII based on antecedent precipitation. We used CNI to compute daily runoff when $API < PI$, where P_I is the precipitation threshold for *ARC I* and API is calculated with Equation 2.3:

Equation 2.3: Daily Runoff Computation using Antecedent Precipitation and CNI

$$AP_I = \sum_{i=1}^{n_I} P_i \quad \text{[Eq. 2.3]}$$

Where n_I is the number of days to sum precipitation when calculating AP_I and P_I is the precipitation for day *i*. The CNIII was used to compute daily runoff when $AP_{III} < P_{III}$., where P_{III} is the precipitation minimum for *ARC III* and AP_{III} is calculate with Equation 2.4:

Equation 2.4: Daily Runoff Computation using Antecedent Precipitation and CNIII

$$AP_{III} = \sum_{i=1}^{n_{III}} P_i \quad \text{[Eq. 2.4]}$$

Where n_{III} is the number of days to sum precipitation when calculating AP_{III} and P_i is the precipitation for day *i*. The Nash-Sutcliffe Model Efficiency (NSE) was maximized through heads-up calibration by systematically adjusting values for n_I , P_I, n_{III} and P_{III} as listed in (Table 2.2). The NSE is a normalized statistic that estimates the relative size of the residual variance compared to the measured data variance (Nash & Sutcliffe, 1970)

Equation 2.5: Nash-Sutcliffe Model Efficiency

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - Y^{mean}\right)^2}\right] \quad \text{...[Eq. 2.5]}$$

Where n is the number of observations, *Y_i^obs* is the i-th observation, *Y_i^sim* is the i-th simulated value, and *Y^mean* is the average of observed values (Nash & Sutcliffe, 1970). The closer the NSE is to 1 indicates a better fit model although anything above NSE = 0.5 is considered accepted (Nash & Sutcliffe, 1970). The CNII was selected based on the Hydrologic Soil Group and the cropping system with CN for moisture conditions I and III selected from tables in the NRCS Engineering Handbook (USDA & NRCS, 2004).

Method 2

Daily runoff was estimated with the modified CN method as described by Guswa et al. (2018). In brief, this modification used annual precipitation in place of daily precipitation and then assumed an exponential distribution of rainfall depths throughout the year (Equation 2.6).

Equation 2.6: Modified Curve Number Method

$$Q = (\alpha - S)exp\left(-\frac{\lambda S}{\alpha}\right) + \frac{S^2}{\alpha}exp\left(\frac{(1-\lambda)S}{\alpha}\right)E_1\left(\frac{S}{\alpha}\right) \quad \text{..................................[Eq. 2.6]}$$

Where *Q* is the average runoff per event, α is the average precipitation per event (calculated as *PA/nP*, where *PA* is annual precipitation and *nP* is the number of precipitation events in a year), S is the maximum potential retention computes as (1000/CN)-10, λS is the initial abstraction, and *E1(x)* is the exponential integral (Equation 2.7).

Equation 2.7: Exponential Integral

$$E_1(x) = \int_x^{\infty}\frac{\exp(-u)}{u}du \quad \text{..[Eq. 2.7]}$$

Calibration of Method 2

Annual runoff is computed as $\bar{Q}$•*nP*. Although *nP* would appear as a simple parameter to determine from historical records of daily precipitation, its estimation is complicated by several issues. First, the application of Equation 2.1 is only applicable to non-frozen precipitation events. Second, precipitation events that over-lap two days (i.e., start at 10 PM and end at 2 AM) would be counted as two events instead of one. Third, climates with many very small precipitation events, which are incapable of producing runoff (i.e., $Pi<Ia$) may skew the dataset. Because of these reasons, estimating *nP* as the number of days with non-zero precipitation will almost always over-estimate the true value of *nP*. We estimated *nP* as the number of days were $Pi>Px$, where *Px* was used to calibrate Method 2 with measured data. The Nash-Sutcliffe Model Efficiency was maximized through heads-up calibration by systematically adjusting *Px* to 0, 0.25, 1.27, 2.54, 3.81, 5.08, 6.35, and 12.7 mm.

The CN values in the NRCS Engineering Handbook were developed with λ=0.2 (USDA & NRCS, 2004). However, as recommended by Guswa et al. (2018), λ was set equal to 0.05 for the application of Method 2. Therefore, the CN values from the NRCS Engineering Handbook were adjusted with Equation 8 when used in Method 2 (Guswa et al., 2018).

Equation 2.8: Modified Curve Number Adjustment where λ = 0.05

$$CN_{0.05} = 0.0054 \cdot (CN_{0.2})^2 + 0.46 \cdot CN_{0.2} \quad \text{[Eq. 2.8]}$$

The uncalibrated estimates of runoff with Method 2 were computed with Equation 6 where *nP* = number of days during the year with Pi > 0.25 mm. By applying the selected method to the state of Kansas, which is a very large geography, users will be able to estimate the effects of agriculture managements based on long term average runoff.

Calibration and Validation Data

Measured runoff used for calibration and validation datasets was obtained from edge-of-field runoff studies conducted in four locations in eastern Kansas, USA (Table 2.1). Calibration data are from the Kansas Agricultural Watershed (KAW) field laboratory from 2015 through 2021 (Carver et al., 2021). Data are average runoff from no-till corn-soybean cropping systems either with cover crops (CC) or without cover crops (NC) (2 treatments total). There are 3 levels of fertilizer management, no fertilizer control (CN), fall broadcast P fertilizer (FB) and spring injected P fertilizer (SI). Total we have 6 different treatments for a total of 18 watersheds. For the data in Table 2.1 the KAW data was split between CC and NC and used average annual values from each of the 9 watersheds for each of the 7 years totaling for 14 data points. The reason the KAW was not split up into more data points was because while the fertilizer management differed this did not directly affect runoff and the P fertilizer rate did not change therefore values were averaged together.

Validation data were collected in Crawford County, Franklin County, and Geary County, Kansas. Crawford data includes average runoff from 5 cropping systems in no-till or conventional till grain sorghum production from 2005 through 2008 with various fertility management (Sweeney et al., 2012). Two of the 5 cropping systems for the year 2007 were left out due to discrepancies in the data. Crawford data was split because each cropping system used a different rate of manure. Franklin data includes average runoff from 3 cropping systems in no-till or conventional till grain sorghum-soybean production from 2001 to 2004 with various fertility management (Zeimen et al., 2006). Geary data includes average runoff from 2 cropping systems in no-till corn-soybean production either with or without winter cover crops from 2018 through 2021 (N.O. Nelson, unpublished data).

Development of Regional Inputs for Method 2

Application of Method 2 for the entire state requires estimates of long-term average annual precipitation and the number of precipitation events for each county in the state. Estimates of long-term average annual precipitation are available from the Kansas Weather Data

Library (https://climate.k-state.edu/). Estimates of the average number of precipitation events in a year were determined for each county through geographic interpolation as described below.

The average annual number of precipitation events, defined as every day with precipitation greater than 2.5 mm, was determined by collecting 30 years of past weather data from Applied Climate Information System (ACIS) using National Oceanic and Atmospheric Administration during 1990 to 2020 in fourteen different counties throughout Kansas (Cowley, Crawford, Franklin, Hamilton, lyon, McPherson, Morton, Nemaha, Ness, Phillips, Republic, Riley, Scott, Stafford, and Sumner). Data was then used in ArcGIS Pro to create a Radial Basis function interpolation map to estimate the 30-year average annual number of precipitation events throughout the state of Kansas. This map was then validated by selecting 10 validation counties throughout Kansas (Chase, Cheyenne, Comanche, Ellis, Ellsworth, Gray, Jefferson, Labette, Stafford, Thomas). The average annual number of precipitation events determined from the historical weather of the validation counties were then compared to the number of precipitation events estimated from the interpolated map. The accuracy of the geographic model was evaluated based on the regression coefficient (R2), root mean square error (RMSE), and Nash-Sutcliffe model efficiency (NSE).

Results and Discussion

Method 1

Estimated runoff with the uncalibrated Method 1 (i.e., no adjustment for antecedent moisture) had a good relationship with the measured runoff for the 14 total data points from the KAW field lab (calibration dataset; Figure 2.1a). Although the regression coefficient indicated a good relationship (R^2=0.82), the slope was much less than 1 (0.23) and the method greatly underestimated runoff for years with large volumes of runoff (i.e., estimated runoff for years with measured runoff of 90 mm were nearly perfect, however the method only estimated 140 mm of runoff when the measured runoff was over 300 mm). This resulted in poor model efficiency (NSE=-0.21). Results were similar when comparing the measured and estimated runoff data from the other three locations (validation dataset; Figure 2.1b).

Method 1 was calibrated by adjusting the CN for ARC by altering the parameters n_I, n_{III}, P_I, and P_{III} as described in Equations 3 and 4. The optimal fit between estimated runoff and measured runoff for the calibration dataset was obtained with parameter n_I=10 days, n_{III}=3 days and parameter P_I=5.08 (mm), P_{III}=10.16 (mm). Calibration of method 1 greatly improved the estimated runoff for the KAW field Lab (calibration data set) with R^2 = 0.9 and NSE = 0.71 (Figure 2.2a). While the R^2 value and model efficiency are both very good, the slope of the regression line is just under 0.5. This results in slight over estimation of runoff below 150 mm of measured runoff and under estimation of runoff at values greater than 200 mm. Although not ideal, it is a vast improvement over the estimates from the uncalibrated method 1 (Figure 2.1). However, the calibrated version of Method 1 resulted in very poor estimates of annual runoff for the Franklin, Crawford, and Geary County locations (validation data set) with R^2 = 0.18 and an NSE = -1.16 (Figure 2.2b). A poor fit to the validation data set might be attributed to differing soil hydrologic conditions at validation locations compared to the calibration location. The use of antecedent precipitation as a method to select the antecedent moisture condition for CN may be very site specific (e.g., dependent on cropping system, soil hydrologic group, or weather patterns). Therefore, using the antecedent precipitation to calibrate Method I resulted in an over-parameterized model that had a good fit for the specific conditions in the calibration dataset but a poor fit for the conditions in the validation set. Therefore, this calibration would not be suitable for wide-scale applications.

Method 2

Estimated runoff with the uncalibrated Method 2 using the modified curve number approach had a good relationship with the measured runoff for the 14 total data points from the KAW field lab (calibration dataset; Figure 2.3a). Although the regression coefficient indicated a good relationship (R^2=0.81), the slope of the regression line was 0.41 and the method greatly underestimated runoff for years with large volumes of runoff (i.e., estimated runoff for years with measured runoff of 80 mm were nearly perfect, however the method only estimated 100 mm of runoff when the measured runoff was over 300 mm). This resulted in poor model efficiency (NSE=-0.49). Results were similar when comparing the measured and estimated runoff data from the other three locations (validation dataset; Figure 2.3b), which further proved the need for Method 2 to be calibrated.

Method 2 was calibrated by adjusting the threshold (*Px*) used to determine the number of precipitation events (*nP*) in each year, where a precipitation event was defined as a day with precipitation (*Pi*) greater than *Px*. The optimal fit between estimated runoff and measured runoff for the calibration dataset was obtained with *Px*=2.5 mm, in other words, the number of precipitation events was determined as the number of days with greater than 2.5 mm of precipitation. Calibration of Method 2 greatly improved the estimated runoff for the KAW field Lab (calibration data set) with R^2 = 0.88, NSE = 0.56 and the slope of the regression line at 0.56 (Figure 2.4a). While the slope value is slightly above 0.5, this results in slight over estimation of runoff below 100 mm of measured runoff and under estimation of runoff at values greater than 300 mm. Although not ideal, it is a vast improvement over the estimates from the uncalibrated Method 2 (Figure 2.3). The calibrated version Method 2 resulted in similar results of annual runoff for the Franklin, Crawford, and Geary County locations (validation data set) with R^2 =

0.66 and an NSE = 0.54 (Figure 2.4b). While the R^2 value and model efficiency are both acceptable, the slope of the regression line was under 0.5 at 0.38. This resulted in over estimation of runoff at 100 mm below 50 mm of measured runoff and under estimation of runoff at 260 mm greater than 400 mm of measured runoff. Although not ideal and a slight decrease in our slope value, the end result was an improvement over the estimates from the uncalibrated Method 2 (Figure 2.3).

Calibration was also attempted by systematically adjusting the CN, however this did not improve the overall calibration. Increasing the CN increased the slope, achieving a slope near 1 by increasing the CN by 12. Although this greatly improved the slope, the model over-predicted runoff as a whole and had a very poor model fit (NSE << 0). Therefore, we did not use this approach.

Guswa et al., 2018, concluded that while their new approach, much like our Method 2, required an estimate of the number or rain events within a given period of time, it was almost as good as methods that used actual runoff events. Therefore, they concluded that this new approach is acceptable to determine the amount of direct runoff from monthly precipitation. Given two big differences that Guswa's new approach is for estimating runoff within a shorter amount of time (monthly) as well as being applied to a watershed. It has similar results to our findings of estimating long-term average annual runoff at field scale.

Application

Runoff estimates using the calibrated Method 2 had a much better relationship and model fit with the validation dataset than the uncalibrated methods (Method 1 or Method 2) or the calibrated version of Method 1. Furthermore, the R^2 and NSE for the validation of Method 2 were both in the acceptable range (Alexander et al., 2015; Ritter & Muñoz-Carpena, 2013);

Therefore, Method 2 was selected for estimating runoff across the state of Kansas. The number of precipitation events were determined as the number of days in a year where precipitation exceeded 2.5 mm. It's important to point out that this decision to use Method 2 was made despite the deficiencies (slope much less than 1) because calibration could not be improved anymore.

Method 2 was used to develop a county-level database of estimated long-term average annual runoff for the state of Kansas, which would allow a user to attain an estimate of runoff based on the county and curve number for their field. The required inputs to develop the database included long-term average annual precipitation and the average annual number of precipitation events for every county in the state of Kansas. Average annual precipitation can be obtained from the Kansas Weather Data Library (NOAA Regional Climate Centers, 2014). However, the daily precipitation data required to compute the long-term average annual number of precipitation events is not readily available from every county. Therefore, daily precipitation data were selected from 24 of the 105 counties across the state of Kansas. Fourteen counties were used to create an interpolation map in ArcGIS Pro to estimate the average number of events in a year for counties without data (Figure 2.5). Next, estimates of the average annual number of precipitation events from the geospatial interpolation map were validated through comparison with 10 counties that were not used for development of the map. When validating this method with 10 selected validation counties across the state of Kansas we had a R^2=0.99 and an NSE=0.85 (Figure 2.6), indicating that the geospatial model provides a good estimate of the average annual number of precipitation events for areas of the state without data.

These data were used to develop the aforementioned database of 30-year average-annual runoff estimates for given CN values and counties throughout Kansas (Appendix B). An example of how this database could be used is within the Kansas Phosphorus index. One of the problems with the P index is that it did not have a quantitative method of estimating runoff. Also, the method used by the P index was based solely on soil properties like soil runoff class and did not account for climatic variation across the state. Finally, using the soil runoff class did not account for how land management factors would influence runoff. Use of the runoff database developed by employing Method 2 to estimate average annual runoff solves all three issues. The database provides a quantitative estimate of runoff. The runoff is estimated as a function of climate (precipitation amount) and land management (reflected in the curve number). Although the use of this method will be used in the Kansas P index it is important to note that it can be used as a basic runoff estimation tool to produce long-term average annual runoff at field scale.

Conclusion

The calibrated modified CN method (Method 2) had the best estimations of annual runoff for both calibration and validation datasets. While runoff estimates from the calibrated Method 1 had a good fit to the calibration dataset, the runoff estimates did not have a good fit to the validation dataset. It can be difficult to accommodate for all known hydrologic soil conditions which can affect runoff amounts. For method one calibration, adjusting the antecedent soil condition based on antecedent precipitation did result in a good runoff estimates when adjusting to a single specific site but the method seemed to over and underestimate runoff when applied to soils with different hydrologic conditions. The Method 2 calibrated model had better model performance and adjusting the minimum precipitation amount used to count the number of runoff events in a year appeared to be an appropriate method of calibration. The validation model using the calibrated Method 2 approach had good overall model performance. Knowing that Method 2 calibrations could not further improve the model, a database was developed of estimated long term average runoff values for the state of Kansas. This method can be used by anyone in the state of Kansas that will be interested in determining their long-term average annual runoff at field scale for their specific location. While this will be mostly used by government and state agency personnel, farmers and ranchers will be able to use this as it is easy to use and takes little to no time to operate. Business and school-related individuals will also have access thus making this method accessible and overall easy to use.

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Tables

Table 2.1: Table showing validation data used from Franklin, Crawford and Geary and calibration data used from the KAW. Managements, number of watersheds, years, and number of data points on graph has been included. The references from where the data was obtained, and a description explaining the data are also included in the table.

Location	Mgmt.	# of Watersheds	Years	# of data points on graph*	Reference	Description
Franklin	No-Till: Grain Sorghum / Soybean rotation. 4 different P fertilizer rates were used and 2 of the rates were either injected or 2 were surface broadcasted (not incorporated).	4	2001 – 2004	4	Zeimen et al., 2006	Used average annual value of 4 watersheds for each year to come up with the 4 points.
Franklin	Conventional-Till: Grain Sorghum / Soybean rotation. 2 different P fertilizer rates were incorporated.	2	2001 - 2004	4	Zeimen et al., 2006	Used average annual value of 2 watersheds for each year to come up with 4 points.
Crawford	No-Till: Grain Sorghum. Control, No turkey litter or fertilizer	2	2005, 2006, 2008**	4	Sweeney et al., 2012	Used average annual value of 2 watersheds for each year to come up with 4 points.
Crawford	No-Till: Gain Sorghum. Fert, N and P fertilizer only	2	2005 – 2008	4	Sweeney et al., 2012	Used average annual value of 2 watersheds for each year to come up with 4 points.
Crawford	No-Till: Grain Sorghum. TLN, Turkey litter only applied based on N rate for the crop (over applies P).	2	2005 – 2008	4	Sweeney et al., 2012	Used average annual value of 2 watersheds for each year to come up with 4 points.
Crawford	No-Till: Grain Sorghum. TLP, Turkey litter applied based on P rate plus N fertilizer to supply the remaining N rate for the crop.	2	2005 – 2008	4	Sweeney et al., 2012	Used average annual value of 2 watersheds for each year to come up with 4 points.
Crawford	Chisel, disk: Grain Sorghum. TLPC, Turkey litter applied based on P rate plus N fertilizer to supply the remaining N rate for the crop.	2	2005, 2006, 2008**	4	Sweeney et al., 2012	Used average annual value of 2 watersheds for each year to come up with 4 points.
Geary	Cover Crop: Corn / Soybean rotation.	2	2018 – 2021	4	Unpublished	Used average annual value of 2 watersheds for each year to come up with 4 points.
Geary	No Cover Crop: Corn / Soybean rotation.	2	2018 – 2021	4	Unpublished	Used average annual value of 2 watersheds for each year to come up with 4 points.
Kaw	Cover Crop: Corn / Soybean rotation.	9***	2015 – 2021	7	Carver et al., 2022	Used average annual value of 9 watersheds for each year to come up with 7 points.
Kaw	No Cover Crop: Corn / Soybean rotation.	9***	2015 – 2021	7	Carver et al., 2022	Used average annual value of 9 watersheds for each year to come up with 7 points.

* For the number of data points, there is one point for each year with a specific management.
** Crawford was split up due to different rates in manure management. Control and TLPC 2007 data were not included due to discrepancies within the data.
*** The Kaw field was not spit up because the only difference was the fertilizer management. 3 Different fertilizer management were used within the watersheds, but they all used the same P fertilizer rates. Fertilizer management was not a factor directly affecting runoff thus averages were used.

Table 2.2: Variables and values used for calibration of Method 1 to determine average annual runoff. Calibration adjusted the precipitation threshold to designate antecedent runoff condition I (ARC I) or antecedent runoff condition III (ARC III) required for selection of the adjusted CN for Equation 2.2.

Variable	Description	Values tested	Units
n_I	number of days to sum precipitation when calculating AP_I (Eq. 3)	1, 2, 5, 6, 7, 10	Days
P_I	precipitation threshold for ARC I	2.54, 5.08, 7.62, 10.16, 12.7	mm
n_{III}	number of days to sum precipitation when calculating AP_{III} (Eq. 4)	1, 2, 3, 4, 5	Days
P_{III}	precipitation threshold for ARC III	10.16, 12.7, 15.24, 17.78, 20.32, 22.86, 25.4	mm

Figures

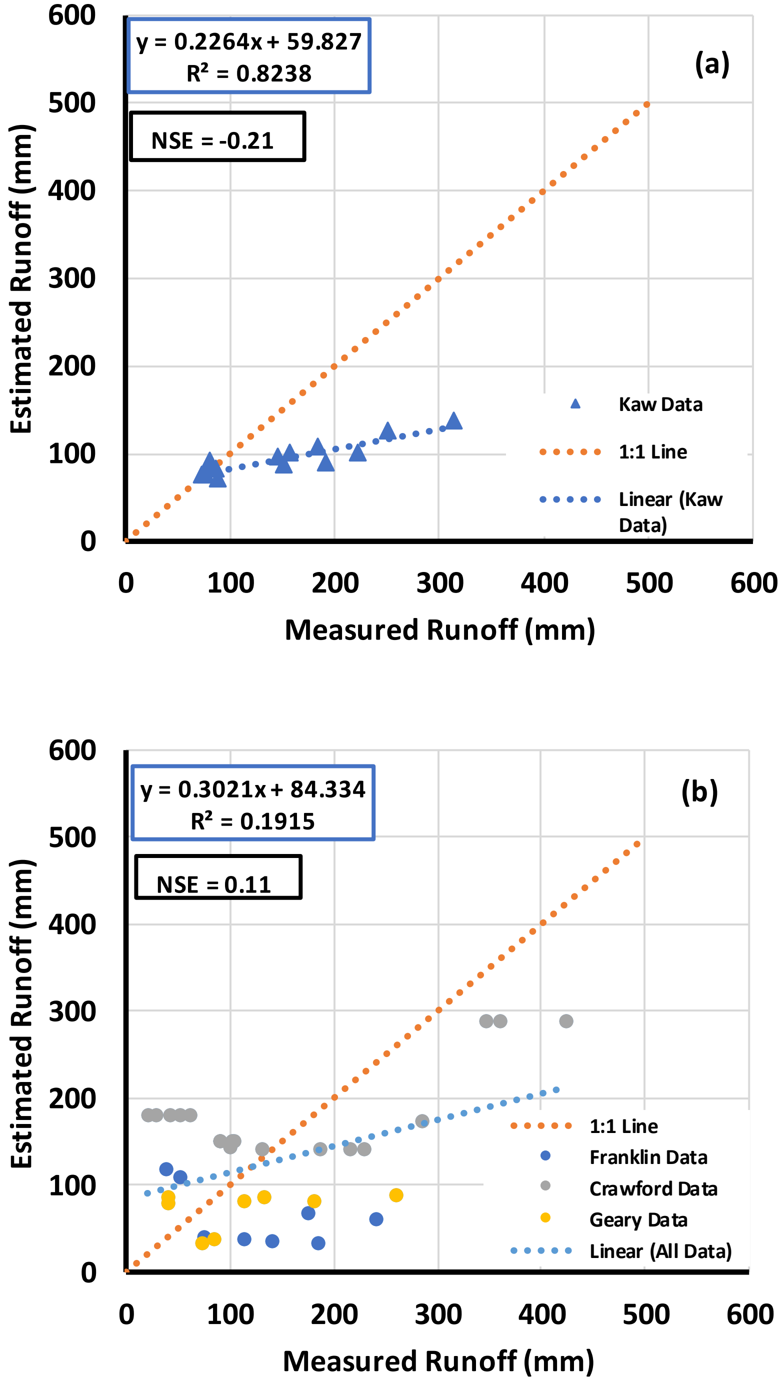

Figure 2.1: Comparison of estimated annual runoff with Method 1 (one without calibration) to measured runoff for the calibration data set (a) and the validation data set (b).

