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Combining Soil Health and Fertility Measurements to Improve the Accuracy of Predicting Corn Grain Yield Responses to P and K Fertilization

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COMBINING SOIL HEALTH AND FERTILITY MEASUREMENTS TO IMPROVE THE ACCURACY OF PREDICTING CORN GRAIN YIELD RESPONSES TO P AND K FERTILIZATION

BY

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This thesis is approved as a creditable and independent investigation by a candidate for the master's degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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ABBREVIATIONS

ACE Protein – Autoclaved citrate-extractable protein
AMF – Arbuscular mycorrhizal fungi
ANOVA – Analysis of variance
AP – Acid-phosphatase
AS – Arylsulfatase
BG – β-glucosidase
C – Carbon
CASH – Comprehensive Assessment of Soil Health
CEC – Cation exchange capacity
CT – conventional tillage
IA – Iowa
K – Potassium
KS – Kansas
MDA – Mean decrease in accuracy
MDG – Mean decrease in gini
MMD – Mean minimal depth
MN – Minnesota
N – Nitrogen
ND – North Dakota
NE – Nebraska
NT – No-till
P – Phosphorus
RSE – Residual standard error
RT – Reduced tillage
S – Sulfur
SD – South Dakota
SE – Standard error
SMAF – Soil Management Assessment Framework
SOM – Soil organic matter
STK – Soil test potassium
STP – Soil test phosphorus
TC – Total carbon
TN – Total nitrogen

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ABSTRACT

Researchers have pointed to changes in climate and land management practices to justify the need to reevaluate the accuracy of current South Dakota (SD) corn (*Zea mays* L.) P and K fertilizer recommendations. Also, an increase in soil health understanding has created the potential for soil health measurements to be used to improve the accuracy of these recommendations. The objectives for this study were to 1) evaluate the current P and K critical values and 2) determine the effect of including soil health indicators on improving fertilizer recommendation accuracy. This project was conducted throughout central and eastern SD from 2019-2021 at 97 experimental areas that varied in management, landform, and soil type. Fertilizer addition treatments of 112 kg P_2O_5 ha^{-1} and 112 kg K_2O ha^{-1} were compared to a control with no P or K fertilizer. Soil health and fertility samples (0-15 cm) were collected before fertilization and analyzed for physical, chemical, and biological characteristics. A linear plateau model indicated the soil test P (STP) critical value needs to be increased from 16 to 20 mg kg^{-1} and soil test K (STK) needs to be decreased from 160 to 140 mg kg^{-1}. However, both new critical values either 1) had low correlation values to yield response or 2) were not significantly better than the old critical values. Therefore, more sites and years of data are needed to confirm if a change in critical values is needed. Random forest variable importance methods found differences among variables, although differences were not substantial enough to clearly identify what variables were most important in predicting yield response to P and K fertilization. Decision tree analysis found several variables for P (STP, CEC, soil respiration, and clay content) and K (STK, tillage, and soil pH) that when split using a decision tree, improved prediction accuracy from 63% (STP or STK used alone) to 74%

and 77%, respectively. These results demonstrate that soil health indicators along with soil fertility testing improves the accuracy of our yield response predictions to P and K fertilizer.

CHAPTER 1: INTRODUCTION

1.1 FERTILIZER IN CORN PRODUCTION

Fertilizer inputs are necessary for the production of high yielding corn. The three primary nutrients for corn are nitrogen, phosphorus, and potassium (N, P, and K). At least one of the three are applied on 98% of corn-producing land in the U.S. (USDA ERS, 2019). While N may be applied at the highest rates, P and K are also applied in considerable amounts, with U.S. use of both nutrients exceeding two million metric tons in 2018 (USDA ERS, 2019). While use of P and K fertilizers has increased across the U. S. Corn Belt, input costs and environmental concerns have opened discussions on the issues caused by excessive fertilization. Developments in soil health understanding have produced new methods for measuring biological and chemical processes in the soil. Increases in conservation management practices such as cover cropping, reduced tillage, and diverse crop rotations have led to improved soil health and quality, potentially impacting nutrient use and availability for corn crops (Nunes et al., 2020; Villamil et al., 2020; Venter et al., 2016). This review discusses the mechanisms that cycle P and K throughout the soil, how fertilizer applications are recommended, what soil health measurements are currently being used, and how soil health measurements may be used to improve the accuracy of predictions of yield response to fertilizer.

1.1.1 Phosphorus

Phosphorus has long been known as an important nutrient for crop production with the use of pulverized phosphate rock dating back to the early 1800’s (Ashley et al., 2011). Use was not widespread due to slow and costly production until the Tennessee Valley Authority (TVA) developed a simple and economic process for producing granular diammonium phosphate in 1961 (Young et al., 1962). Since the creation of this formulation, fertilization of P has risen dramatically across the U.S. (USDA ERS, 2019).