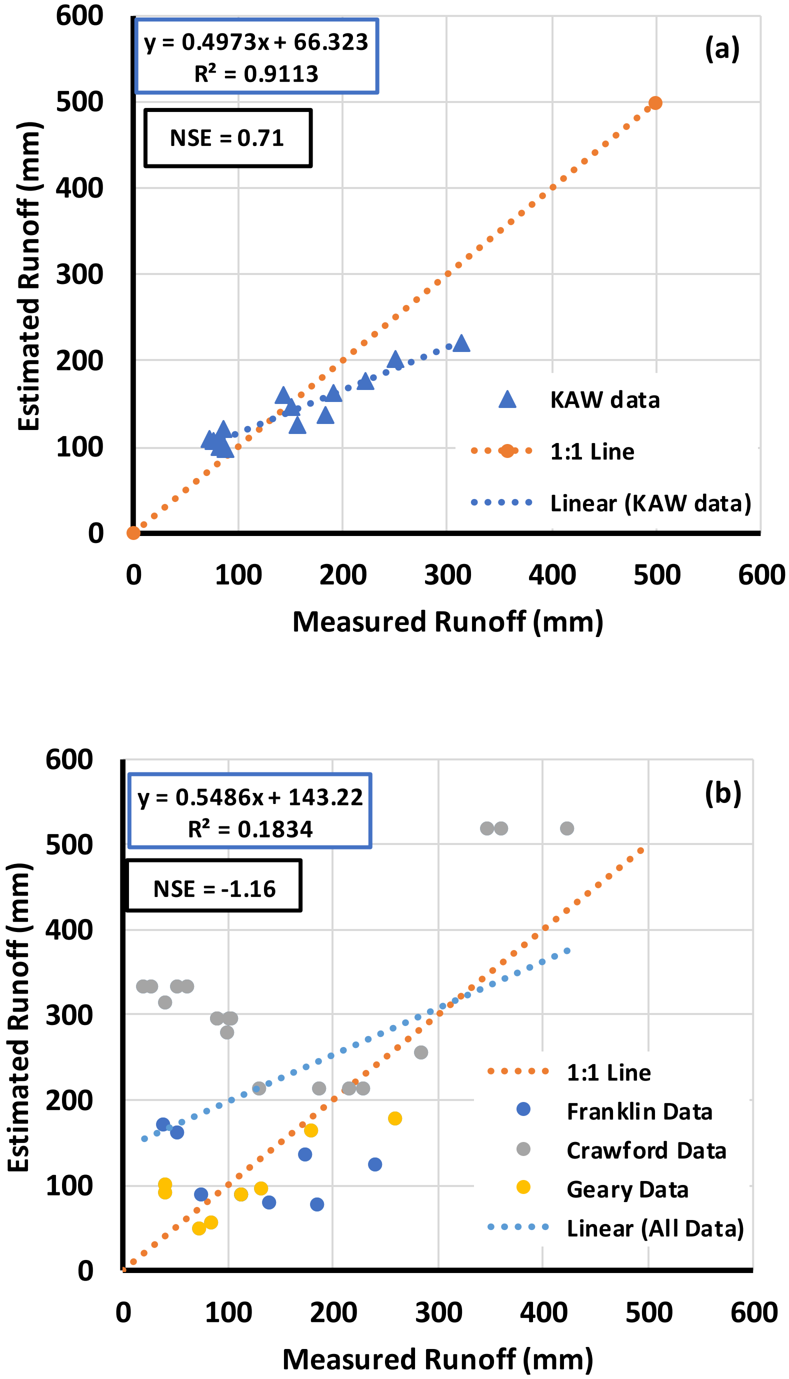

Figure 2.2: Comparison of estimated annual runoff with Method 1 (with calibration) to measured runoff for the calibration data set (a) and the validation data set (b).

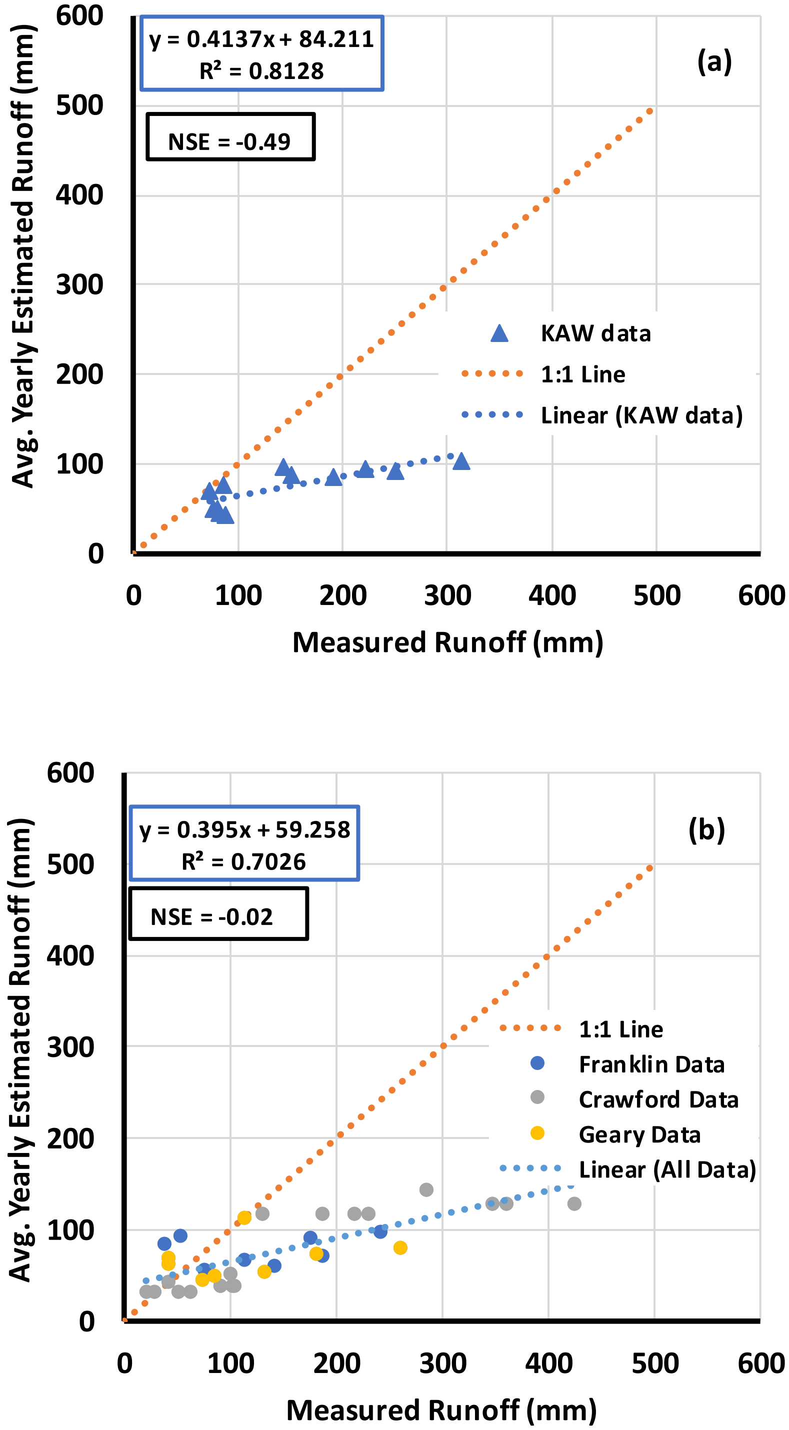

Figure 2.3: Comparison of estimated annual runoff with Method 2 (without calibration) to measured runoff for the calibration data set (a) and the validation data set (b). : The number of precipitation events in a year was determined by counting every day with measurable precipitation (> 0.25 mm) as an event.

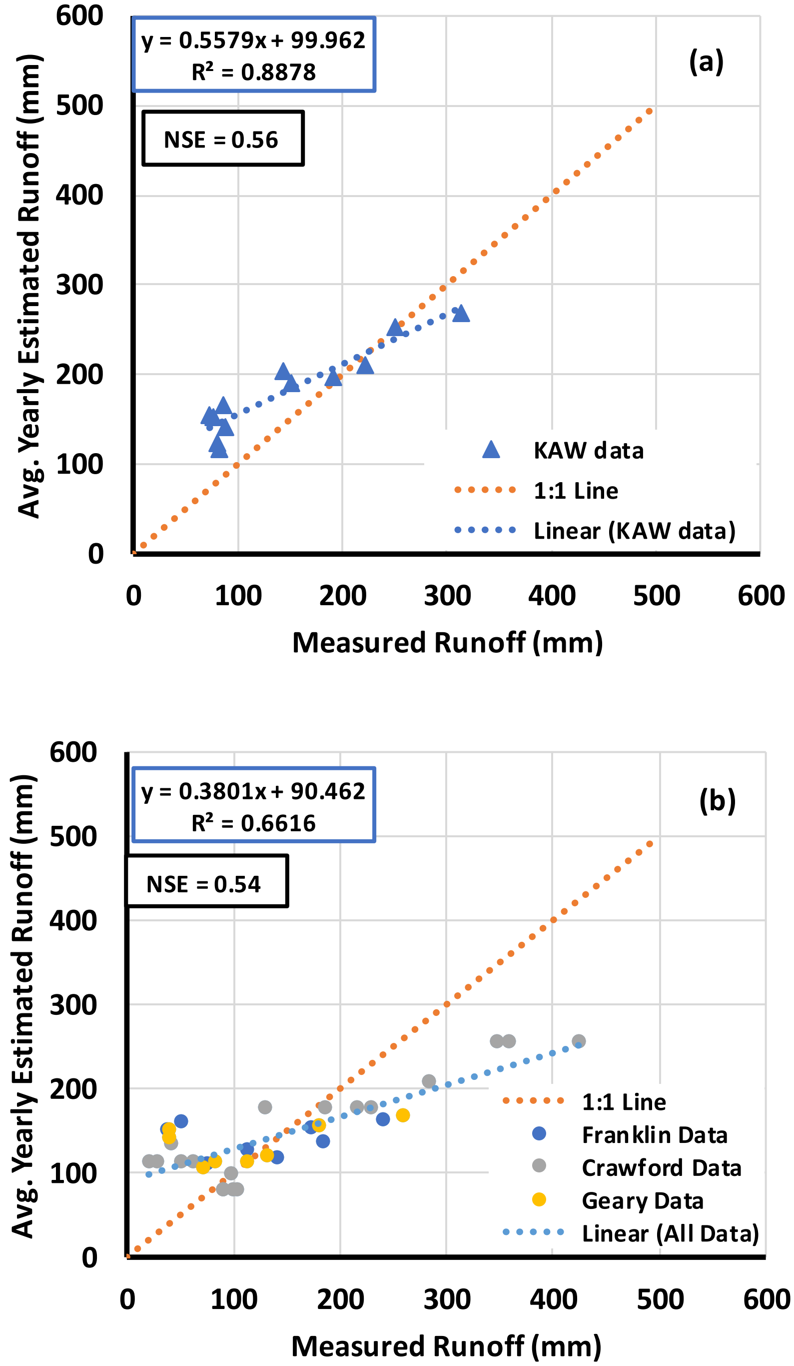

Figure 2.4: Comparison of estimated annual runoff with Method 2 (with calibration) to measured runoff for the calibration data set (a) and the validation data set (b). The number of precipitation events in a year was determined by counting every day with precipitation > 2.5 mm as an event.

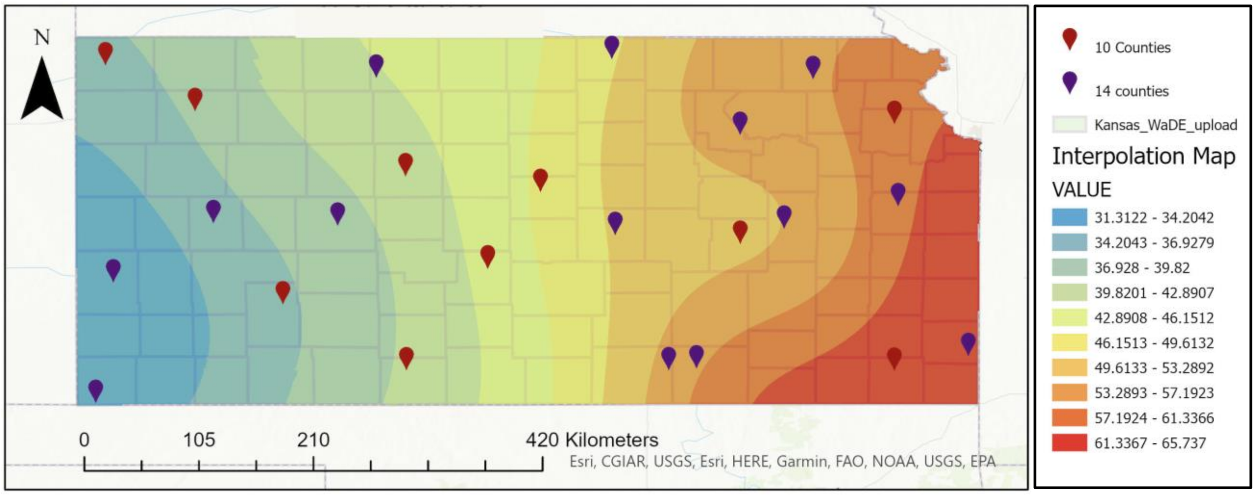

Figure 2.5: Map of long-term average annual number of precipitation events for the state of Kansas. A required input for Equation 6 is the average precipitation per event, calculated as annual precipitation divided by the number of precipitation events in a year. The 14 purple points were used to build a geospatial model. The 10 red points were used to validate the estimates from the geospatial model.

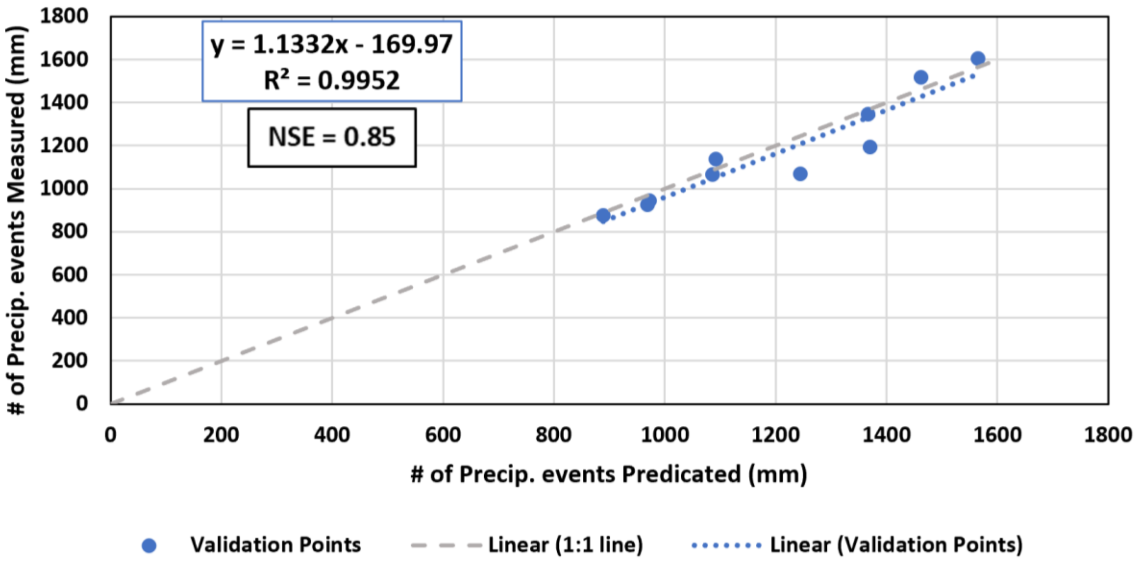

Figure 2.6: Comparison of the estimated number of precipitation events in a year using the geospatial model in Figure 2.5 with the average annual number of precipitation events determined by historic weather data.

Chapter 3 - Development of Revised P-index.

Introduction

The purpose of this study was to develop a new phosphorus index for the state of Kansas. The Kansas multiplicative phosphorus index (MPI) currently does not meet USDA/NRCS standards outlined in the title 190 and there are some discrepancies with a few of the inputs to the current Kansas index. Phosphorus indices help farmers and ranchers calculate a P loss risk assessment for a specific field, cropping system, and other important land factors. Regarding P indices, every state has its own version of a P index that operates slightly differently and is geared directly to that specific state and the management systems and practices that are used there.

Phosphorus loss can be a problem due to multiple land management factors, in the United States. Phosphorus loss from non-point agricultural is a known contributor to the degradation of surface-water quality (Carpenter et al., 1998; Carver, 2022); Phosphorus is the primary cause of eutrophication in surface water, which can lead to a rise in aquatic vegetation and algae development, which leads to decreased dissolved oxygen concentration and increased costs for water treatment (Carpenter et al., 1998; Sharpley et al., 1994). In the United States, the most prevalent degradation of surface waterways is eutrophication, which is brought on by excessive inputs of phosphorus (P) and nitrogen (N) (Carpenter et al., 1998). These excessive inputs are usually a direct result of land management decision pertaining to cropping systems and fertilizer management. Ways to help combat water quality issues are to go back to the source and help farmers and ranchers make better land management decisions. One tool that can help is the phosphorous index. This gives an overall risk assessment rating to potential P loss of a given field using a specific land management scenario. Knowing one's P loss rating can allow that person to adjust land management decisions to help minimize P loss form a specific field.

Nonpoint source pollution is challenging to quantify and control because it comes from dispersed sources and varies depending on the environment (Bennett et al., 2001). Some locations may need special management attention due to their higher likelihood of increased sediment delivery rates and severity of eutrophication (Bennett et al., 2001). According to estimates, non-point agricultural sources can account for up to 70% of all the P inputs into surface water specifically (Havlin et al.,2005). Therefore, more energy and devotion may be needed to decrease sediment supply, drawing down soil P, and balancing the P budgets of nearby agricultural areas. Phosphorus runoff to aquatic ecosystems and eutrophication have typically been addressed by policies and regulations as issues specific to the lake, river reach, or estuary in question rather than as a part of a larger pattern, but controlling non-point P pollution is not just a local issue (Bennett et al., 2001). The application of phosphorus-based fertilizers in agricultural soils is to blame for the over 75% increase in global net P storage for both aquatic and terrestrial ecosystems compared to pre-industrial levels (Bennett et al., 2001; Zhou et al., 2017).

Balancing P inputs and outputs at the farm, watershed, or regional sizes is the first step in stopping P losses (McDowell, 2012). Consequently, to achieve a level of P loss suitable for the environment and agriculture, mitigating measures are also needed in addition to a negative P balance (McDowell, 2012). Confined animal feeding operations (CAFOs), may be responsible for substantial amounts of P-loss, especially when there is not enough space to properly utilize the manure, which results in soil P enrichment (McDowell, 2012). Many of the mitigation techniques used on farms that raise crops and farms that confine animals can help reduce P loss over time (McDowell, 2012). Knowing that a lot of P loss can come from agricultural land due to farming and CAFO's it is important to recognize the important role fertilizers and manures play in contributing to P loss. The application of fertilizers and manure are essential inputs to the Kansas P index directly affecting one's overall P risk assessment.

Phosphorus Indices

Because of water quality issues, many states have developed guidelines for P application and watershed management based on tools that rate the potential for P loss in agriculture runoff. The P index concept was first proposed in 1992/93 (J. L. Lemunyon & R. G. Gilbert, 1993) and after a historic agreement between the USEPA and USDA to address concerns about nutrient runoff from livestock feeding operations, various versions of the P Index were developed and used in the US in the early 2000s (USDA & USEPA, 1999). The structure and content of P indices have undergone significant alterations since the first P index was developed by researchers (Nelson & Shober, 2012). For instance, the computational design of many P indices was altered from additive (being the first generation) to multiplicative or component index in the second or third generations (Nelson & Shober, 2012).

The original index or first generation index was the additive index where it was computed as the sum of P loss factors multiplied by respective weighting factors (J. L. Lemunyon & R. G. Gilbert, 1993). The initial index is known as an additive index because the impact of each P loss component is added to obtain the final index rating (Nelson & Shober, 2012). For example, a field site could be ranked with a very high-risk assessment based on site management factors alone, even though no surface runoff or erosion occurred (Sharpley et al., 2003). Also, a field site with a high potential for surface runoff or erosion but with low soil phosphorus is not at risk for a high P loss and would get a low risk assessment rating unless fertilizer or manure was applied (Sharpley et al., 2003).

The second generation is the MPI which was first proposed by Gburek et al. (2000) (Nelson & Shober, 2012) and subsequently revised by others (Sharpley et al., 2003). A MPI is therefore the result of P source factors (S) and P transit factors (T) (Nelson & Shober, 2012). Although separating the source and transport factors is contradictory with how process-based P loss models depict P loss (Bolster et al., 2012), a multiplicative formulation more accurately captures the processes controlling P loss than the original additive PI formulation of Lemunyon & Gilbert (1993).

The third generation or component index is an improvement over the multiplicative index and better represents how different combinations of P sources and related transport processes are represented by each component (Bolster et al., 2012). This index is more in line with how P loss manifests itself in the real world and how process-based P loss models mimic P loss (Bolster et al., 2012). Each state was encouraged to develop their own P index and major differences exist among P indices across the United States (Sharpley et al., 2003). Because of this a component index will have to have State specific factors that influence the development of the index (Sharpley et al., 2003).

Kansas Phosphorus Index

The state of Kansas uses an MPI and is applied as a planning tool and qualitative risk assessment. The MPI (PI_m) is calculated as follows:

Equation 3.1: Kansas Phosphorus Index

$$PI_m = (Pc + 0.1(Pfr) + Pfm + 0.1(Por) + Pom\ ) * (2(E) + Rc + Dc + Ifc + Isc) \quad \text{[Eq. 3.1]}$$

Where, *Pc* is the soil test P category risk, *Pfr* is the annual average fertilizer P application rate (lbs P_2O_5/ac), *Pfm* is the P fertilizer application method risk factor, *Por* is the annual average organic P application rate (lbs P2O5/ac), *Pom* is the organic P source application method risk factor, *E* is the soil erosion by water (tons/acre/year) (RUSLE), *Rc* is the soil run-off classification category risk factor, *Dc* is a categorical factor related to the proximity of field to perennial streams, perennial surface water bodies, or intermittent streams, *Ifc* is the furrow irrigation erosion risk category, and *Isc* is the sprinkler system erosion/run-off risk category.

Equation 3.1 can be simplified by combining some similar factors (such as Pfr and Por) and written as followed in Equation 3.2:

Equation 3.2: Simplified Version of the Kansas Phosphorus Index

			(2)	Erosion	(+)	
	Soil Test P	(+)		Soil Runoff Class	(+)	
(0.1)	P Application rate	(+)		Distance to water body	(+)	
	Application Method/Timing			Irrigation Erosion		
	P Source Factors	**X**		**Transport Factors**		**= Risk**

Issues with The Kansas P Index

In order to meet new standards made by the USDA title 190, certain inputs would have to be revised (NRCS & USDA, 2017), including soil test P (STP), runoff, and application method and timing. Figure 3.1 shows the effect of STP on the MPI. As STP increases, the MPI increases in a step like fashion until 200 ppm is reached then the MPI rating does not change even though your STP value continues to increase. Figure 3.2 shows how the rating for the runoff input within the MPI would remain the same for different locations no matter the soil type or precipitation amount. Even when picking locations throughout Kansas with different precipitation gradients, the MPI shows that they would all have the same P index risk assessment rating. So, to make the revisions necessary from the title 190, the Kansas index will be updated from a MPI to a component phosphorus index (CPI). While these revisions could be made directly in the MPI, the main reason this was not done was because certain inputs from the source factors had a direct effect with inputs from the transport factors. The MPI is not set up this way therefore, the only way to make this revision is to move to a component P index where each one of the source and interconnected transport factors is multiplied to obtain a final P risk assessment rating. Such component P indices are used in several states, including Wisconsin, Iowa, Missouri, North Carolina, and Georgia (Bolster et al., 2012). Although component indices are developed for these other states, they cannot be directly applied to Kansas because each state's index is based on specific needs of that state and customized to such things as cropping systems, climate, and soils. On top of this, published literature does not adequately explain inputs to these indices, how they were formulated, and how they may be adapted to Kansas conditions.

Another solution to improving the MPI would be to revise it. While this is an option, this revision would not address the USDA/NRCS concerns with the new standards made from the title 190 document. For example, having certain input (STP) zero out (have an environmental threshold). On top of this the revision would still not address the relationship certain source factors had with interconnecting transports factors like a component index does. The MPI keeps both source and transport factors separated until the sum of both factors where then multiplied to get an overall P risk assessment rating. This study has four objectives: 1 Optimize coefficients to the components of the revised Kansas multiplicative P index). 2a. Develop a component P index. 2b Revise inputs such as soil test phosphorus and application method and timing so they are in line with the new NRCS/USDA standards. 3. Determine the relationship between measured P loss and the P indices (current, revised, and component).

Methods

A (CPI) for Kanas was developed following similar methodology that was used to develop a CPI for Kentucky (Bolster et al., 2014). A new method for accounting for application timing and method had to be developed that would fit into the concepts of a CPI. The coefficients of the component model were empirically determined through multiple linear regression with estimated P loss data from the APEX model. The MPI was similarly revised with empirically determined coefficients. The CPI, revised multiplicative index (rMPI), and (MPI) were evaluated by comparison with measured P loss data to determine if the CPI was an improvement over the current MPI.

Application Method and Timing Methodology

Timing of Fertilizer Application

For timing, National Oceanic and Atmospheric Administration (NOAA) Regional Climate Center 30-year daily precipitation data was queried from the Applied Climate Information System (ACIS) data base for 25 counties across Kansas (Crawford, Cheyenne, Comanche, Cowley, Elk, Ellis, Ellsworth, Franklin, Gray, Hamilton, McPherson, Morton, Nemaha, Ness, Republic, Riley, Scott, Sumner, Thomas, Lyon, Stafford, Phillips, Chase, Labette, Jefferson). While collecting data, 5 counties (Comanche, Ellsworth, Stafford, Labette, and Jefferson) did not have complete 30-year daily precipitation data and therefore were left out of this data set leaving 19 counties in total (Figure3.3). Overall, to find the percent of annual runoff the first calculation included the average monthly precipitation, second is the average monthly number of precipitation events (n), third is the average precipitation for an event in the given month (α), fourth finding runoff by having a given curve number (in this case modified 0.05), S (0.05) and $\lambda = 0.05$. The values used included CN(0.05) = 69 which was calculated by (0.0054*78^2+0.46*78), S(0.05) which was calculated by (1000/69)-10 = 4.5.

That Data set used in calibrating are from Crawford, Franklin4 and Franklin8 county data from the APEX simulation data (Table 3.1). APEX is used as a simulation tool to estimate runoff erosion and crop growth, all of which are minimum requirements for the model to also calculate

P loss (Gassman et al., 2010). Apex can simulate a wide range of management practices such as tillage, terraces, buffer strips, and land application of manure or poultry etc. (Gassman et al., 2010). The data used for this research came from Bhandari's, 2016 dissertation which used weather, watershed characteristics and management practices which were required inputs required to drive the APEX simulation model to obtain this data (Bhandari, 2016).

The data started with 2,890 data points with 4 months (January 15th, April 1st, October 15th, and November 15th) being used for three cropping systems (CC) Continuous Corn, (CS) Corn-Soybean, (CWS) Corn-Winter Wheat-Soybean while 5 months (January 15th, April 1st ,June 1st October 15th, and November 15th) were used for a single cropping system (GS) Grain Sorghum-Soybean. The data used in this research ended with 1360 data points.

Method of Fertilizer Application

When updating the application method, research focused on determining if there are qualitative differences between surface application, subsurface application and incorporated. This was done to check that our modeled data followed the general trends that we would expect from literature. The next step involved determining ratings for each category injected, incorporated and surface application for different respected times of the year.

To do this journal articles with published data were found to get a qualitative assessment of the differences between surface broadcast, incorporation and injection to determine the percentage of P loss due to phosphorus fertilizer (Table 3.2). Articles that had both a control and one of the three fertilizer methods were found. An example would be, taking a control (0 fertilizer) with 1 lbs./ac. P loss, surface broadcast (35 lbs of P_2O_5/ac.) with 5 lbs./ac. P loss and injected (35 lbs of P_2O_5/ac.) with 2 lbs./ac. P loss and calculating the difference between P loss due to fertilizer (injected) and P loss due to fertilizer (surface broadcast). This can be seen in Equation 3.3 below.

Equation 3.3: Calculation for Method Application Factor

$$\frac{(Injectted)-(Control)}{(Surface\ Broadcast)-(Control)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..[\text{Eq. } 3.3]$$

To calculate fertilizer P loss due to runoff in lbs. P_2O_5 for injected and surface broadcast, one would use Equation 3.3. Injected; (2 lbs./ac P loss – 1 lb./ac P loss) = 1. Surface broadcast (5 lbs./ac P loss – 1 lb./ac P loss) = 4. Next, injected is divided from surface broadcast (1/4 = 0.25). Therefore, the coefficient for injected would be 0.25 and surface applied would be 1 because we are assuming that surface broadcast has the most fertilizer P loss due to runoff.

Kansas Component P Index Methodology

The component index equation focused specifically on what Kansas agriculture needed and its relation to other P indices in the United States. The final equation was run through SAS (Statistical Analysis System) using Proc Mix to ensure all inputs were significant data used to do this came from Table 3.1. The Kansas component index is below in Equation 3.4:

Equation 3.4: Kansas Component Phosphorus Index

$$\text{Ploss} = \beta_1 + \beta 2(S_{n1} \times \text{Q}) + \beta_3(S_{n1} \times\ T_m) + \beta_4(S_{n2} \times AF \times Q) \quad \ldots\ldots\ldots\ldots\ldots[\text{Eq. } 3.4]$$

(Sn_1) = Soil test phosphorus, ($Sn2$) Phosphorus rate, (Tm) RUSLE 2 sediment loss, (AF) Application method and timing, (Q) Long-term average annual runoff estimated by modified curve number equation. The simplified version of Equation 3.4 is below in Equation 3.5.

Equation 3.5: Simplified Version of Kansas Component Phosphorus Index

β_1						(+)
β_2	(Soil Test P	(x)	Runoff: Long-term average annual)			(+)
β_3	(Soil Test P	(x)	Erosion: RUSLE 2 sediment loss)			(+)
β_4	(P Application Rate	(x)	Runoff: Long-term average annual	(x)	Application Method and Timing)	(+)
	P Source Factors	(x)	**Transport Factor**	(x)	**Source Factor**	**= Risk**

Coefficients or beta values to the component P-index were produced by using SAS (Statistical Analysis System) Proc mixed with Equation 3.4. The beta values were produced to help calibrate the CPI model. The code can be found in Appendix C.

Revision of the Kansas Multiplicative P Index Methodology

To see if improvement could be made to the current P index in the state of Kansas, it was revised and updated with coefficients. The index was calibrated with data collected from both Crawford and Franklin counties (Table 3.1). The new revised index uses Equation 3.6 seen below:

Equation 3.6: Revised Kansas Phosphorus Index

Revised Ploss = $\beta_0 + (\beta_1 \times S_{n1} + \beta_2 \times S_{n2} + \beta_3 \times AF \text{ rating}) \times (\beta_4 \times (T_m \times 0.44617) + \text{Soil Runoff rating})$ ……………………………………………………..[Eq. 3.6]

(Sn_1) Soil test phosphorus, (S_{n2}) Phosphorus rate in lbs of P_2O_5 per acre, (Tm) RUSLE 2 sediment loss, (*AF*) Application method and timing rating (category risk) given by the original P index, and soil runoff rating (category risk) given by the original P index.

Comparing Equation 3.6 to Equation 3.1, (*Pc*) Soil Test P was not used as this was the rating category risk therefore, we used the actual Soil Test P value (Sn_1). (*Pfr*) and (*Por*) were used separately in Equation 3.1, instead they were treated as one value in Equation 3.6 (S_{n2}). (*Pfm*) and (*Pom*) were used separately in Equation 3.1, instead they were treated as one value in Equation 3.6 (*AF*). In Equation 3.1 (*E*) RUSLE is the same as (*Tm*) in Equation 3.6. The Soil Runoff rating in Equation 3.6 is the same as (*Rc*) in Equation 3.1. Inputs not included in Equation 3.6 but were in Equation 3.1 include: (*Dc*) Proximity of field to perennial streams, perennial surface water bodies, or intermittent streams, (*Ifc*) Furrow Irrigation Erosion category risk, (*Isc*) Sprinkler System Erosion/Run-off category risk. These inputs were left out because they were either not part of our P loss dataset (eg., irrigation erosion and runoff) or they are not uniquely associated with a specific cropping system (eg., proximity to surface water). Coefficients or beta values to the revised multiplicative P-index were produced by using SAS (Statistical Analysis System) Proc mixed with Equation 3.6. The beta values were produced to help calibrate the CPI model. The code can be found in Appendix C.

Validation of the Kansas Component Phosphorus Index Methodology

Once Equation 3.4 of the CPI was complete, the new method would now need to be validated. Data for this came from existing counties including Riley, Crawford, Franklin, and Geary County and can be seen in Table 3.4. Validation was conducted by relating the P index values to measured P loss data from edge-of-field runoff experiments. The P-index values were calculated with two different techniques. First, we used measured annual erosion and runoff as inputs to the P-indices and then compared the resulting index to measured annual P loss, similar to the way other studies have evaluated P indices against measured data (Osmond et al., 2017; Bolster et al., 2014; Bolster et al., 2012). Second, we computed the P index for each location and management using the RUSLE2 erosion and estimated annual average runoff from a modified curve number approach (Chapter 2) which was then summarized as inputs. This was then related to the average annual P loss over the period of record for the location and management. The annual data included 74 total data points: 42 points from Riley County, 20 for Crawford County, 12 from Franklin County, and 4 from Geary County (Table 3.4). The summarized data included 20 points: 12 points from Riley County, 5 for Crawford County, 3 from Franklin County, and 2 from Geary County (Table 3.4).

Results and Discussion

Application Timing and Method

Fertilizer application timing can have a direct effect on the amount of P lost from an agricultural system. This direct effect can happen when runoff occurs because of increased precipitation during certain months of the year. For example, when surface applying fertilizer, the granules usually end up remaining on the soil surface which makes it susceptible to runoff especially if applied in months that have more runoff potential. Due to this interaction timing will only be applied to surface application of fertilizer for the CPI. Timing ratings for surface application were obtained from Figure 3.3. In this figure, the percentage of annual runoff throughout a year averaged over 31 years for 19 different counties was obtained. With this figure, three main grouping of months stood out (low percent of annual runoff, moderate percent of annual runoff and high percent of annual runoff. The figure showed that months (January – March, November and December) had the lowest percent of annual runoff, months (April, September and October) had a moderate percent of annual runoff and months (May-August) had the highest percent of annual runoff. Professional judgment guided by monthly rainfall throughout the state helped in determining the timing ratings for Table 3.3.

Fertilizer application methods include surface application of fertilizer, incorporation of surface applied fertilizer and injection of fertilizer below the soil surface. Surface applied is when fertilizer (inorganic or organic forms) is applied directly to the soil surface. Incorporation of fertilizer is when fertilizer is applied directly to the soil surface then tilled into the soil. Fertilizer applications that are injected are placed underneath the soil surface, usually with or alongside the seed that is being planted. Fertilizer application method can directly affect P loss in agricultural fields. Surface application of fertilizer affects P loss the most as granules on the surface can be lost due to runoff. Injection of fertilizer affects P loss the least as it is applied beneath the soil surface being directly available for plant uptake and not being affected by runoff. Incorporation of fertilizer affects P loss more than injected but less then surface application as fertilizer is tilled up into the soil leaving small amounts of fertilizer left on the soil surface which can potentially be lost due to runoff. While this may be using professional judgement, journal articles were also found to support differences in fertilizer application method (Table 3.2).

Articles form Table 3.2 were found that tested both a control site and a fertilizer application method (Carver et al., 2022; Kimmell et al., 2001; Tarkalson & Mikkelson, 2004). Carver et al., 2001 and Kimmel et al, 2001 articles were used to determine the difference between surface application and injection to calculate the percent loss due to P fertilizer. Tarkalson & Mikkelson et al., 2004 was used to determine the difference between surface application and incorporation to calculate percent loss due to P fertilizer. Table 3.3 further proved that there is a difference between injected and incorporation. Other sources including (Daverede et al., 2004; Jokela et al., 2016; Kleinman et al., 2009) also found differences in Total P loss between incorporated and surface applied in their studies. This further suggests that these application methods should hold different weighting factors when used to determine P loss.

The timing and placement of phosphorus fertilizers or manure have a significant impact on the amount of phosphorus lost in surface runoff, which can outweigh the impacts of other inputs like soil test P (Hart et al., 2004; Kleinman et al., 2002). Application of fertilizers or manures is specifically important as losses in P may happen from subsurface flow or surface runoff (viz. subsurface runoff) (McDowell, 2012). When averaged over several years and studies, adding P fertilizer below the soil's surface can reduce dissolved and total P losses by 50 and 40 percent, respectively (Carver et al., 2022; Kimmell et al., 2001; M B Zeimen et al, 2006). When P fertilizer is applied in the fall, the likelihood of runoff may increase in some climates where the soil is typically wet and rainfall is frequent (Richards et al., 2010), but it may decrease in other climates where the soil is dry and winter precipitation is sparse(Carver et al., 2022). In general, as more time passes for P to bind to soil surfaces, the chance of P loss diminishes since there is more time between P application and runoff-producing rains (Vadas et al., 2008). In no-till settings, it has also been discovered that subsurface application of P-based fertilizer reduces bioavailable P losses by over 70% as compared to broadcast application (Kimmell et al., 2001). In a paper by (Schwab et al., 2006) comparing surface P placement to subsurface placement, certain studies demonstrated that there was a yield advantage with subsurface P placement when soil test P is average to below average. Other studies showed no difference between subsurface P fertilizer placement and broadcast (Bordoli & Mallarino, 1998; Fernández & White, 2012).

For manure, application should be limited to times of year when runoff is uncommon since the availability of manure-P reduces significantly with time after application (including snowmelt) (McDowell, 2012). Utilizing application techniques that provide manure to the soil as a slurry also reduces P loss by enhancing contact and sorption with the soil matrix (Daverede et al., 2003). In contrast, adding P to the plough layer right after application can reduce P losses if erosion is kept to a minimum (McDowell, 2012).

Finally, due to our findings with application timing and method we based our new ratings (Table 3.3) off the Pennsylvania index, these values ranged from 0.2 to 1. This approach is different than the application method and timing ratings of the current Kansas MPI, where this approach uses factors less than 1 to reduce P loss when the best management practices are used. The current index uses larger numbers as seen in appendix A that range from 0 to 8. The larger factors are used for poor practices to increase the index rating. Original creators to the current index have stated that ratings were arbitrarily selected, and caution should be taken when developing new ratings for these inputs (J. L. Lemunyon & R. G. Gilbert, 1993).

Other inputs to the Kansas P index brought up in the issues with the Kansas multiplicative P index section that were not touched on much include, the Soil test phosphorus (STP) and the runoff input. STP and runoff were both updated strictly from categorical to a qualitative assessment. For STP, this update was simple where the categorical values were replaced with exact STP values in ppm taken from the field. Thus, this gives an environmental threshold for which STP can relate to P loss. Figure 3.4 shows this relationship, and as STP increases, we get an increase in the CPI index. The runoff component was explained more in chapter two but by looking at (Figure 3.5), it shows that with an increase in runoff in (m) there is an increase in our component index rating. With the previous runoff input in the MPI we would see all the listed locations in Figure 3.5 be given the same runoff rating value which would not correlate with the precipitation gradient in which each specific location lies.

The revised soil test phosphorus and application method and timing factors would work within the updated P index as it meets the new NRCS standards stated in 2017 The National Instruction for Nutrient Management Policy Implementation (Title 190) which was amended to include minimum criteria for P indices, known as section D (Minimum Criteria for State P-Index Tools), which has six different criteria (NRCS & USDA, 2017). By using the revised STP and application method and timing, the Kansas P-Index will meet criteria (iii) and criteria (vi). Criteria (iii) which states "*A P index tool must demonstrate that risk increases with increasing STP and also depends on method of application (surface application versus* *injection/incorporation)* …"(NRCS & USDA, 2017). Criteria (vi) which states "*The P-Index must "zero-out" at some point (environmental threshold)...*"(NRCS & USDA, 2017).

Component P Index

When calibrating the (CPI) with the Beta values we see that every one of the beta values within the equation (Where, β_1, β_2, β_3, and β_4 are fitting parameters 0.4251, 0.04128, 0.002990, and 0.1220 respectively) are all significant at $p<0.0001$. (Figure 3.8) shows what the component P index looks like using existing data from Crawford and Franklin counties. When comparing (Figures 3.6 and 3.8) the relationship shows improved model performance of an R squared of 0.41 from the MPI to an R squared of 0.82 with the CPI. We also see an improved model performance from the rMPI with R squared of 0.62 to an R squared of 0.82 with CPI. This revision addresses all specific concerns and updates regarding the Kansas Phosphorus Index title 190 stated from USDA/NRCS. Therefore, the CPI would be a sufficient model to use in the Kansas P Index.

Finally, when validating all the models using annual data Figure 3.3.9 shows an increase in model performance between the CPI and the MPI and rMPI. An increase in model performance can be seen when looking at graph (b) the rMPI $R^2 = 0.07$, to graph (a) the MPI $R^2 = 0.09$, and again to graph (c) the CPI $R^2 = 0.71$. Overall, with the annual data the MPI would have a poor model performance along with the rMPI and would not be a sufficient model to use for the Kansas P index. However, the CPI does have an improved model performance and would be a sufficient model to use for the Kansas P index. When validating again with summarized data Figure 3.10 shows an increase in model performance with graph (b) rMPI R2 = 0.68, graph (a) MPI $R^2 = 0.73$, and graph (c) CPI $R^2 = 0.85$. Overall, in the annual data the CPI would be a sufficient model to use for the Kansas P index. However, with the summarized data all models show good model performance although the CPI would be the favored model to use with a higher R squared over the MPI and rMPI.

When comparing our findings to (Osmond et al., 2017) findings show that both the multiplicative and component P indices has similar USDA / NRCS loss rating correspondence to 60 and 64 percent respectively. When comparing that to what we found while the summarized data may have decent R squared values there is a 15 percent difference between our MPI and CPI indexes thus telling us that there is a difference between an MPI and a CPI. The improvement in the component index is a result of changing the inputs and structure of the index and not a result of the process of improved fitting parameter. This improvement to the fitting parameters was also conducted on the rMPI and if this were a main reason for the improvement of the CPI, similar results would have been expected in the rMPI and those results were not seen.

Revised Multiplicative P Index

When calibrating the MPI to obtain the rMPI there were some overall improvements. When calibrating rMPI with the Beta values we see that every one of the beta values within the s (where, the β_0, β_1, β_2, β_3, and β_4 are fitting parameters -0.4822, 0.0329, 0.00101, 0.0113, and 4.1852 respectively) (Figure 3.7) shows what the revised multiplicative index looks like using existing data from Crawford and Franklin counties. When comparing (Figure 3.6 and 3.7) the relationship shows improved model performance of an R squared of 0.41 to an R squared of 0.62. This revision does not address specific concerns and updates regarding the Kansas Phosphorus Index title 190 stated by USDA/NRCS. The revised multiplicative index would not be a sufficient model to use because by calibrating the rMPI with beta values this did not seem to improve the index thus changes to the inputs and the structure of the index would be needed.

Finally, when validating all the models with annual data Figure 3.9 shows a decrease in model performance between the MPI and the rMPI. Graph (a) MPI $R^2 = 0.09$ has a better R squared values than graph (b) rMPI $R^2 = 0.07$. Using summarized data Figure 3.10 also shows a decrease in model performance with graph (a) MPI $R^2 = 0.73$ to graph (b) rMPI $^{R2} = 0.68$. Overall, in the annual data both the MPI and rMPI have poor model performance and would not be sufficient models to use for the Kansas P index. However, with the summarized data both models show good model performance although the MPI would be the favored model to use with a higher R squared over the rMPI although the MPI is not an adequate model as it does not meet USDA/NRCS standard form Title 190.

Conclusion

P Index assessments or research could result in improvements such as better weighting factors, the creation and use of regional P indices, and a better P Index framework (i.e., additive, multiplicative, or component) (Nelson & Shober, 2012). The best strategies for updating the P Index framework and improving the weighting elements for the P Index should be determined through further study (Nelson & Shober, 2012). This chapter goes over the updated inputs needed in a component index for the state of Kansas and the need for it to meet Title 190 requirements set forth but the USDA/NRCS. Overall, the component P index has a much better relationship with the estimated P loss (R^2 = 0.82) indicating that it may be an improvement over the current multiplicative P index for estimating the relative risk of P loss from agricultural fields. For Validation, there seems to be an improvement from MPI to CPI in correlation to P loss with an improved (R^2 = 0.85). However, Further research will need to be done to Evaluate effects of the component P index on producers across Kansas. Throughout the review and development process, the eventual index interpretation and implementation should be taken into account(Nelson & Shober, 2012). A crucial factor to remember is that despite producing continuous (or semicontinuous) numerical output, P indices interpret the overall output as a qualitative risk rather than a numerical value (Nelson & Shober, 2012).

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Tables

Table 3.1: Apex simulation data. Represents the locations. Cropping systems and managements used as well as the total number of data points used represented on graphs.