In addition to inorganic fertilizers, other sources of P include soil minerals, organic matter, and manure (Prasad and Chakraborty, 2019). Minerals that contain P, such as apatite, are chemically weathered to slowly release P into the soil (Lajtha and Schlesinger, 1988). In the soil, P atoms either form compounds with cations in the soil (bound) or stay in the soil solution (available) where they remain plant available. Since available and bound P are in equilibrium, as plants remove P from the solution, more P is replaced from the bound portion (Prasad and Chakraborty, 2019).

In the soil, P is constantly cycled when plants and microbes associate with the different forms present. When plants take up P, most is immobilized in the plant until the plant dies. When crops are harvested, most of the P is returned to the soil as organic matter, although some is removed in the harvested grain. Over time, organic P is incorporated into or released into the soil solution by soil microbes, a process called phosphorus mineralization (Spohn and Kuzyakov, 2013). Understanding the P cycle can improve placement and timing of P fertilizer applications as well as improve soil testing methods.

Since there is no gaseous form of P, it cannot be lost to the atmosphere like nitrogen, thus weathered P can remain in the soil for a long time. Since P-containing minerals weather slowly, losses cannot be quickly replaced by the minerals in the soil alone (Filippelli, 2008). While the potential for P losses to the environment compared to N is low, losses do occur and usually involve crop removal and erosion events (Karbo et al., 2017; Han et al., 2021). When significant water erosion events occur, soil-associated

P can move with soil particles out of the field where it can pollute lakes and waterways. In the U.S., algal blooms caused by excessive P and N in surface water is the most common impairment of surface waters. (Conley et al., 2009). Extensive water pollution of major rivers and lakes has led to calls for research with hopes of reducing P inputs and the adoption of management practices that reduce erosion.

Availability of P in the soil is highly dependent on several factors including texture, pH, and microbial communities (O'Halloran et al., 1987; Penn and Camberato, 2019; Richardson et al., 2011). Slight changes in pH can result in changes in the availability of P. For example, at near neutral pH (6.5-7.0), P availability is at its highest (Penn and Camberato, 2019). At low pH levels (<5), P is fixed to iron in the soil whereas at high pH (>8), it is fixed to calcium. Even at near neutral pH, aluminum fixation of P is prominent in the soil. However, at a pH of 6.5-7.0, both aluminum and calcium fixation are at their lowest and iron fixation is no longer prevalent, meaning this pH results in the highest P availability to plants (Penn and Camerato, 2019).

Soil P also has a complex relationship with soil microbes. Soil microbes release enzymes that promote the turnover of organic P into inorganic, plant-usable phosphates (Turner et al., 2006). As microbial activity increases, enzymes break down more organic matter and release more plant available P (Alori et al., 2017). Therefore, management practices that promote non-disturbance of soil microbes can help facilitate the turnover of P. Applications of P fertilizers may also increase microbial activity by giving them a key nutrient needed for cell processes (Spohn and Schleuss, 2019). Research focus has been placed on improving P availability by increasing microbial activity. The hope of such research is that microbes can supply enough P to crops that P fertilizer applications can be reduced, saving money for farmers and reducing the harmful environmental impacts of P runoff. Therefore, due to microbial influences on soil P, including soil biological indicators in fertilizer recommendations along with soil fertility measurements may help better predict yield responses to P applications.

1.1.2 Potassium

Potassium has long been used as a fertilizer for plants. Before chemistry even discovered K, wood ash was marketed and sold as fertilizer in Europe. Wood ash, leading to the name potash, was used extensively as a high-K fertilizer (Allanore et al., 2015). In the 1800's mineral potash was discovered in Germany and provided a cheaper source of K. Since then, K usage in areas with low native K fertility has been vital to the yields of many crops. Use of K for U.S. corn has increased as native soil K has been used up in many parts of the country by intensive cropping (USDA ERS, 2019; Sarkar et al., 2014).

Accumulation of K in the soil usually results from chemical weathering of soil minerals or nutrient applications. Physical weathering of feldspars results in clay particles with high surface area. From the clay surfaces, K ions can be chemically weathered and released into the soil solution. Areas high in native K fertility are usually young soils that are still undergoing physical and chemical weathering of K-containing minerals (Schroeder et al., 1980). While many areas in the U.S. need to consistently apply K fertilizers to keep K levels sufficient in the soil, many areas of SD have high native K fertility (Ward and Carson, 1975). Despite this, K fertilizer usage on SD corn has climbed in recent years. In 1964, the average rate of K rate for SD corn was only 11 kg/ha but has risen to over 60 kg/ha in 2017 (USDA ERS, 2019). Dramatic increases in K fertilizer rates illustrate the need to re-examine current K recommendations.