Location	Tillage	Management	Cropping System	Number of P Application Times *	Number of P Application Rates **	Number of initial STP values***	# of data points on graph. ****
Crawford	No-Till	Surface Broadcast	Continuous Corn	~~(4)~~ 2	5	5	50
Crawford	No-Till	Surface Broadcast	Corn / Soybean	~~(4)~~ 2	5	5	50
Crawford	No-Till	Surface Broadcast	Corn / Wheat / Soybean	~~(4)~~ 2	5	5	50
Crawford	No-Till	Surface Broadcast	Grain Sorghum / Soybean	~~(5)~~ 2	5	5	50
Crawford	Conventional Till	Incorporated	Continuous Corn	~~(4)~~ 2	5	5	50
Crawford	Conventional Till	Incorporated	Corn / Soybean	~~(4)~~ 2	5	5	50
Crawford	Conventional Till	Incorporated	Corn / Wheat / Soybean	~~(4)~~ 2	5	5	50
Crawford	Conventional Till	Incorporated	Grain Sorghum / Soybean	~~(5)~~ 2	5	5	50
Franklin 4	No-Till	Surface Broadcast	Continuous Corn	~~(4)~~ 2	4	5	40
Franklin 4	No-Till	Surface Broadcast	Corn / Soybean	~~(4)~~ 2	4	5	40
Franklin 4	No-Till	Surface Broadcast	Corn / Wheat / Soybean	~~(4)~~ 2	4	5	40
Franklin 4	No-Till	Surface Broadcast	Grain Sorghum / Soybean	~~(5)~~ 2	4	5	40
Franklin 4	No-Till	Sub-surface Application	Continuous Corn	~~(4)~~ 2	4	5	40
Franklin 4	No-Till	Sub-surface Application	Corn / Soybean	~~(4)~~ 2	4	5	40
Franklin 4	No-Till	Sub-surface Application	Corn / Wheat / Soybean	~~(4)~~ 2	4	5	40
Franklin 4	No-Till	Sub-surface Application	Grain Sorghum / Soybean	~~(5)~~ 2	4	5	40
Franklin 4	Conventional Till	Incorporated	Continuous Corn	~~(4)~~ 2	4	5	40
Franklin 4	Conventional Till	Incorporated	Corn / Soybean	~~(4)~~ 2	4	5	40
Franklin 4	Conventional Till	Incorporated	Corn / Wheat / Soybean	~~(4)~~ 2	4	5	40
Franklin 4	Conventional Till	Incorporated	Grain Sorghum / Soybean	~~(5)~~ 2	4	5	40
Franklin 8	No-Till	Surface Broadcast	Continuous Corn	~~(4)~~ 2	4	5	40
Franklin 8	No-Till	Surface Broadcast	Corn / Soybean	~~(4)~~ 2	4	5	40
Franklin 8	No-Till	Surface Broadcast	Corn / Wheat / Soybean	~~(4)~~ 2	4	5	40
Franklin 8	No-Till	Surface Broadcast	Grain Sorghum / Soybean	~~(5)~~ 2	4	5	40
Franklin 8	No-Till	Sub-surface Application	Continuous Corn	~~(4)~~ 2	4	5	40
Franklin 8	No-Till	Sub-surface Application	Corn / Soybean	~~(4)~~ 2	4	5	40
Franklin 8	No-Till	Sub-surface Application	Corn / Wheat / Soybean	~~(4)~~ 2	4	5	40
Franklin 8	No-Till	Sub-surface Application	Grain Sorghum / Soybean	~~(5)~~ 2	4	5	40
Franklin 8	Conventional Till	Incorporated	Continuous Corn	~~(4)~~ 2	4	5	40
Franklin 8	Conventional Till	Incorporated	Corn / Soybean	~~(4)~~ 2	4	5	40
Franklin 8	Conventional Till	Incorporated	Corn / Wheat / Soybean	~~(4)~~ 2	4	5	40
Franklin 8	Conventional Till	Incorporated	Grain Sorghum / Soybean	~~(5)~~ 2	4	5	40

* (4) 15- Jan, 1- Apr, 15- Oct and 15- Nov. / (5) 15- Jan, 1- Apr, 5- Jun, 15- Oct and 15- Nov. Only the data for application times of 1-Apr and 15-Nov. were used for this study.
** Continuous corn application rates were 0, 51.1, 102.2, 204.4, 408.8. All other cropping systems' application rates were 0, 25.55, 51.1, 102.2, 204.4.
*** For all STP rates the 5 used are as indicated: 25, 50, 100, 200, 400.
****Represents number of data points on Figures 3.#, 3.# and 3.#.

Table 3.2: Journal articles with published data used to assess the differences between surface application and incorporated or injected to determine the percent loss due to phosphorus fertilizer. The table includes references and management information from articles.

Reference	Location	P source	Application method	Method factor(s) in Kg/ha	Notes
Carver et al., 2022	Manhattan, Kansas	Fertilizer	Injected	0.14, 0.5, 1, 0.79	Field study; plot size (0.5 ha) with 3 P rates
Tarkalson & Mikkelsen, 2004	Raleigh North Carolina	Fertilizer	incorporation	0.45, 0.02, 0.10	Rain simulator; plot size (2x2) with4 P rates
Tarkalson & Mikkelsen, 2004	Raleigh North Carolina	litter	incorporation	0.10, 0.08, 0.03, 0.09	Rain simulator; plot size (2x2) with4 P rates
Kimmell et al., 2001	Ottowa, Kansas	Fertilizer	Injected	2.5, -0.9, 0.2, 1	Field Study with chisel and No Till systems

Table 3.3: Application Method and Timing input ratings: This table shows the rating value given to each application method and timing scenario for the Kansas component index. Updated based on seasonal runoff estimates in published data. The values are based on values ranging from 0.2 to 1 from the Pennsylvania index. Used fraction of runoff occurring in each month to develop monthly grouping in application timing.

Application method	Application Timing	Value
Injected		0.2
Incorporated		0.4
Surface Application	(November – March)	0.6
Surface Application	(April, July, August – October)	0.8
Surface Application	(May and June)	1

Table 3.4: Annual and Summarized data used in validation the CPI. Shows site and cropping system and management used in what years. Also shows the number of data points used represented on graphs.

Site	Tillage	Fertilizer Management **	Cropping System	Cover *	Years	# of data points on graph Annual	Range of STP (ppm) ****	Range of Runoff (mm) ****	Range of erosion (Kg/ha) ****	# of data points on graph Summarized***
KAW	No-Till	CN: Control, No P fertilizer	Corn / Soybean	2	2016 - 2019	8	7.3 – 32	55 - 307	22 - 6012	2
KAW	No-Till	FB: fall surface broadcast P fertilizer	Corn / Soybean	2	2016 - 2019	8	7.3 – 32	55 - 307	22 - 6012	2
KAW	No-Till	SI: Spring Injected P fertilizer	Corn / Soybean	2	2016 - 2019	8	7.3 – 32	55 - 307	22 - 6012	2
KAW	No-Till	BM: Spring Injected P fertilizer	Corn / Soybean	2	2020 - 2022	6	2.7 – 30	76 - 243	52 - 2095	2
KAW	No-Till	CN: Control, No P fertilizer	Corn / Soybean	2	2020 - 2022	6	2.7 – 30	76 - 243	52 - 2095	2
KAW	No-Till	SF: Spring Injected P fertilizer	Corn / Soybean	2	2020 - 2022	6	2.7 - 30	76 - 243	52 - 2095	2
Crawford	No-Till	Control, No turkey litter or fertilizer	Grain Sorghum.	-	2005 - 2008	4	8.5 – 52.5	21 - 424	7 - 574	1
Crawford	No-Till	Fert, N and P fertilizer only	Grain Sorghum.	-	2005 - 2008	4	8.5 – 52.5	21 - 424	7 - 574	1
Crawford	No-Till	TLN, Turkey litter only applied based on N rate for the crop (over applies P)	Grain Sorghum.	-	2005 - 2008	4	8.5 – 52.5	21 - 424	7 - 574	1
Crawford	No-Till	TLP, Turkey litter applied based on P rate plus N fertilizer to supply the remaining N rate for the crop	Grain Sorghum.	-	2005 - 2008	4	8.5 – 52.5	21 - 424	7 - 574	1
Crawford	Chisel, disk	TLPC, Turkey litter applied based on P rate plus N fertilizer to supply the remaining N rate for the crop	Grain Sorghum.	-	2005 - 2008	4	8.5 – 52.5	21 - 424	7 - 574	1
Franklin	Chisel, disk	CTBC: P fertilizer incorporated	Grain Sorghum.	-	2001 - 2004	4	6 - 27	38 - 275	78 - 2659	1
Franklin	No-Till	NTDB: surface broadcast P fertilizer	Grain Sorghum.	-	2001 - 2004	4	6 - 27	38 - 275	78 - 2659	1
Franklin	No-Till	NTSA: Injected P fertilizer	Grain Sorghum.	-	2001 - 2004	4	6 - 27	38 - 275	78 - 2659	1
Geary	No-Till	-	Corn / Soybean	2	2018 – 2021	4	11.2 – 20.3	39 - 251	195- 5331	1
Geary	No-Till	-	Corn / Soybean	2	2018 - 2021	4	11.2 – 20.3	39 - 251	195- 5331	1

*When cover has a (2), there are two option; (CC) cover crop and (NC) no cover crop. When (-) is present, indicates cover not defined in data.
** When (-) is present, indicates no specific management was defined in data.
*** (Description) Used average annual values of (Years) with either the (Cover – like in KAW and Geary) or (Fertilizer Management – Crawford and Franklin) to produce summarized data points for graph.
**** Use in Annual data set.

Figures

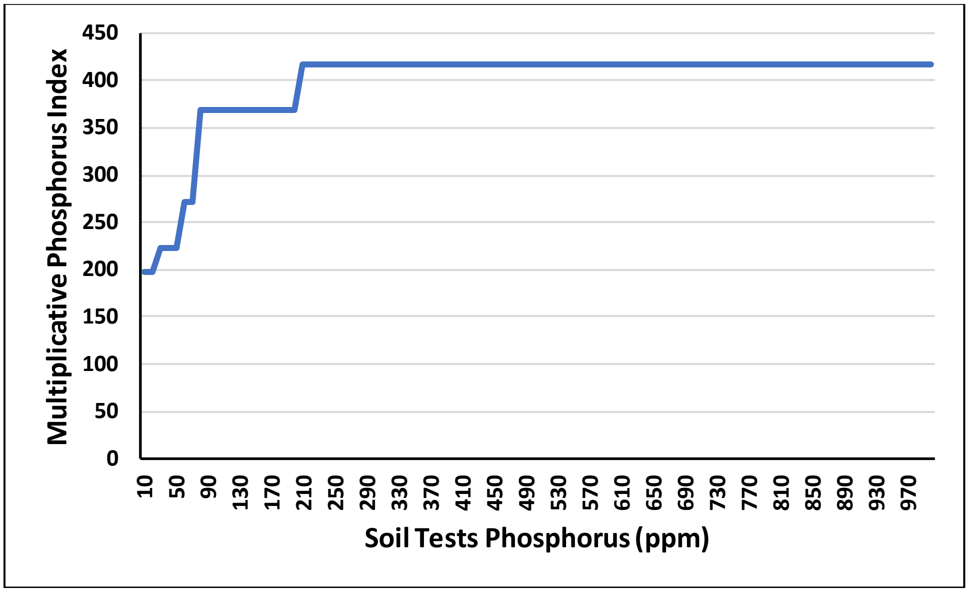

Figure 3.1: Multiplicative P Index Soil Test P: This figure shows how soil test P correlates with the multiplicative index. As STP increases, the MPI increases in a step like fashion until 200 ppm is reached then your MPI rating does not change even though your STP value continues to increase.

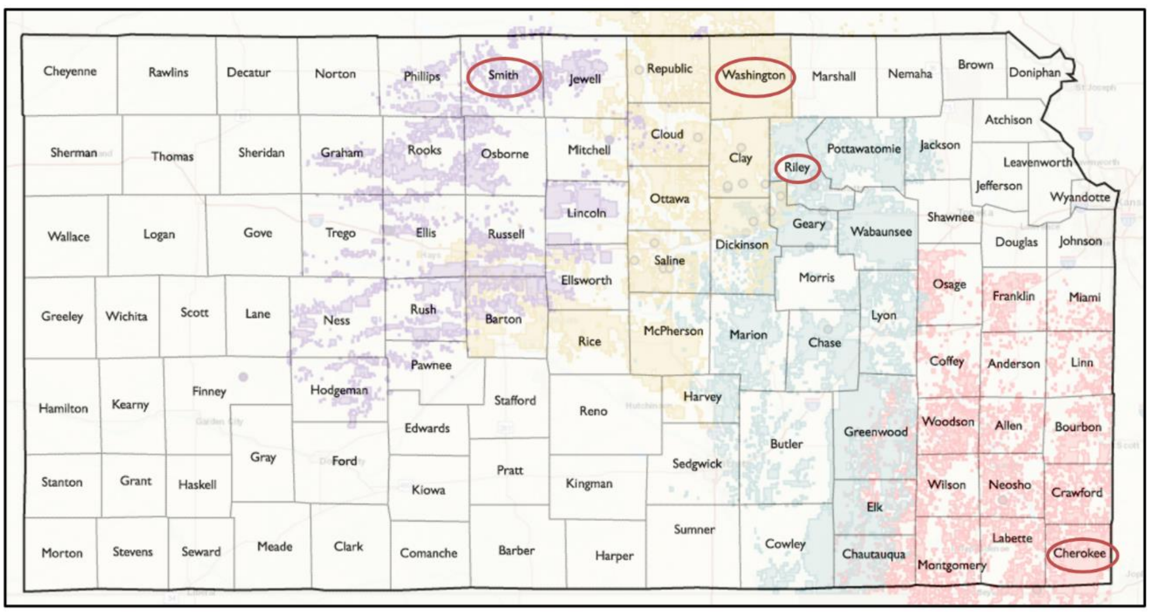

Figure 3.2: Map of Kansas counties and soil series: Map of the Wakeen (Purple), Crete (Yellow), Clime (Blue), and Dennis (Red) soil series, which all have a "high" runoff classification based on the hydraulic conductivity of the soils. The runoff factor used in the Kansas P-index is the same for each series even though the annual rainfall varies from 26 inches (for Smith) up to over 50 inches (for Cherokee). Therefore, even if you are using the same cropping management practices within any one of the four-soil series, you will get the same P-loss risk factor.

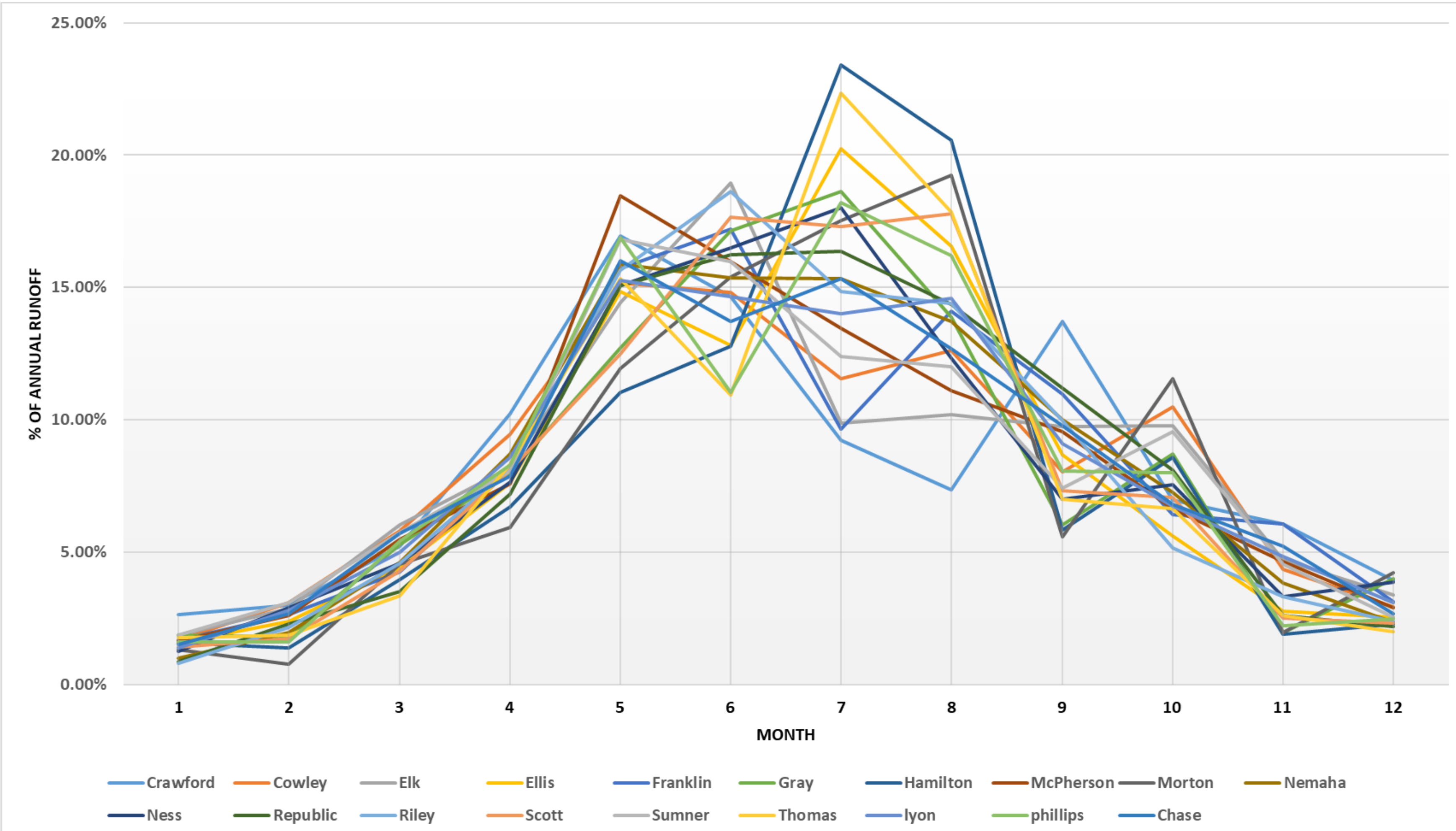

Figure 3.3: Percent of annual runoff throughout a year averaged over 31 years: Represents 19 different counties across the state of Kansas with different yearly precipitation values. Shows which months receive more or less percent of annnul runoff throught a year.

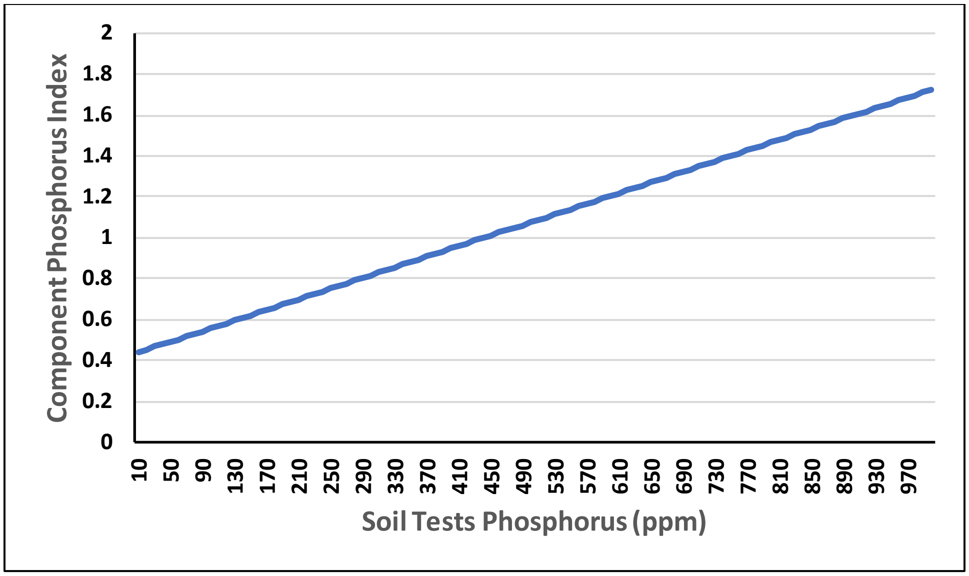

Figure 3.4: Component Phosphorus Index Soil Test Phosphorus: This figure shows how the component index increases linearly with soil test P. As STP increases, the CPI also increases. The CPI rating increases as your STP value continues to increase. This allows there to be an environmental threshold once one is in place then we can distinguish from what constitutes and a low, medium, and high STP values affecting your overall P loss value.

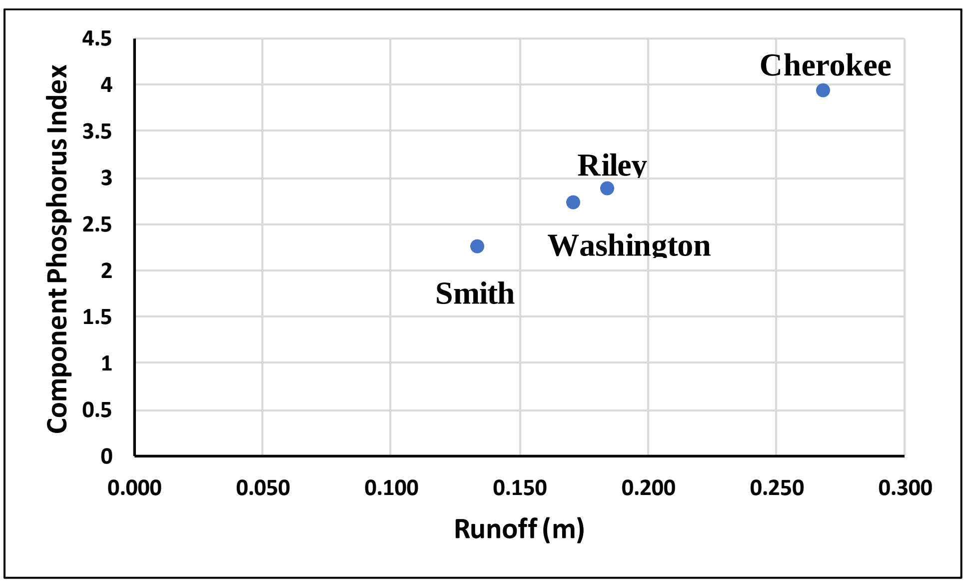

Figure 3.5: Component Phosphorus Index Runoff: This figure shows that with the new runoff input in the component index, that with an increase in runoff in (m) there is an increase in our component index rating. With location selected throughout Kansas, as our precipitation gradient increases from Smith County (northwest) to Cherokee county (southeast) there is an increase in runoff (m) and thus an increase in the CPI rating.

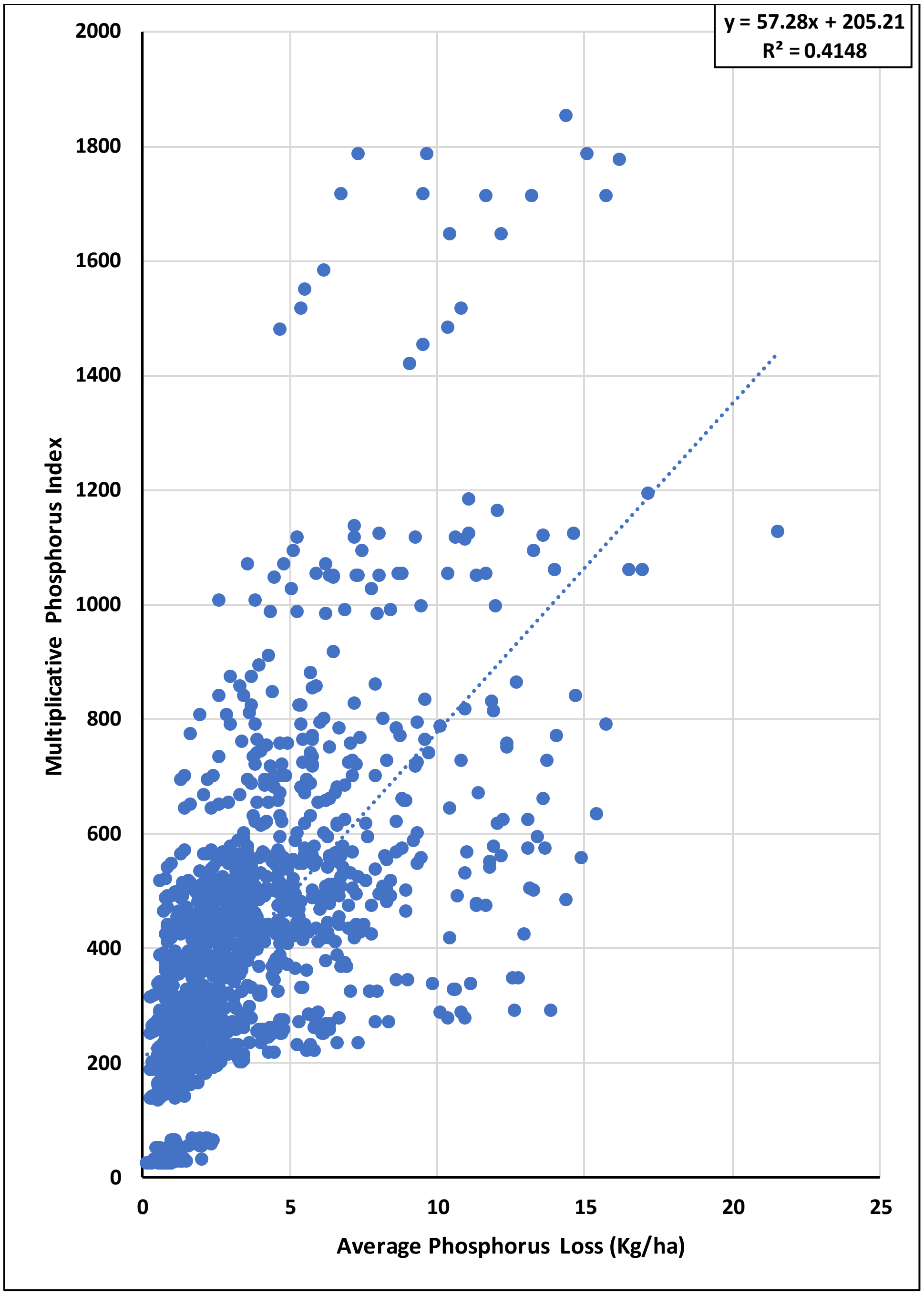

Figure 3.6: Multiplicative Phosphorus Index: This figure shows the correlation between the multiplicative index (unitless) and the average Phosphorus loss in (Kg/ha) from 2 field sites, one in Crawford County and one in Franklin County.

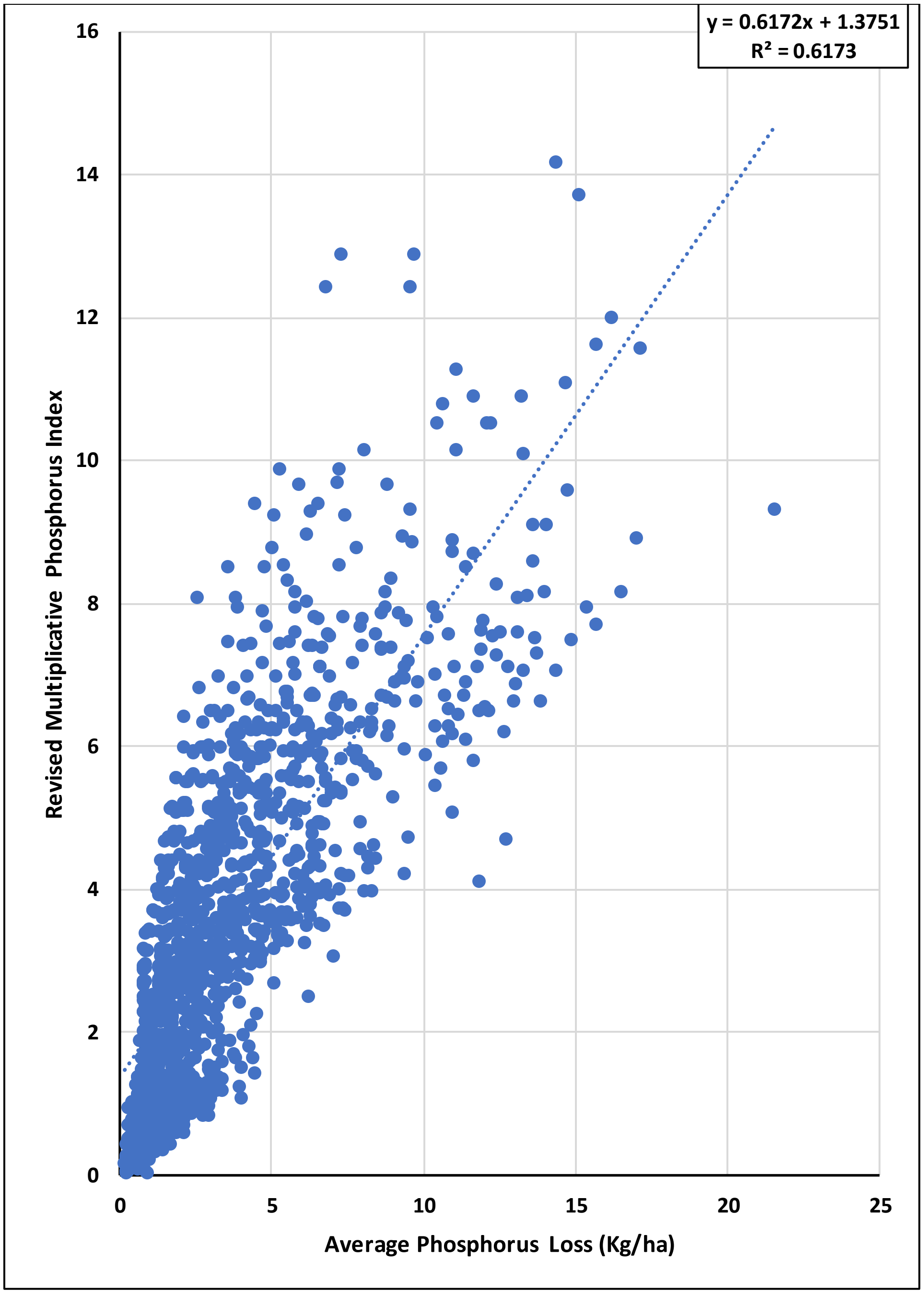

Figure 3.7: Revised Multiplicative Phosphorus Index: This figure shows the correlation between the revised multiplicative index (unitless) and average phosphorus loss in (Kg/ha) from 2 field sites, one in Crawford County and one in Franklin County.

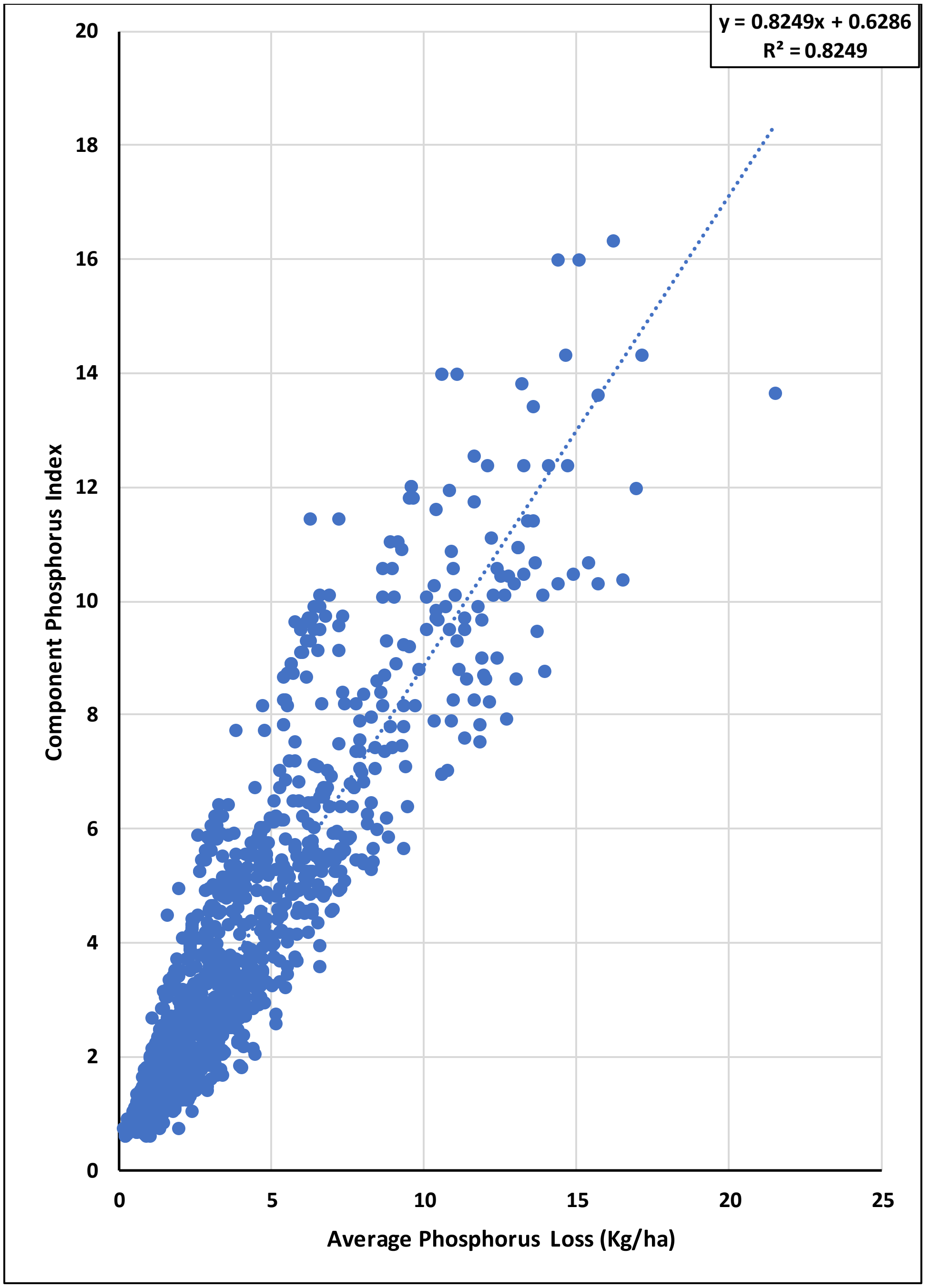

Figure 3.8: Component Phosphorus Index: This figure shows the correlation between the proposed component index (unitless) and average phosphorus loss in (Kg/ha) from 2 field sites, one in Crawford County and one in Franklin County.

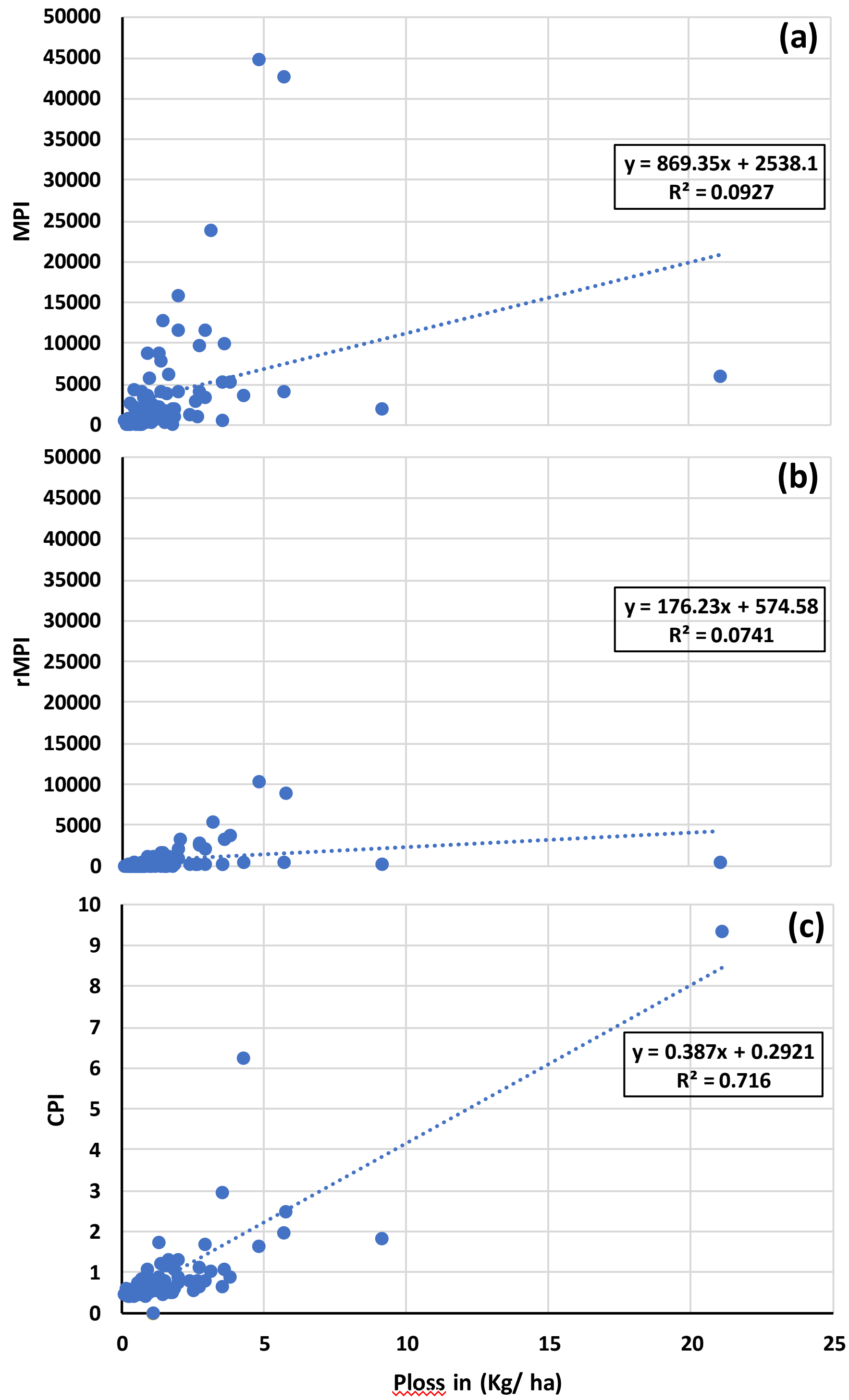

Figure 3.9: Validation of annual data comparing (a) the multiplicative P index (MPI), (b) the revised multiplicative P index(rMPI), and (c) the component index (CPI): all figures show the index (unitless) in correlation to P loss in (Kg/ha).

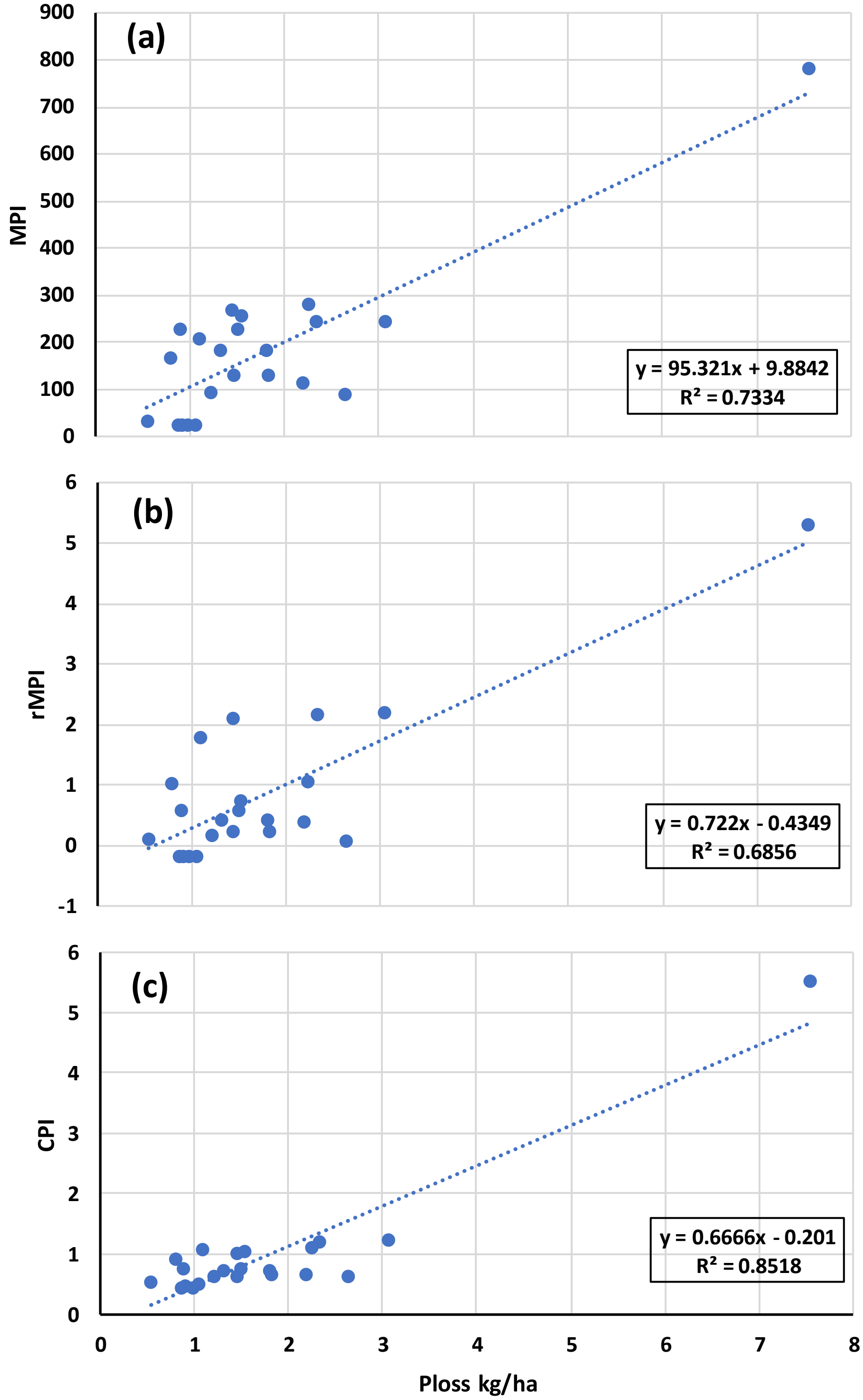

Figure 3.10: Validation of summarized data comparing (a) the multiplicative P index (MPI), (b) the revised multiplicative P index(rMPI), and (c) the component index (CPI): all figures show the index (unitless) in correlation to P loss in (Kg/ha).

Chapter 4 - Effects of Cover Crops on Ephemeral Gully Erosion.

Introduction

The purpose of this study is to quantify sediment loss from ephemeral gullies (EG's) in crop fields with cover crops and without cover crops. This is being conducted to see if cover crops have the potential to decrease EG erosion in crop fields. While there is currently little information out there on the effects of cover crops on EG formation. There are many techniques used to collect data including hand measurements as well as using aerial imagery which can be used to determine elevation differences in crop fields.

A cover crop is any living ground cover that is sown after, during, or before a main cash crop but is eliminated before planting the following cash crop, according to Hartwig & Ammon, 2002. Cover crops can contribute to environmental quality and soil health in many ways. In particular, it has been established that cover crops can reduce soil erosion, enhance soil aggregate stability, lessen weed pressure, limit surface runoff, increase soil water storage, and lessen nutrient leaching and runoff (Dabney et al., 2001; Loss et al., 2015). In a review of thirteen studies on sediment loss, Blanco-Canqui, 2018 discovered that cover crops can reduce sediment losses by up to 100% when compared to areas without them. Nevertheless, for one field site under consideration, cover crops had no effect on sediment losses (Blanco-Canqui, 2018).
In a cover cropping system, a "permanent" layer of plant residue covers the soil surface (Carver, 2022). Surface vegetation is widely known for preventing soil erosion by reducing the effect of rainfall, obstructing the flow of surface runoff, and stabilizing the soil through plant root growth (Gyssels et al., 2005; Morgan, 2009; Perret et al., 1996). Cover crop residue is also known to help reduce weed problems and help limit use of chemical fertilizers (Kruidhof et al., 2009).

Cover crops also have been known to reduce both interrill and splash erosion, and guard against soil aggregate degradation, surface sealing, and topsoil compaction (Kaspar et al., 2001; Morgan, 2009; Ryder & Fares, 2008). In temperate climates, they cover the soil's surface during the winter to shield it from physical degradation and splash erosion (e.g. aggregate destruction, topsoil compaction and surface sealing) (De Baets et al., 2011). At the start of winter, many of the covered crop's freeze. As a result, the soil's above-ground biomass is less effective at preventing water erosion (De Baets et al., 2011). In conjunction with the advantages of above-ground biomass in protecting the soil against raindrop impacts and reducing flow velocities by the retarding effects of their stems and leaves, Plant roots also play a significant role in improving soil strength and enhancing the resistance of topsoil's against concentrated flow erosion (De Baets et al., 2007; Gyssels et al., 2005; Knapen et al., 2007).

However, the impact of cover crop roots on concentrated flow erosion has received little attention (De Baets et al., 2011). Although, one study by De Baets et al., 2011 showed that at the top 30 cm of the soil, the roots of the cover crop are firmly established. As a result, they have a great potential to improve soil cohesiveness (De Baets et al., 2011). In situations where the above-ground biomass has vanished (such as after a frost), roots can be crucial in preventing concentrated runoff from eroding the topsoil (De Baets et al., 2011). The study found that the highest topsoil root density values are seen in species with fibrous root systems, including *Lolium perenne* (ryegrass), *Avena sativa* (oat) and *Secale cereale* (rye). Researchers found that the cover crops under study are not all equally successful at reducing g soil loss by concentrated flow erosion at the end of the growing season through laboratory flume tests examining the resistivity of topsoil's penetrated with various types of cover crop roots (December–January)(De Baets et al., 2011). The study also found *Sinapis alba* (white mustard) and *Raphanus sativus* *subsp. oleiferus* (fodder radish) are less efficient than ryegrass and rye cover crops which have fine-branched roots in mitigating soil losses from concentrated flow erosion. Hence, in order to choose the best cover crops for a particular field, we must take into account both above-ground and below-ground plant properties (De Baets et al., 2011). The effectiveness of cover crops relies on the issues that need to be solved, the erosion process that is of interest, or the goal of environmental protection (De Baets et al., 2011). In the literature, the effects of cover crops on sediment losses in crop fields are widely documented (Blanco-Canqui, 2018; Kaspar et al., 2001; Morgan, 2009).