The K cycle begins when mineral-bound K is chemically weathered or applied as an organic or inorganic fertilizer. From there, K ions either associate with clay molecules (adsorption) or stay in the soil solution in equilibrium with adsorbed K (Murrell et al., 2021). Notably absent from the K cycle is microbial immobilization, a process that is important for N and P cycling. Although microbes do not typically immobilize K in the soil, K ions adsorb to clay minerals where they are not easily lost. Ionic forms of K, which are plant available, are not associated with clay and may be lost due to leaching or runoff (Murrell et al., 2021).

Soil K availability is affected by several physical and chemical soil factors. For example, low moisture negatively impacts plant available K. As soil moisture is diminished, plant-available K, which moves with water, may not reach root hairs (Kuchenbuch et al., 1986). The availability of K is also affected by the cation exchange capacity (CEC) of a soil. Soils with high CEC can adsorb more K ions and release them when solution K begins to diminish (Schroeder et al., 1980). Although organic matter does not contain much K within its structure, it can have CEC values notably higher than soil molecules and can thus increase K held in the soil (Hamed et al., 2011). Although microbes do not actively immobilize K in considerable amounts, they still can impact K availability. For example, some bacteria can solubilize K that was otherwise fixed or on exchange sites (Meena et al., 2016). Therefore, improvements in soil biological health could, in theory, improve K solubility and plant usability. Because of this, soil biological indicators may be helpful in understanding yield responses to K fertilizer applications.

1.1.3 P and K Uptake and Use in Plants

Both P and K have vital function in plants that, if deficient, can disrupt plant processes. To complete these processes, plants need to take up nutrients from the soil and transport them to areas that need them. Plants commonly can only adsorb soil P as orthophosphate ($H_2PO_4^-$) from the soil (Lambers, 2022). Once inside the plant, P is vital for photosynthesis as well as the formation of phospholipids and nucleic acids (Veneklaas et al., 2012). Plants also utilize P in ATP creation, a molecule vital for most energy-driven chemical reaction in a plant, including photosynthesis (Lambers, 2022). Plant P deficiencies can negatively impact photosynthesis and severely limit plant growth and development.

Uptake of K is vital for some processes in plants including protein metabolism, enzyme activities, and metabolic processes, and osmotic functions (Miller et al, 1996; Grabov et al., 2006). Taken up by roots, K is stored in vacuoles where it helps with osmoregulation for cell growth and turgor pressure (Ragel et al., 2019). Inside plants, K is also a key factor in defending plants against biotic and abiotic stressors (Guo et al., 2013). Deficiencies of K in plants may result in problems with turgor pressure and osmosis which disrupt transport of other nutrients throughout the plant (Hafsi et al., 2014).

1.1.4 P and K Impact on Yield

Both P and K are essential to plant growth and function, and deficiencies of these nutrients will likely result in disruption of plant growth and function as well as yield losses. Since a majority of soils in the U.S. are deficient in P and K, application of fertilizers is necessary to maintain soil fertility and provide enough nutrients for the crop to maximize yields and profitability. For example, there are significant positive correlations between P fertilization and corn yields (Schlegel and Havlin, 2017; Mallarino and Dodd, 2005; Ruiz Diaz et al., 2019). When available P was considered low in the soil, applications increased yield in the first few years (Mallarino and Dodd, 2005). Long term buildup and maintenance of soil P has also been used to improve otherwise unproductive farmland (Ibrikci et al., 2005). Impacts of soil K on corn yield has been unclear.

While a general consensus is that K applications are necessary for high yielding corn, researchers have received mixed results. For example, some studies find high rates of K (84 and 157 kg/ha) are needed to increase corn yields (Vyn and Janovicek, 2001; Muir and Hedge, 2003) while others conclude K applications don't improve yield, even at low levels in the soil (Wortmann et al., 2009; Khan et al., 2014). To this point, soil fertility measurements were the best-known predictors for determining yield responses to fertilizer applications. Because of new soil health indicators and better understanding the role of soil biology in nutrient cycling and availability, soil health indicators used along with fertility measurements may improve yield response predictions to P and K fertilizers.