Unlike sheet and rill erosion, which is caused by raindrops and water flowing on the soil surface, EG erosion is caused by concentrated flow of surface runoff along a defined channel, as well as subsurface flow through seepage and preferred paths (USDA, NRCS, ARS, 2007). Therefore, many incidents of runoff from agricultural land causing harm to watercourses and properties (both sediment and chemical) are related to (ephemeral) gullying (Poesen et al., 2003). Because the surface topography of the field does not vary significantly in some areas, EG's frequently return at or near the same position on an annual basis (S. J. Bennett et al., 2000). As a result, gully erosion monitoring, experimental, and modeling investigations are needed to forecast the impacts of environmental change (climate and land use changes) on gully erosion rates (Poesen et al., 2003). Despite the importance of EG erosion, limited information on soil loss rates and the physical properties of actively eroding gullies exists (S. J. Bennett et al., 2000). On top of this the USDA, NRCS and ARS face a major challenge in accounting for EG erosion. While EG erosion may be addressed in conservation schemes by using grassed waterways, terraces, and vegetative barriers, cover crops have not been seriously studied as a way to help mitigate gully erosion in crop fields (USDA et al., 2007). The quantity of soil conserved because of using conservation techniques to limit EG erosion is not assessed because the agency lacks a mechanism to anticipate and quantify EG erosion, including the potential for nonstructural interventions to reduce it (USDA et al., 2007). Therefore, this study has three objectives: 1) determine if cover crops or P fertilizer treatments influence cover crop residue amounts left on the fields surface; 2) determine the effect of cover crops on EG erosion; and 3) Determine whether digital elevation models (DEM's) collected by drone arial imagery through multiple years can help determine the contribution of EG erosion to annual sediment loss.

Materials and Methods

For this project, the research was conducted from summer 2021 through summer 2023 at the Kansas Agricultural Watershed (KAW) field laboratory located near Manhattan, Kansas. The KAW field lab is comprised of eighteen, small-scale watersheds averaging approximately 0.5 ha in size with treatments that are structured in a 3 x 2 complete factorial arranged in a randomized complete block design (blocked by landscape position) and replicated three times (Figure 4.1). There are three P fertilizer management systems including: no P fertilizer control (CN), build and maintain (BM) which used a build and maintain method where there has been an annual application during the build for 5 years then after it is maintain, and sufficiency fertilizer (SF) which also used a build and maintain method where there has been an annual application during the build for 5 years then there was no application after the first 5 years. Each P fertilizer management practice was combined with one of the 2 levels of cover crop, no cover crop (NC) or a winter cover crop (CC) for a total of six treatments imposed in a no-till corn-soybean rotation. Cereal rye (*Secale cereale* L.) was planted at 74 kg ha^{-1} on 13 October 2020 and terminated on 13 April 2021. Corn (*Zea mays* L.) was planted at 63,000 seeds ha^{-1} on 29 April 2021 and harvested on 17 September 2021. Cereal rye was planted at 74 kg ha^{-1} on 24

September 2021 and terminated on 20 May 2022 followed by soybean (*Glycine max* (L.) Merr.) planted at 346,000 seed ha^{-1} on 15 June 2022 and harvested on 20 October 2022. Details about prior management can be found in Nelson et al. (2023).

For Objective 1, the line transect method was used to estimate crop residue cover within the KAW fields following NRCS guidelines (USDA & NRCS, 2001). The line transect method has been proven effective in estimating the percent of the ground surface covered by plant residue at any time during the year (USDA & NRCS, 2001). For this method a 100-foot field measuring tape was used, it was laid out perpendicular (east to west) within each of the 18 plots. Three different measurements were taken in different locations in each plot going from South to North. Once the measuring tape was laid out, each person measured a 25-foot section. Each person also walked along the line in 25-foot sections, stopping at each 1-foot mark. To obtain the results each person's eyes were positioned directly over a 1-foot mark. If that 1-foot mark was directly over a piece of residue, then a yes (Y) was written down. If there was no residue, no (N) was written down. Percent residue was calculated as the number of times residue intersected the 1-ft marks in the 100 ft transect. Residue transects were collected on 14 June 2021 (in soybean residue) and 29 June 2022 (in corn residue).

For Objective 2, EGs were quantified in each field plot at the KAW field lab. The hand measuring method was used, where a measuring tape and a pole were used to measure the cross-section (depth, width of top and bottom) of gully. Gully length was determined with a measuring wheel. The volume of sediment removed from each gully was determined with the volume equation (Length x Width x Depth). Geographic coordinates of each gully were determined to the nearest 1.67 cm with an RTK GPS receiver (REACH RS2+; L1/L2/L5 RTK GNSS Receiver).

Objective 3 was conducted using high-resolution elevation data from UAV to determine the ephemeral gully formations in fall 2016, 2020, and 2022. Data was imported into ArcGIS Pro to compare elevation changes between the 2016-2022, 2016-2020, and 2020-2022 digital elevation models (DEMs) to get 6-, 4- and 2-year differences, respectively. Next, calculation was conducted using "compute change raster" in ArcGIS Pro to estimate the amount of sediment loss between the years by collecting the topographical differences. This was used to determine the contribution of EG erosion to annual sediment loss.

Statistical Analysis

Analysis of variance (ANOVA) was used to determine treatment effects on EG length, EG number, EG soil loss, and the percent residue cover using SAS proc glimmix with cover crop, P fertilizer management, and their interaction as fixed effects and replication as a random effect. Denominator degrees of freedom were computed with the Satterthwaite method. The protected least significant difference method was used for pairwise comparisons of treatment means with α=0.05. Independent analyses were conducted for each year of data collection.

Results and Discussion

Residue Data

The effect of cover crop on the amount of residue remaining on the surface is significant for both 2021 with P-value = 0.0004 (Figure 4.2a) and 2022 with P-value = <.0001 (Figure 4.2b). Cover crop significantly increased the amount of residue remaining on the surface for both years 2021 and 2022. An article by Kaye & Quemada, 2017 found similar results, saying that the use of cover crops has been successful at building up soil surface residue. Next, testing the effect that Fertilizer treatments (BM: build and maintain, CN: no P fertilizer control, and SF: sufficiency fertilizer) had on percent residue remaining on the surface, there was a significant main effect on fertilizer management. The amount of residue remaining was significantly higher in the BM and the SF treatments than that in the CN. Fertilizer treatments did seem to have a positive effect on the amount of residue left on the crop field. Literature found also came to similar conclusions that fertilizer treatments increase the potential for residue remaining on the field suggesting it may have something to do with increased C/N ratios (Balkcom et al., 2018; Reiter et al., 2008; Tewolde et al., 2015). The CN had less of an amount of residue remaining on the surface in both 2021 with P-value = <.0001 (Figure 4.3a) and 2022 with P-value = <.0001 (Figure 4.3b).

Gully Data

Ephemeral gullies were identified in 7 of the 18 plots at the KAW field lab (Figure 4.4). Because the field was tilled at the beginning of the study (November 2014), all these EGs formed within the respective cover crop and P fertilizer management treatments formed after the transition to no till in 2015. Six of the 7 plots with EGs were in no-cover crop plots and only one of the cover crop plots had EGs. Therefore, 67% of the no-cover crop plots had EGs and only 11 % of the cover crop plots had EGs. An article by Knapen & Poesen, 2010 found a direct relationship with cover crops and their ability to reduce soil erodibility. They were able to find that soil erodibility has a direct relationship to gully cross-sectional dimensions of concentrated flow paths in fields, suggesting that cover crops can help mitigate the formation of gullies in crop fields.

Although the average length of EGs, number of EGs, and volume of sediment lost from EG erosion were all numerically greater for the NC treatment compared to the CC treatment, none of these differences were statistically significant based on the standard ANOVA (Figure 4.5). This could be a result of the number of zero values included in the dataset which may make it difficult to fit the standard parametric statistical model to the data. It is possible that a binary data analysis may be more appropriate for this dataset.

With regards to P fertilizer management, two plots that were CN, two plots that were SF, and three plots that were BM had EGs (Figure 4.4), indicating approximately equal likelihood of EG erosion in plots based on P fertilizer management, probabilities of 1/3, 1/3, and 1/2 for CN, SF, and BM respectively. The main effect of the ANOVA indicated no significant effect of P fertilizer management on EG length, number or volume of sediment removed from EG erosion (Figure 4.6).

Elevation Data

The elevation difference between the years 2016 and 2022 indicates the amount of topsoil removed by erosion for a six-year period in meters (Figure 4.7). Where erosion removed topsoil is indicated by a negative value (east and west sides of the Kaw field) and a positive value (central parts of the Kaw field) indicate topsoil was accumulated. This figure does a good job indicating where the watershed outlets are, however, it does a poor job at detecting where EG's are present in the field. The elevation differences between year 2016 and 2020 indicate the amount of topsoil removed by erosion for a four-year period (Figure 4.8). A good portion of the Kaw field lost topsoil due to erosion with the main amount lost mostly found in the southern fields of the KAW. Similar to Figure 4.7, 4.8 does a good job indicating where watershed outlets are but does a poor job at detecting the presence of EG's in the KAW field. The elevation differences between the years 2020 and 2022 indicate similar findings to Figure 4.8 overall not detecting EG's present in the KAW field. DEM resolution of 0.03 (m) was used and elevation between years was subtracted to obtain the amount of topsoil lost between years in each figure. While each figure was able to show a gradient of soil loss, the figures failed to show ephemeral gullies in the field. One reason for this might be because of DEM resolutions. DEM resolution can play a part in the accuracy of certain topographic indexes (TI models) or models used in GIS (Daggupat et al., 2013; Momm et al., 2013). Keeping in mind most DEM's are used when trying to calculate TI models, this final step in calculating a TI model was not completed in this research paper. Momm et al. (2013) found that high resolution DEMs (e.g., 2 m) were more beneficial for simulating EG formation in fields than low resolution DEMs (10 to 30 m). Sheshukov et al., (2018) used a DEM resolution of 3 meters was used when processing their data for calculation TI models. EG's were not able to be identified in any of the Figures 4.7, 4.8 or 4.9. GPS data points of the EG's taken by hand out in the KAW field in 2021 were overlayed on all the maps. (Figure 4.10) shows the relation of GPS point taken in 2021 to the amount of topsoil loss between 6 (4.10a), 4 (4.10b) and 2 (4.10c) years, respectively. While the figures do show the topsoil loss gradient in meters, the figures do not indicate the presence of EG's. Closely following the points on each one of the figures (a, b, and c) multiple colors can be seen indicating both the addition and subtraction of soil. Points on Figure 4.10 represent Knickpoints, head cuts and foot points. With the DEM's used to help calculate topsoil loss between a certain number of years, it is shown that this may not be the best method used to help determine where EG's develop in agricultural fields. The estimates of EG erosion from elevation data are not similar to the EG data that was collected by hand, this could be because this DEM data is not the exact elevation of the ground and includes canopy cover. Other methods that could be used to calculate the total volume of soil lost due to erosion include possible DEM resolution change with a TI index, the hand method listed earlier or possibly the pin frame method (Karimov & Sheshukov, 2017). Overall, there are many different methods to estimate topsoil loss from agricultural fields as well as methods that show EG's in fields, but more research needs to be done to determine which methods work best.

Conclusion

In this study, the overall conclusion indicates that cover crops do not play a significant role in decreasing ephemeral gully formations in crop fields. Even when comparing cover crops and treatments, no significant effects were found. However, when looking at percent residue on the field there were indications that cover crops do in fact increase residue. Same goes for different fertilizer treatments, while there is an increase in residue with spring injected treatments vs no fertilizer control treatments we cannot say for sure if this will always be the case as further research will need to be conducted specifically looking at how percent residue cover remaining in crop fields changes with fertilizer treatments across crop fields as a long-term study. Elevation data collected by aerial imagery did not give the best results in defining EG's in agricultural fields. While it did give an array of topsoil loss through a field. This method would not be best for identifying EGs in agricultural fields.

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Figures

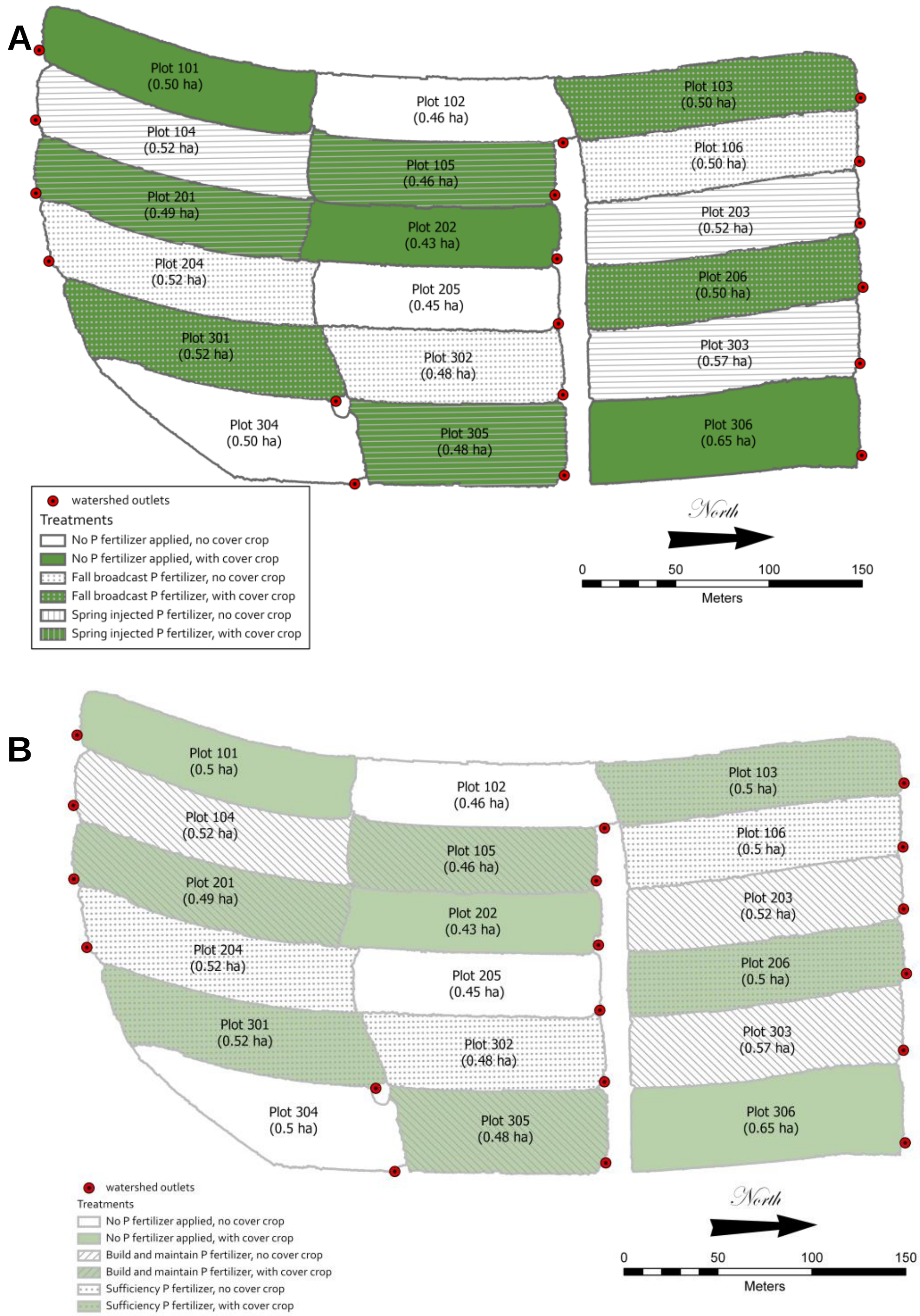

Figure 4.1: Plot maps and treatments for phase 1 (A; 2015 through 2019) and phase 2 (B; 2019 through 2024) for the Kansas Agricultural Watershed Field Laboratory at Ashland Bottoms near Manhattan, KS.

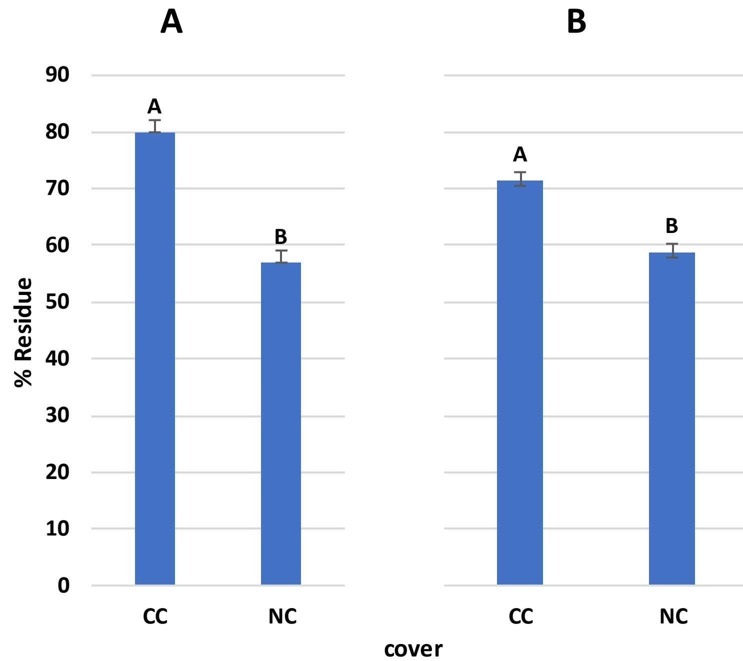

Figure 4.2: 2021 results (A) and 2022 results (B) comparing cover (CC: cover crop, NC: No cover crop) to percent residue remaining on the surface.

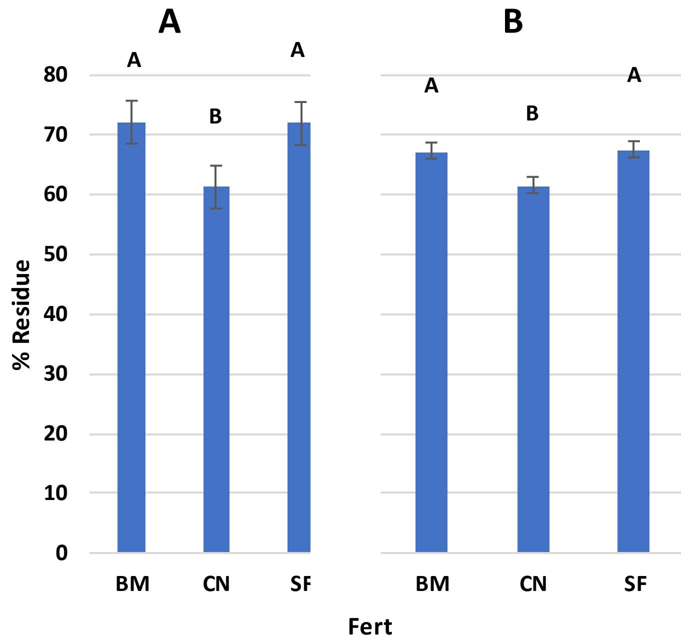

Figure 4.3: 2021 results (A) and 2022 results (B) comparing (Fert) Fertilizer treatments (BM: build and maintain, CN: no P fertilizer control, and SF: sufficiency fertilizer) to percent residue remaining on the surface.

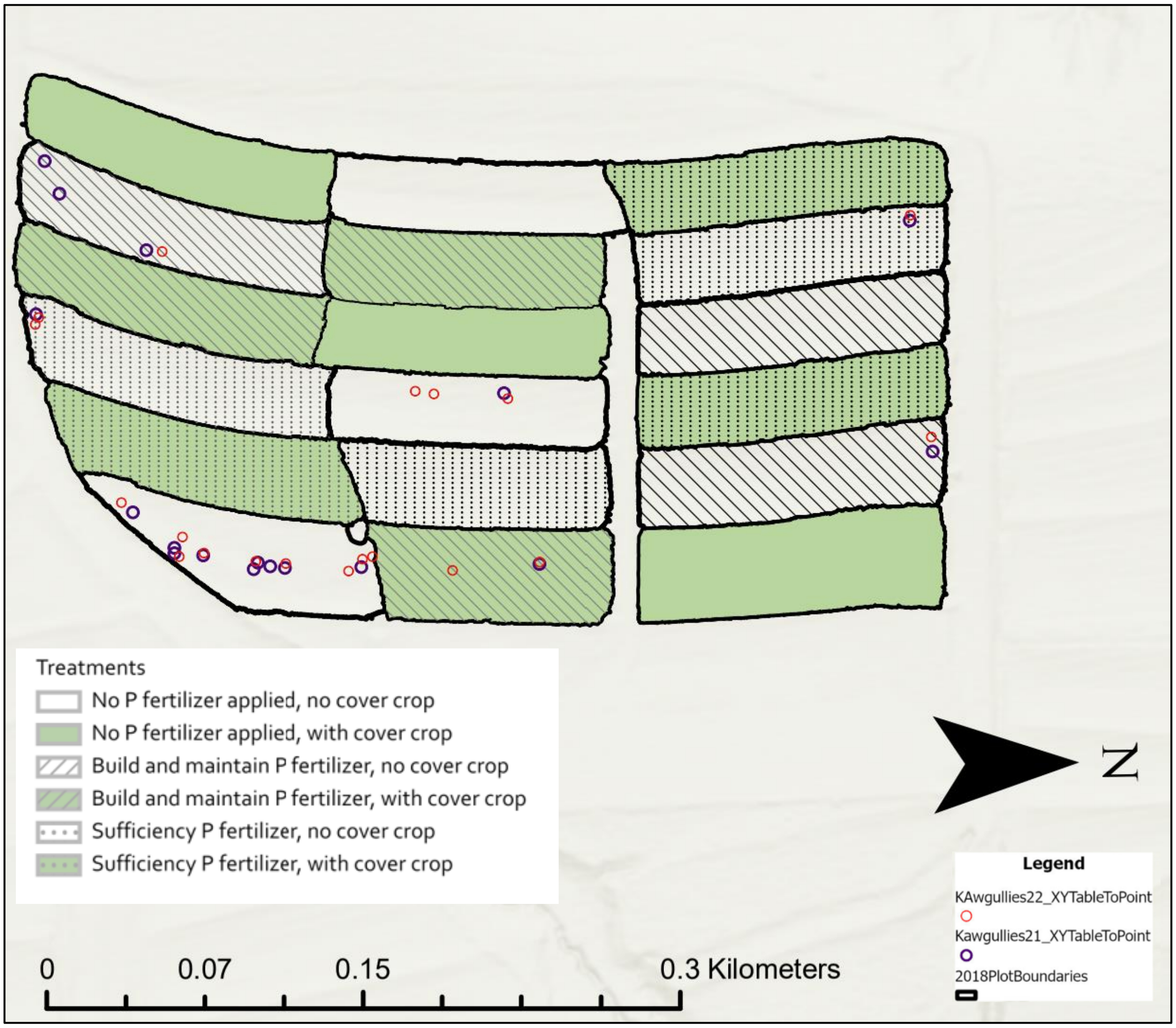

Figure 4.4: Kaw field with locations of Gullies. This figure shows the Knickpoints (the start) of each gully. The dark purple rings represent 2021 data and the red rings represent 2022 data. The black outline is the KAW field boundary lines.

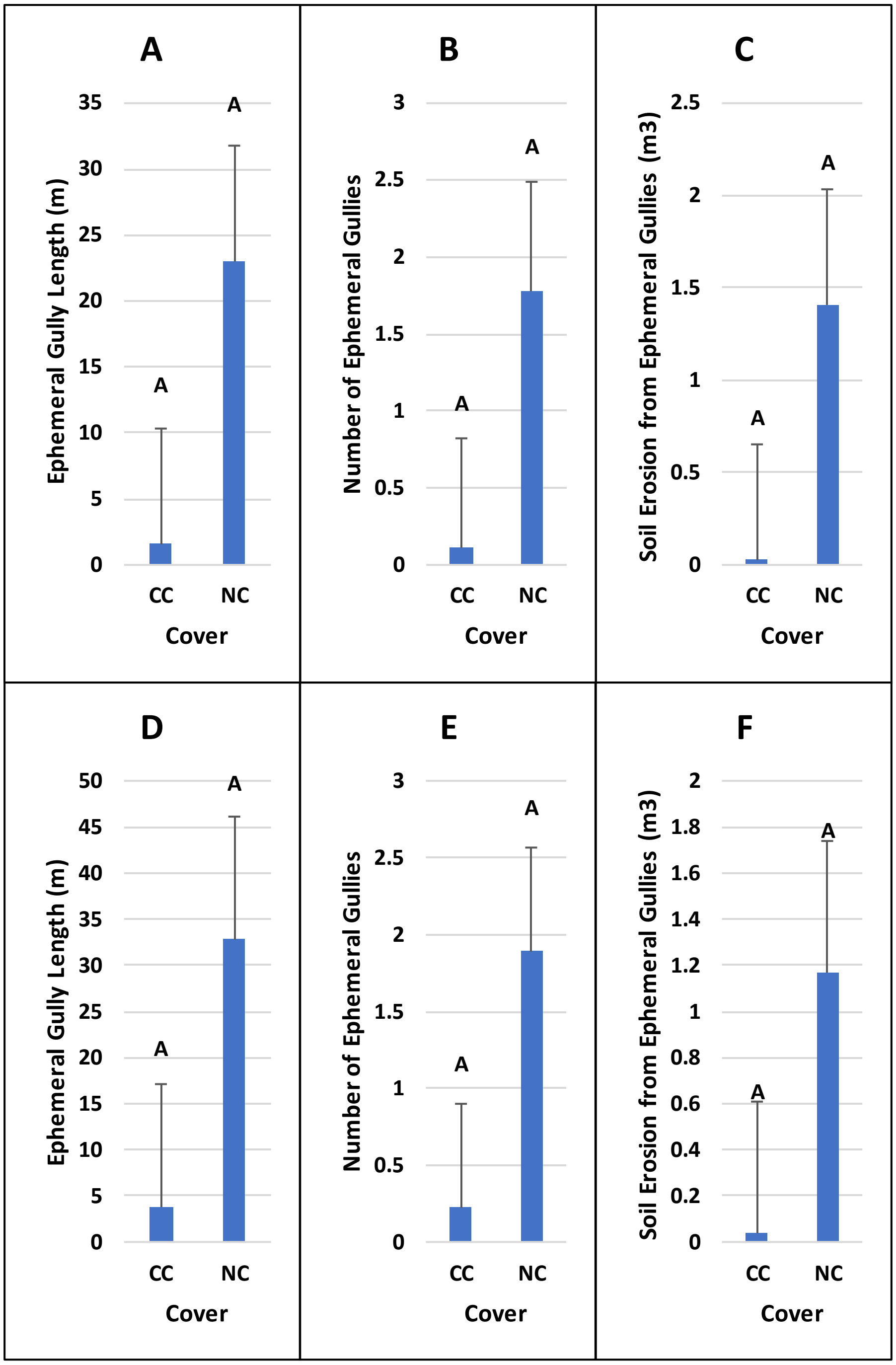

Figure 4.5: Ephemeral gully length (A and D), number (B and E), and volume of sediment removed (C and F) as measured in 2021 (A, B, and C) and 2022 (D, E, and F) at the Kansas Agricultural Watershed Field Laboratory averaged by year and cover crop treatment. Within each frame, bars with the same letter are not significantly different at α=0.05).

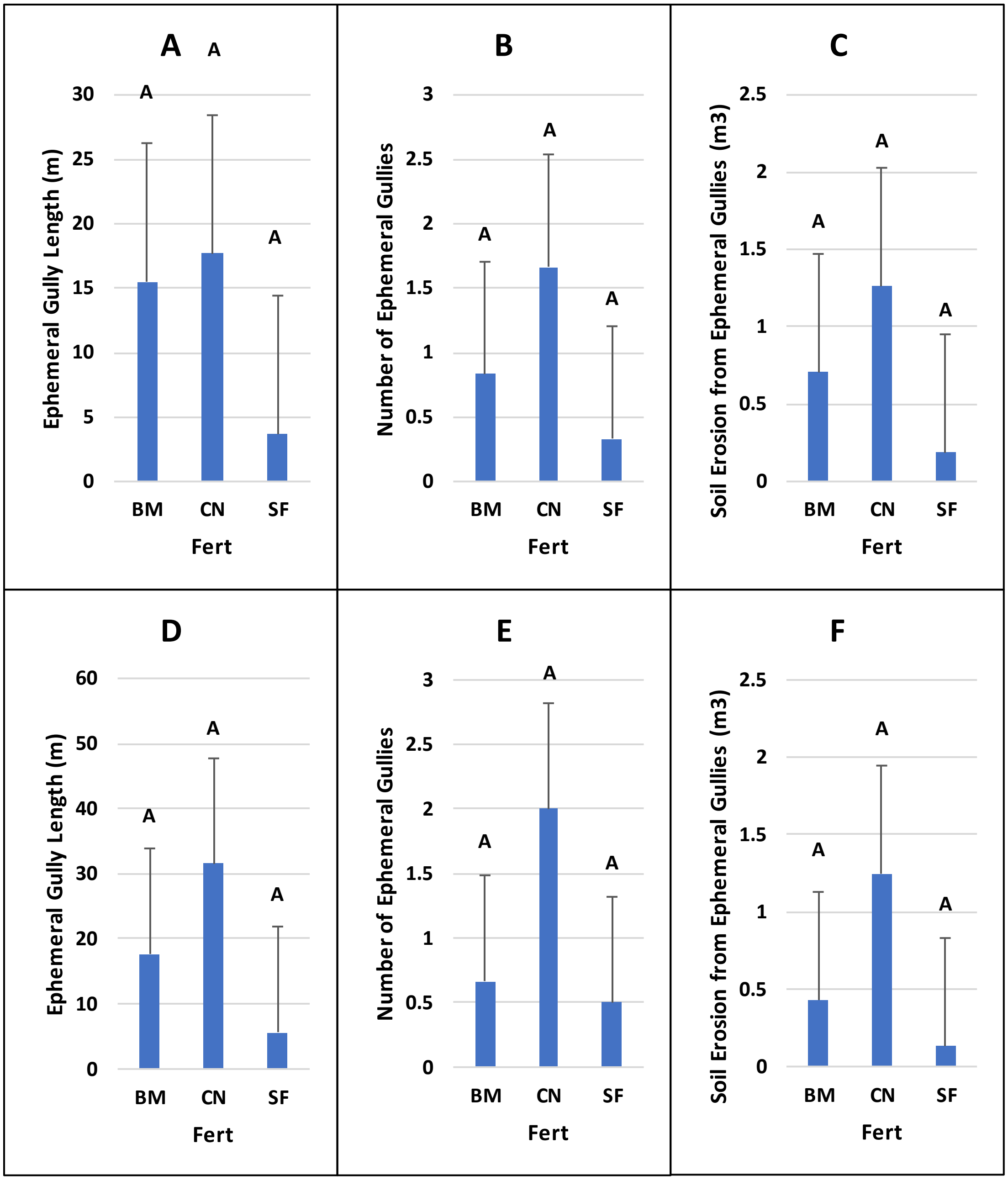

Figure 4.6: Ephemeral gully length (A and D), number (B and E), and volume of sediment removed (C and F) as measured in 2021 (A, B, and C) and 2022 (D, E, and F) at the Kansas Agricultural Watershed Field Laboratory averaged by year and (Fert) Fertilizer treatments. (BM: build and maintain, CN: no P fertilizer control, and SF: sufficiency fertilizer). Within each frame, bars with the same letter are not significantly different at α=0.05).

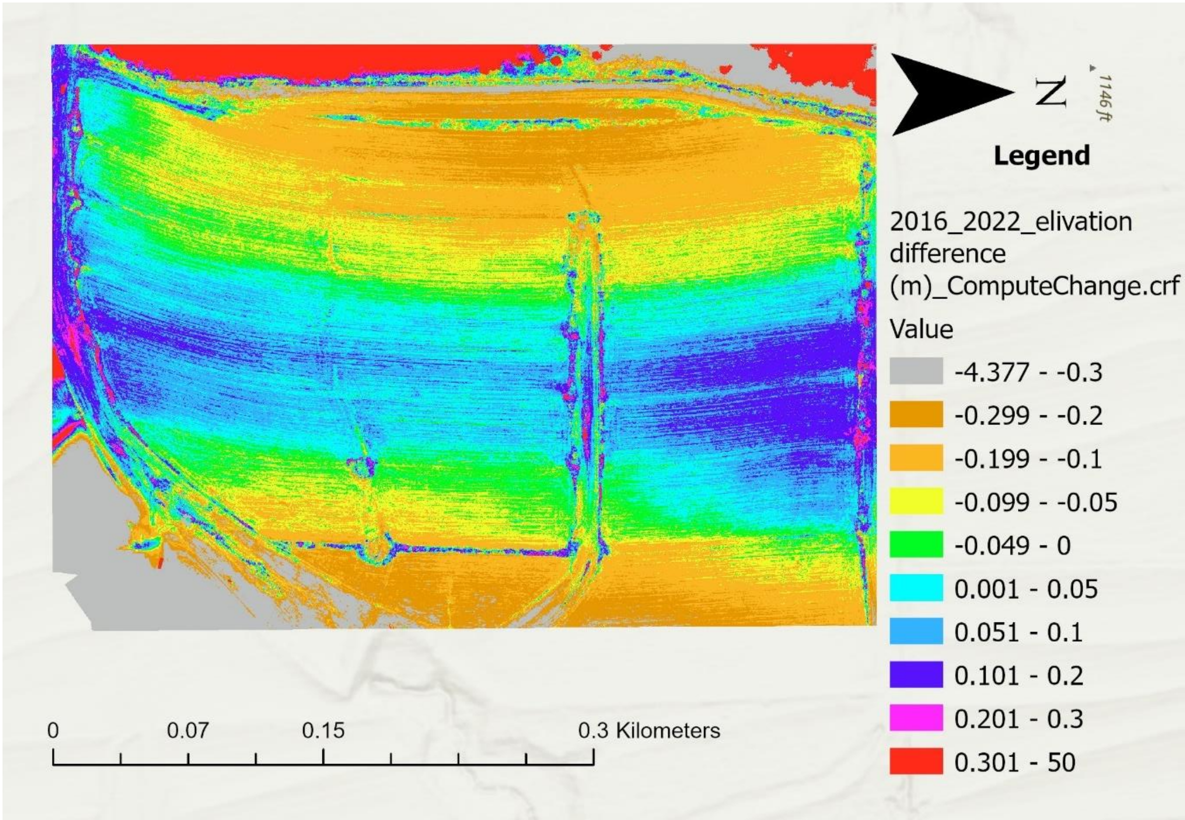

Figure 4.7: 2016 – 2022 Elevation difference in meters at KAW field site: Showing the amount of topsoil removed by erosion for a six-year period in meters using a 0.03 m DEM resolution.

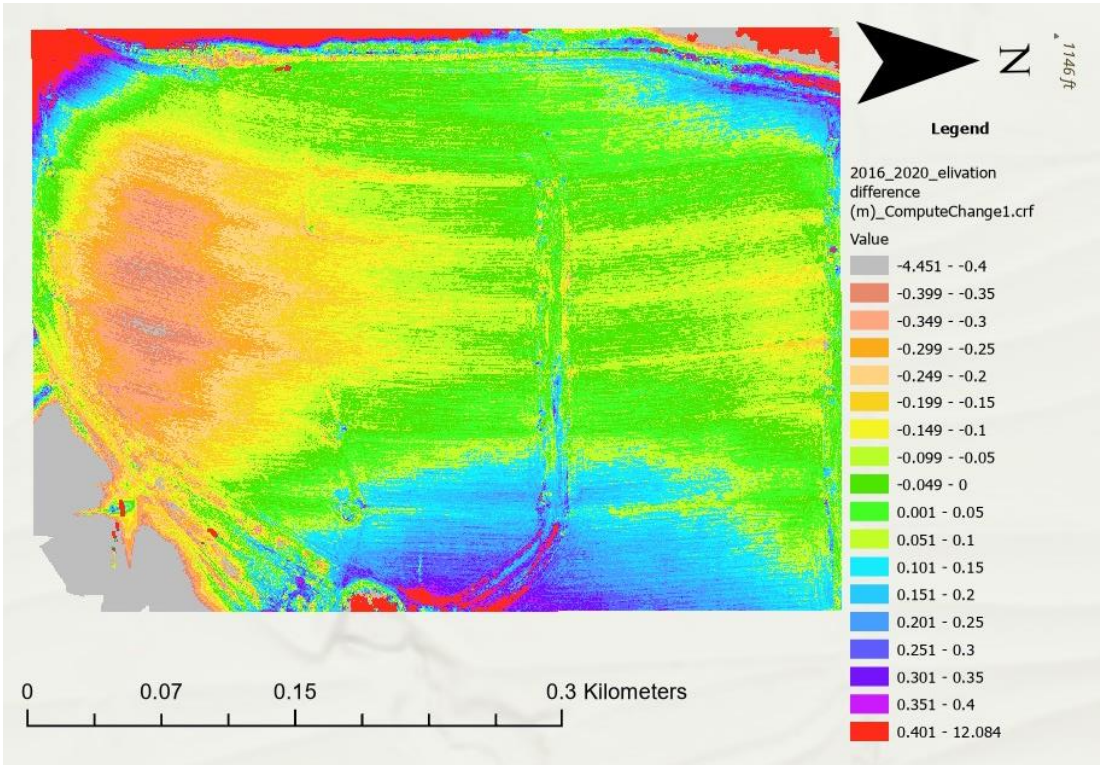

Figure 4.8: 2016 – 2020 Elevation difference in meters at KAW field site: Showing the amount of topsoil removed by erosion for a four-year period in meters using a 0.03 m DEM resolution.

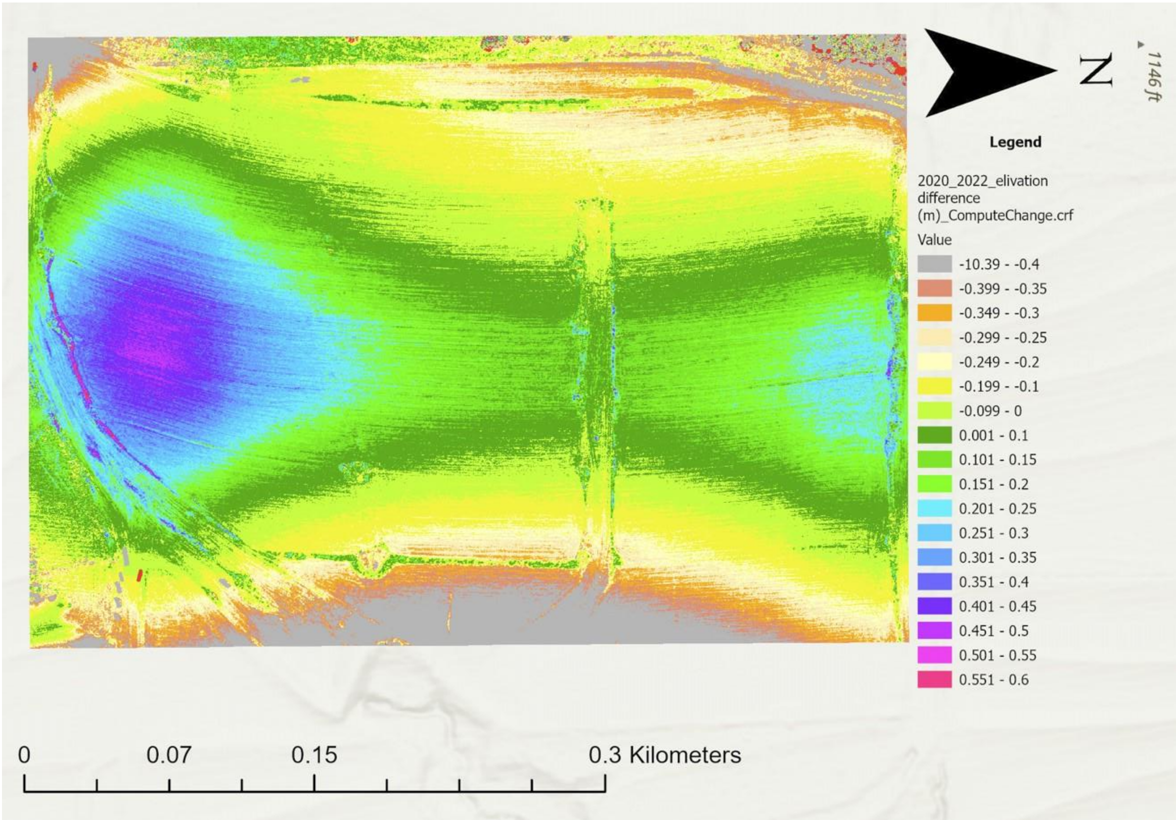

Figure 4.9: 2020 – 2022 Elevation difference in meters at KAW field site: Showing the amount of topsoil removed by erosion for a two-year period in meters using a 0.03 m DEM resolution.

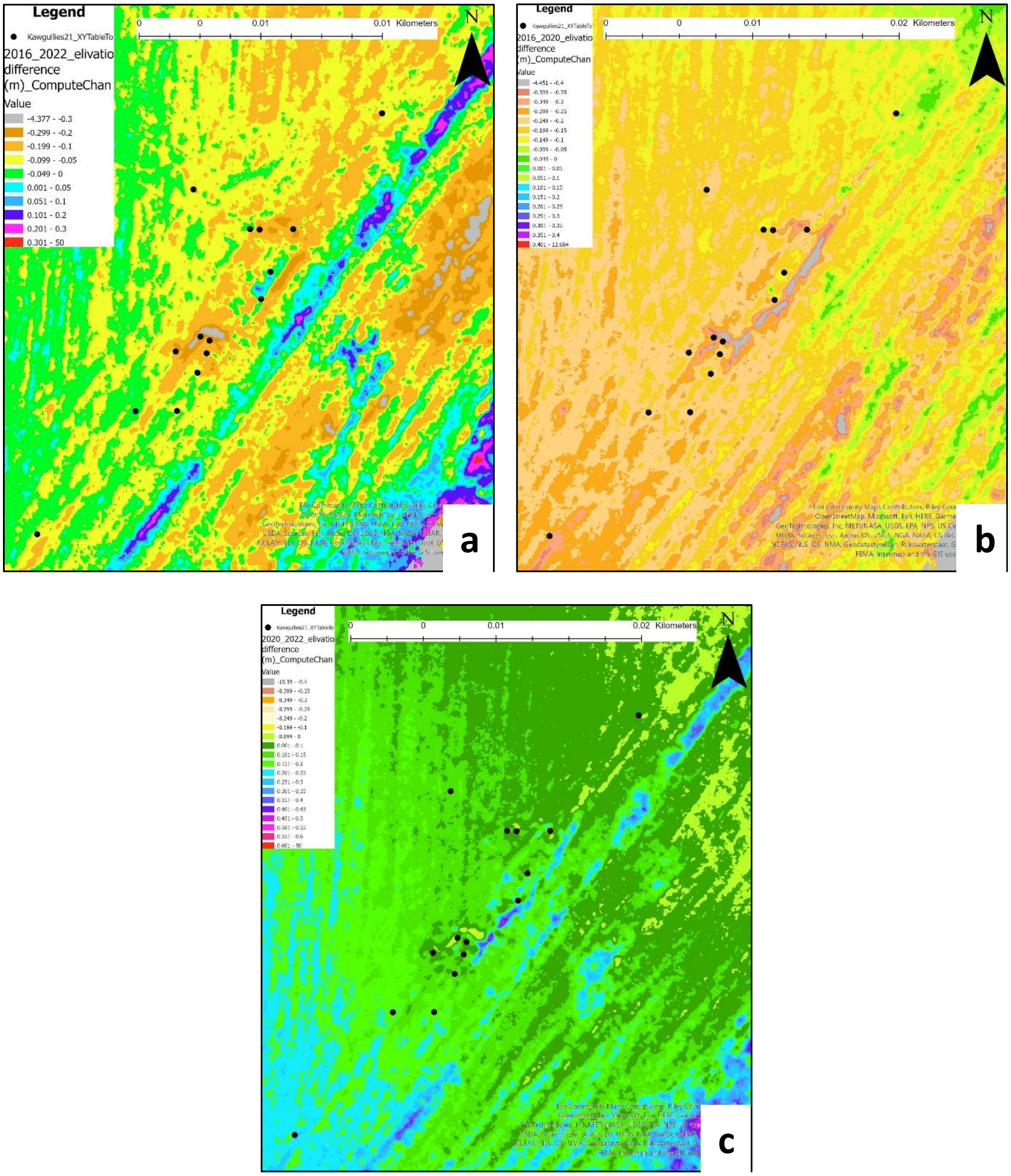

Figure 4.10: Maps showing 2021 ephemeral gully points zoomed in section of Plot 304 in the southeast section KAW field. Showing the amount of topsoil removed by erosion for a certain time period in meters using a 0.03 m DEM resolution. (a) represents zoomed in section from 2016 – 2022 elevation map. (b) represents zoomed in section from 2016 – 2020 elevation map and (c) represents zoomed in section from 2020 – 2022. All black dots represent parts of an ephemeral gully (either the head, knickpoint or foot of a gully).

Appendix A - Kansas Phosphorous Index

Appendix A Figure A.1: Kansas Phosphorous Index

Source Characteristics	Phosphorus Loss Rating			Selected Value: Bench mark	Selected Value: After
Soil Test P	Bray P1 or Mehlich III Soil P Test	Olsen Soil P Test			
	< 25 ppm	< 16 ppm	1		
	26 - 50 ppm	17 - 31 ppm	2		
	51 - 75 ppm	32 - 47 ppm	4		
	76 - 200 ppm	48 - 62 ppm	8		
	>200 ppm	> 62 ppm	10		
Annual Average Fertilizer P Application Rate (lbs P_2O_5/ac)		Lbs P_2O_5 Applied			
		0.10 X (lbs P_2O_5)		0.0	0.0
P Fertilizer Application Method	None applied		0		
	Starter applied at planting or injected deeper than 2 inches		1		
	Broadcast AND incorporated Nov-Feb or July-Aug OR Broadcast / NOT incorporated Nov-Feb or July-Aug with standing corn, sorghum or smallgrain residue or hay and pasture land		2		
	Broadcast / NOT incorporated Nov-Feb or July-Aug (no residues or pasture) OR Broadcast / NOT incorporated Sept-Oct or Mar-June with standing corn, sorghum or smallgrain residue or hay and pasture land OR Broadcast AND incorporated Sept-Oct or Mar-June (no residue or pasture)		4		
	Broadcast / NOT incorporated Sep-Oct and Mar-June		8		
Annual Average Organic P Application Rate (lbs P_2O_5/ac)		Lbs P_2O_5 Applied Contained In Manure or Compost			
		0.10 X (lbs P_2O_5)		0.0	0.0
Organic P Source Application	None applied		0		
	Starter applied at planting or injected deeper than 2 inches		1		
	Broadcast AND incorporated Nov-Feb or July-Aug OR Broadcast / NOT incorporated Nov-Feb or July-Aug with standing corn, sorghum or smallgrain residue or hay and pasture land		2		
	Broadcast / NOT incorporated Nov-Feb or July-Aug (no residues or pasture) OR Broadcast / NOT incorporated Sept-Oct or Mar-June with standing corn, sorghum or smallgrain residue or hay and pasture land OR Broadcast AND incorporated Sept-Oct or Mar-June (no residue or pasture)		4		
	Broadcast / NOT incorporated Sep-Oct and Mar-June		8		
		Total Source Value		0.0	0.0

Kansas Site Assessment Index - Phosphorus

Transport Characteristics			Selected Value Bench mark	Selected Value After
Soil Erosion by Water (tons/acre/year)	Average From Ephemeral and Classic Gully			
	2 X (tons/ac./yr.)		0.0	0.0
	Tons From RUSLE			
	2 X (tons/ac./yr.)		0.0	0.0
Soil Run-off Classification (From NRCS Kansas Map Unit Descriptions)	Very Low	0		
	Low	2		
	Medium	4		
	High	8		
	Very High	16		
Proximity of field to perrenial streams, perrenial surface water bodies, or intermitant streams	Field not in proximity of intermittent stream	0		
	Within 300 feet of intermittent stream 180 to 300 feet of perennial stream or water body - with effective buffer *	2		
	180 to 300 feet of perennial stream or water body - without effective buffer * Within 180 feet of perennial stream or water body - with effective buffer *	4		
	Within 180 feet of perennial stream or water body - without effective buffer * Immediately adjacent to perennial stream or surface water - with effective buffer *	8		
	Immediately adjacent to perennial stream or surface water - without effective buffer *	16		
Furrow Irrigation Erosion QS is gallon/minute/furrow divided by the slope. Soil eroibility hazard factors are in Table 1.	N/A	0		
	With tail water recovery, QS < 6 severe erodibility hazard soils and QS < 10 other soils	2		
	QS > 10 for slight erodibility hazard soils	4		
	QS > 10 for moderate erodibility hazard soils	8		
	QS > 6 for severe erodiblity hazard soils	16		
Sprinkler System Erosion/Run-off (Sandy soils include all sands and loamy sands. Non-sandy soils include all others. (See Table 2)	N/A or little or no runoff indicated	0		
	LP on 0 to 3% slopes or HP on 0 to 8 % slopes for non-sandy sites or all sandy sites	2		
	HP on non-sandy sites > 8 % slope, and LP on non-sandy sites 3 to 5 % slopes	4		
	LP on non-sandy sites 5 to 8 % slopes	8		
	LP on non-sandy sites 8 % or steeper slopes	16		

* *Effective buffers meet NRCS standards*

	Bench mark	After
Total Transport Value	0.0	0.0
X		
(From Page 1) Total Source Value	0.0	0.0
Total Transport Value X Total Source Value = *P Loss Rating Value*	0	0
P Loss Risk		

P Loss Rating Value		Site Interpretation for P Loss Rating
0 - 75 76 - 150	VERY LOW LOW	If current farming practices are continued and site characteristics do not change, there is low probability of an adverse impact to surface waters from P losses at this site. Nitrogen based nutrient management planning is satisfactory for this site.
151 - 300	MEDIUM	Implement practices to reduce P losses by surface runoff and erosion. Consider crops with high P removal capacities. In some cases P fertilizer will not be needed. Restrict manure application and a long-term P management plan should be used.
301 - 600	HIGH	If current practices are continued and site characteristics do not change, there is a risk of adverse impacts on surface water. P management needs to be modified to reduce the risk of P movement. Use phosphorus-based nutrient management planning.
> 600	VERY HIGH	Current practices are likely creating adverse impacts on surface water quality. Management practices should be modified to reduce hazards. Additional P applications are not warranted.

Source: https://efotg.sc.egov.usda.gov/references/public/KS/phosphorusIndex2008.xls

Appendix B - Table of Average Annual Long-Term Runoff Estimates in (mm) for the State of Kansas

Please see added supplemental file for the table of runoff estimates in (mm) for the state of Kansas. An example section of the table and a description is below.

Appendix B Table B.1: Example table of average annual long-term runoff (mm) for seven counties in Kansas

This table has seven counties in the state of Kansas and curve numbers 80 through 85. By selecting your county and curve number you can obtain the average annual long-term runoff value in (mm) for your specific area and cropping system. An example: Say you live in Riley County, Kansas, and for your cropping system you find that you have a curve number of 81. By looking up this information on the table below, you would have an average annual long-tern runoff value of 139.11 mm for your specific area and cropping system.

	85	84	83	82	81	80
Crawford	272.63	254.84	238.42	223.20	209.08	195.93
Ellis	126.96	117.99	109.76	102.17	95.17	88.69
Franklin	236.16	220.50	206.07	192.71	180.32	168.80
Geary	194.60	181.48	169.39	158.22	147.88	138.27
Pratt	155.46	144.82	135.03	125.99	117.63	109.87
Riley	184.01	171.38	159.76	149.03	139.11	129.90
Sherman	97.69	90.70	84.29	78.39	72.96	67.93

Appendix C - SAS Data and Code for Chapter 3 (Revising the Kansas Phosphorus Index)

Data

```
/*----------------------------------------------------------------------
----------------------\
|  Dataset name and description
|
|  Variables
|  loc     Location: Crawford, Franklin_8 = Franklin plot #8,
Franklin_4=Franklin plot #4
|  crop CC=corn-corn, CS=corn-soybean, CWS=corn-wheat-soybean,
GS=grain sorghum-soybean
|  till    Tillage: NT=no-till, CT=conventional till
|  app_method:  Application method SB=surface Broadcast,
INC=incorporated, SSA=Subsurface Band
|  App_daate: day-month of application day
|  STP: soil test P (ppm)
|  Prate: P application rate (kg P2O5/ha)
|  Ploss: APEX estimated P loss (kg P/ha) - average of 100 simulations
|  PlossMax: Maximum annual P loss estimated by APEX (kg P/ha)
|  AQ: apex estimated runoff (mm)
|  AS: apex estimated sediment loss (Mg/ha)
|  RQ: RUSLE2 estimated runoff (mm)
|  RS: RUSLE2 estimated sediment loss (Mg/ha)
|  MR: method-timing factor used in the 2008 multiplicative KS P-index
|  AppTime1: first trial at an independent application timing factor
|  AppTime2: second trial at an independent application timing factor
|  Appmeth1: first trial at an independent method of application
factor
|  MCNQ: runoff estimated by the modified curve number approach (mm)
|
 ---------------------------------------------------------------------
---------*/
proc print;
data CPI; input loc$ Crop$ till$ App_method$ App_date$ STP Prate Ploss
PlossMax AQ AS RQ RS MR AppTime1 AppTime2 AppMeth1 MCNQ;
cards;
```

(Sample of Data):

```
Crawford    CC    NT    SB    15-Jan     25    0     1.45  3.21  140   0.01
     254   0.43  2     0     1     4     272.63
```

```
Crawford    CC    NT    SB    15-Jan      25    51    2.76  6.13  142   0.02
     254    0.43  2     0     1     4     272.63
Crawford    CC    NT    SB    15-Jan      25    102   4.13  9.20  143   0.02
     254    0.43  2     0     1     4     272.63
Crawford    CC    NT    SB    15-Jan      25    204   7.07  15.83 144   0.02
     254    0.43  2     0     1     4     272.63
Crawford    CC    NT    SB    15-Jan      25    409   13.66 30.94 145   0.03
     254    0.43  2     0     1     4     272.63
Crawford    CC    NT    SB    1-Apr 25    0     1.98  4.58  143   0.03  254
     0.43   4     1     2     4     272.63
Crawford    CC    NT    SB    1-Apr 25    51    2.29  5.38  137   0.01  254
     0.43   4     1     2     4     272.63
Crawford    CC    NT    SB    1-Apr 25    102   3.22  7.65  137   0.01  254
     0.43   4     1     2     4     272.63
Crawford    CC    NT    SB    1-Apr 25    204   5.31  13.91 138   0.01  254
     0.43   4     1     2     4     272.63
Crawford    CC    NT    SB    1-Apr 25    409   10.36 30.67 139   0.02  254
     0.43   4     1     2     4     272.63
Crawford    CC    NT    SB    15-Oct      25    0     1.39  3.06  143   0.01
     254    0.43  4     1     2     4     272.63
Crawford    CC    NT    SB    15-Oct      25    51    2.22  5.00  150   0.04
     254    0.43  4     1     2     4     272.63
Crawford    CC    NT    SB    15-Oct      25    102   3.07  7.05  151   0.05
     254    0.43  4     1     2     4     272.63
Crawford    CC    NT    SB    15-Oct      25    204   4.89  11.44 153   0.07
     254    0.43  4     1     2     4     272.63
Crawford    CC    NT    SB    15-Oct      25    409   8.70  20.75 155   0.10
     254    0.43  4     1     2     4     272.63
Crawford    CC    NT    SB    15-Nov      25    0     1.36  3.03  141   0.01
     254    0.43  2     0     1     4     272.63
Crawford    CC    NT    SB    15-Nov      25    51    2.19  5.03  145   0.02
     254    0.43  2     0     1     4     272.63
Crawford    CC    NT    SB    15-Nov      25    102   3.05  7.15  146   0.03
     254    0.43  2     0     1     4     272.63
Crawford    CC    NT    SB    15-Nov      25    204   4.91  11.68 148   0.04
     254    0.43  2     0     1     4     272.63
Crawford    CC    NT    SB    15-Nov      25    409   9.05  22.00 151   0.06
     254    0.43  2     0     1     4     272.63
```

Code

```
*/* Select only data from April and November ;
```

```
Data CPIr; set CPI; where App_date in ('1-Apr', '15-Nov');
proc print data=CPIr;

* set the application factors;
Data CPIr; set CPIr;
     if App_method='SSA' then AF=0.2;
     if App_method='INC' then AF=0.4;
     if App_method='SB' and App_date='15-Nov' then AF=0.6;
     if App_method='SB' and App_date='1-Apr' then AF=0.8;
     MCNQ=MCNQ/1000; *convert runoff from mm to m;

proc print data=CPIr;
run;

proc mixed data = CPIr;
  model Ploss = STP*MCNQ STP*RS Prate*AF*MCNQ / solution;
  Title 'New Kansas Component PI 01';
run;

b1= 0.04128;
b2= 0.002990;
b3= 0.1220;

CPI=b0 + b1*STP*MCNQ + b2*STP*RS + b3*MCNQ*Prate*AF;
keep loc crop till App_method App_date STP MCNQ RS Prate AF Ploss b0
b1 b2 b3 CPI;

proc print data=graph;
run;

proc reg data=graph;
   model CPI=Ploss;
run;


*/* Code to compute optimal coefficents for the Kansas P index;

* Add STP category and soil runoff classification catagory;

Data KPI; set CPIr;
     if STP<=25 then STPc=1;
     if STP>25 and STP<=50 then STPc=2;
     if STP>50 and STP<=75 then STPc=4;
     if STP>75 and STP<=200 then STPc=8;
     if STP>200 then STPc=10;
```

```
     if loc='Crawford' then SRc=16; else SRc=8;
     KPI =(STPc+(Prate/1.12)*0.1+MR)*((RS*0.44617)*2+SRc+16); *NOTE:
converts Prate to lb/ac and RUSLE2 erosion to ton/ac;
     *Ploss=Ploss*1000; *convert Ploss from kg/ha to g/ha;
proc print data=KPI;
run;
*compute coefficents for the multiplicitive KS PI;
proc nlin data= KPI;
parms b0=100 b1=100 b2=10 b3=10 b4=100;* b5=100;

model Ploss =b0 + (b1*stpc + b2*(Prate/1.12) + b3*MR)*(b4*(RS*0.44617)
+ SRc);
run;

*/*calculate revised multiplicitive KS PI;

b4= 4.1852;
     rKPI = b0 + (b1*STPc + b2*(Prate/1.12) + b3*MR)*(b4*(RS*0.44617)
+ SRc);
     keep loc crop till App_method App_date STP STPc RS Prate MR Src
Ploss KPI b0 b1 b2 b3 b4 rKPI;
run;

proc print data=rMKPI;
run;

proc reg data=rMKPI;
   model KPI=Ploss;
run;

proc reg data=rMKPI;
   model rKPI=Ploss;
run;


*/*;
proc export data = WORK.graph DBMS=XLSX
       outfile = "C:\Users\nonelson\Documents\My SAS
Files\9.4\test.XLSX" replace;
       sheet=CPI_test;
proc export data = WORK.rMKPI DBMS=XLSX
       outfile = "C:\Users\nonelson\Documents\My SAS
Files\9.4\test.XLSX" replace;
       sheet=rMKPI;
run;
```

```
This code was developed to test if we would get a better fit by using
a
P source coefficent (PSC) of 0.8 for poultry litter as recommended by
the
Pennsylvania PI.  In the end, it did not improve the r2 at all.;

Data CPIr2; set CPIr;
      if loc='Crawford' then PSC=0.8; else PSC=1;
      if loc='Crawford' then MPrate=Prate; else MPrate=0;
     if loc='Crawford' then Prate=0; else Prate=Prate;

proc print data=CPIr2;

proc mixed data = CPIr2;
  model Ploss = STP*MCNQ STP*RS Prate*AF*MCNQ MPrate*PSC*AF*MCNQ /
solution;
  Title 'New Kansas Component PI 02';
run;

data graph2; set CPIr2;
CPI=0.1633+STP*MCNQ*0.04388+STP*RS*0.002869+MCNQ*Prate*AF*0.2268+MCNQ*
AF*MPrate*PSC*0.1515 ;
keep loc crop till App_method App_date STP MCNQ RS Prate AF PSC MPrate
Ploss CPI;
run;
/*;
proc export data = WORK.graph2 DBMS=XLSX
       outfile = "C:\Users\nonelson\Documents\My SAS
Files\9.4\test.XLSX" replace;
       sheet=CPI2_test;
*/*******************************************************************
****;
run;
quit;
```

Appendix D - SAS Data and Code for Chapter 4 (Ephemeral Gullies)

Data

```
*
This file contains the ephemeral gully data from the KAW for summer
2021

plot - plot number
rep - replicate or block
fert$ - fertilizer trt     CN = 0 kg P2O5/ha
                                SF = sufficiency
                                BM = build and maintain
cover$ - cover crop treatment (NC = no cover crop; CC = cover crop)
residue - percent residue cover measured by line transect
EG_l - ephemeral gully length in meters
EG_n - number of ephemeral gullies per plot
EG_v - total volume of sediment eroded from ephemeral gullies in cubic
meters

*/
```

(2021 Data)

```
data aaa; input plot rep fert$ cover$ residue EG_l EG_n EG_v;
cards;
101 1 CN CC 63.3 0 0 0
102 1 CN NC 48.3 0 0 0
103 1 SF CC 79.3 0 0 0
104 1 BM NC 57.3 61 3 3.40
105 1 BM CC 82.0 0 0 0
106 1 SF NC 57.7 6 1 0.22
201 2 BM CC 88.7 0 0 0
202 2 CN CC 76.7 0 0 0
203 2 BM NC 59.0 0 0 0
204 2 SF NC 62.7 16 1 0.89
205 2 CN NC 58.0 7 1 0.20
206 2 SF CC 84.0 0 0 0
301 3 SF CC 86.7 0 0 0
302 3 SF NC 61.3 0 0 0
303 3 BM NC 60.7 18 1 0.59
304 3 CN NC 47.7 99 9 7.37
```

```
305 3 BM CC 85.3 14 1 0.24
306 3 CN CC 73.7 0 0 0
;
```

(2022 Data)

```
data aaa; input plot rep fert$ cover$ residue EG_l EG_n EG_v;
cards;
101 1 CN CC 66 0 0 0
102 1 CN NC 54.7 0 0 0
103 1 SF CC 75.3 0 0 0
104 1 BM NC 60.3 48 1 1.9
105 1 BM CC 69.7 0 0 0
106 1 SF NC 64 11 1 0.14
201 2 BM CC 75.3 0 0 0
202 2 CN CC 70 0 0 0
203 2 BM NC 63.3 0 0 0
204 2 SF NC 60.3 23 2 0.65
205 2 CN NC 63.3 22 3 0.31
206 2 SF CC 70.3 0 0 0
301 3 SF CC 77 0 0 0
302 3 SF NC 56.7 0 0 0
303 3 BM NC 59.3 24 1 0.34
304 3 CN NC 48 167 9 7.17
305 3 BM CC 74.3 34 2 0.34
306 3 CN CC 65.7 0 0 0
;
```

Code

```
* Transpose dataset to make it easy to get results from multiple
variables;
proc sort data=aaa; by plot cover fert rep;
proc transpose data=aaa
     out=bbb(rename=(_Name_=var) rename=(col1=XXX));
   var residue EG_l EG_n EG_v ;*bmoist N K Ca Mg S Cu Fe Mn Zn ;
   by plot cover fert rep;

*/* ANOVA on individual point samples with a repeated measures
analysis (accounts for missing data);

proc sort data=bbb; by var;
proc glimmix data = bbb noitprint; by var;
class rep cover fert ;
model XXX = cover|fert/ddfm = satterth;
```

```
random rep rep*cover*fert;
lsmeans cover|fert/lines alpha=0.05 pdiff;
ods output LSmeans=Means Tests3=ANOVA LSMlines=lines;

*/* process result datasets and make graphs and p-value table;

data lines; set lines (where=(effect is not missing)); keep var effect
fert cover estimate line: ;
data lines; set lines; array dx line:; call sortc(of line:); x =
catt(of line:); *This sorts the letters alphabetically and stores them
as a single variable.;

data lines; set lines;
      length barlabel $ 5; *sets the label as 5 characters;
      barlabel = x;
      barlabel2=cat(barlabel,'(',round(estimate,0.1),')'); *makes a
label with letters and value;
      if cover='NC' then csort=1;
      if cover='CC' then csort=2;
      if fert='CN' then fsort=1;
      if fert='SF' then fsort=2;
      if fert='BM' then fsort=3;
proc sort data=lines; by var effect csort fsort;

data means; set means;
      if cover='NC' then csort=1;
      if cover='CC' then csort=2;
      if fert='CN' then fsort=1;
      if fert='SF' then fsort=2;
      if fert='BM' then fsort=3;
proc sort data=means; by var effect csort fsort;

*/* make graphs and tables;
* plot means of cover by fert interaction with letters atop bars;
proc sgplot data=lines; by var;
      vbarparm category=cover response=estimate/group=fert
GROUPDISPLAY=CLUSTER datalabel=barlabel2 DATALABELPOS=data
barwidth=0.9;
      label estimate='estimate';
      styleattrs datacolors=(CXA5A5A5 CXED7D31 CX5B9BD5)
datacontrastcolors=(CXA5A5A5 CXED7D31 CX5B9BD5);
      where effect='cover*fert';
* plot fert means with letters and means atop bars;
proc sgplot data=lines; by var;
```

```
     vbarparm category=fert response=estimate/group=fert
GROUPDISPLAY=CLUSTER datalabel=barlabel2 DATALABELPOS=data
barwidth=0.9;
     label estimate='estimate';
     styleattrs datacolors=(CXA5A5A5 CXED7D31 CX5B9BD5)
datacontrastcolors=(CXA5A5A5 CXED7D31 CX5B9BD5);
     where effect='fert';
* plot cover means with letters and means atop bars;
proc sgplot data=lines; by var;
     vbarparm category=cover response=estimate/group=cover
GROUPDISPLAY=CLUSTER datalabel=barlabel2 DATALABELPOS=data
barwidth=0.9;
     label estimate='estimate';
     styleattrs datacolors=(CX7F6000 CX007800)
datacontrastcolors=(CX7F6000 CX007800);
     where effect='cover';

*make a table of p-values;
proc sort data=anova; by effect var;
proc transpose data=ANOVA out=p_values;
  by effect;
  id var;
  var ProbF;
data p_values; set p_values; drop _Name_ _label_;
     if effect='cover' then id=1;
     if effect='fert' then id=2;
     if effect='cover*fert' then id=3;
data p_values; retain id effect; set p_values; *places id as the first
column, followed by effect (other variable follow in order as is);
proc sort data=p_values; by id;
proc print data=p_values;


proc reg data=aaa;
model EG_l EG_n EG_v = residue;
run;
quit;
```

Appendix E - Ephemeral Gully Data: Supplemental Material

Appendix E Table E.1: Table of each ephemeral gullies knickpoint (start) on Kaw field site Table of each ephemeral gullies knickpoint (start) on Kaw field site. Shows ephemeral gully knickpoint location with latitude and longitude coordinates. Also represented on the table is the plot number, gully ID and length in meters and soil loss in cubic meters of each gully.

(Table on Next Page)

Year	Knickpoint (np) (Long.)	Knickpoint (np) (Lat.)	Plot #	Gully ID	Length (m)	Soil Loss (m^3)
2021	-96.647	39.12764	104	1041-np	37	2.46
2021	-96.6473	39.12727	104	1042-np	9	0.26
2021	-96.6475	39.12721	104	1043-np	15	0.68
2021	-96.6471	39.1309	106	106-1 np	6	0.22
2021	-96.6466	39.12716	204	2041-np	16	0.89
2021	-96.6461	39.12916	205	2051-np	7	0.20
2021	-96.6458	39.13098	303	3031-np	18	0.59
2021	-96.6455	39.12756	304	3041-np	16	0.68
2021	-96.6453	39.12774	304	3042-np	22	3.49
2021	-96.6453	39.12774	304	3043-np	7	0.62
2021	-96.6453	39.12786	304	3044-np	7	0.43
2021	-96.6452	39.12809	304	3045-np	4	0.14
2021	-96.6452	39.12808	304	3046-np	19	1.51
2021	-96.6452	39.12815	304	3047-np	4	0.10
2021	-96.6452	39.12821	304	3048-np	7	0.17
2021	-96.6452	39.12853	304	3049-np	13	0.22
2021	-96.6452	39.1293	305	3051-np	14	0.24
2022	-96.647	39.1277	104	104-np12	48	1.9
2022	-96.6471	39.1309	106	106-np2	11	0.14
2022	-96.6466	39.12717	204	204-np12	17	0.52
2022	-96.6466	39.12716	204	204-np22	6	0.13
2022	-96.6461	39.12917	205	205-np12	7	0.11
2022	-96.6462	39.12886	205	205-np22	7	0.08
2022	-96.6462	39.12878	205	205-np32	8	0.12
2022	-96.6459	39.13097	303	303-np12	24	0.34
2022	-96.6456	39.12751	304	304-np12	40	0.95
2022	-96.6453	39.12776	304	304-np22	31	2.88
2022	-96.6454	39.12777	304	304-np-32	12	0.60
2022	-96.6453	39.12786	304	304-np42	9	0.29
2022	-96.6452	39.12808	304	304-np52	24	1.31
2022	-96.6452	39.12821	304	304-np62	11	0.27
2022	-96.6452	39.12848	304	304-np72	8	0.19
2022	-96.6452	39.12854	304	304-np82	20	0.47
2022	-96.6453	39.12858	304	304-np92	12	0.21
2022	-96.6452	39.1293	305	305-np12	20	0.22
2022	-96.6452	39.12892	305	305-np22	14	0.12
2021	Total length (m)				221	
2022					329	
2021	Total volume (m^3)					12.91
2022						10.84