1.2 FERTILIZER RECOMMENDATIONS

1.2.1 Fertilizer Recommendations in SD Corn

Application of fertilizers is vital to the economy of SD by improving corn grain output. According to the USDA Census of Agriculture (2017), corn yields have increased from about 4800 kg/ha in 1987 to over 9000 kg/ha in 2017 while being grown on one million more hectares in 2017. To supplement the massive increase in land-use and yields, fertilizer usage and rates have increased dramatically. Rates of P and K have jumped from 42 to 57 kg/ha and 22 to 51 kg/ha, respectively, between 1987 and 2017 (USDA ERS, 2019). Further, total fertilizer expenses in SD have jumped from $96 million in 1987 to nearly $800 million in 2017 (USDA, 2017). Along with increased use, fertilizer prices have drastically increased as well. For example, the national average price of potash was $165/ton in 2000 but has skyrocketed to $511 in 2010 (USDA ERS, 2019). As fertilizer costs have continued to increase, farmers and researchers alike have been searching for ways of maintaining high yields while lowering fertilizer requirements.

1.2.2 How are P and K Applied in SD?

Along with increased fertilizer use, fertilizer application methods have changed as well. Traditionally, both P and K are broadcast over the soil in the spring before planting and incorporated into the soil by tillage. Once incorporated into the soil, these nutrients have a much lower chance of off-site movement due to rainfall and erosion (Chambers et al., 2000; Bertol et al., 2003). In reduced-till systems, fertilizers may be left on the soil surface. Nutrients that are not incorporated, especially P, collect in the top layers of the soil where they are more prone to runoff by rainfall events (Yuan et al, 2018; Lupwayi et al., 2006). To prevent fertilizers from collecting on the soil surface, banding of P and K near the seed at planting has become extensively used in SD. Banding offers several advantages including reducing runoff losses (Yuan et al., 2018) and improving early season seedling development (Mallarino et al., 1999). Although the SD recommendation states that banded P applications can be reduced by 1/3, yield impacts and the possibility of reducing fertilizer rates have been unclear (Mallarino and Bordoli, 1998; Ebelhar and Varsa, 2000).

1.2.3 How Has Land Use Changed in SD?

Along with rising fertilizer use, agricultural land usage has changed as well. Since the 1980's, land used to grow oats and wheat has given way to an increase in corn-soybean crop rotations (USDA, 2017). The adoption of new rotations is due to improved drought-resistant corn hybrids and higher commodity prices (McFadden et al., 2019). Changes in crop rotations have transformed how and when fertilizers are applied to the field while also changing physical, chemical, and biological soil properties. While crop rotations may have just included wheat, corn, or soybean in previous years, many farmers have adopted more diverse rotations that may include sunflower, peas, oats, or sorghum in SD. The adoption of intensive crop rotations has led to better nutrient cycling and reduced losses of P and K (Bowman and Halvorson, 1997; Rosolem and Calonego, 2013). Although correlations have been made between crop rotations and increased nutrient cycling of P and K, how this can impact yield responses to fertilizer applications remains unclear.

1.2.4 Current Recommendations for P and K

Currently in SD, fertilizer recommendations are provided in the South Dakota Fertilizer Recommendation Guide (Gerwing et al., 2019). The fertilizer guide provides fertilizer recommendations based on 0-15 cm soil test P (STP) and soil test K (STK) using the Olsen or Bray P test (depending on pH) and ammonium acetate K mg/kg soil tests, respectively. The P test method recommendation varies by pH. In high pH, calcareous soils, the Olsen method is recommended while soils with a lower pH either method can be used (Olsen et al., 1954). Another soil test method for P and K that is not recommended in SD but in other states is the Mehlich-3 test. This method is not used as it has not been successfully correlated with SD crop yield responses. The SD Fertilizer Recommendation Guide breaks down the recommendations into nutrient sufficiency categories: very low, low, medium, high, and very high. When STP or STK reaches the "very high" category, it has reached the critical value. Below the critical value, a positive yield response would be expected with a fertilizer application of that nutrient, but when the soil test value is below the critical value, a yield increase from fertilization is no longer expected. The current critical values for SD are P 16 mg/kg (Olsen) and K 160 mg/kg (ammonium acetate). The research for these recommendations was conducted prior to 2005, before conservation management practices were extensively adopted in the state. Since then, adoption of conservation management in SD has drastically increased with over 50% of the state now practicing no-till farming (USDA NRCS, 2019). Changes in input costs, weather patterns, and corn hybrids have also exposed the need to revisit current fertilizer recommendations.

Each state has their own growing conditions, crop rotations, and management practices which means research conducted in one state may not correlate well with what a neighboring state has been finding. For example, K recommendations in Minnesota may be different than in SD due to different soil textures, lower native-K soils, and differences in clay mineralogy. In Minnesota, K recommendations change based on application method (band vs. broadcast) and cation exchange capacity (CEC) while North Dakota K recommendations change based on location in the state, irrigation practices, and clay mineralogy (Kaiser et al., 2020; Franzen, 2017). While SD nitrogen recommendations change based on tillage practices, management impacts on P and K recommendations have remained absent.

Growing conditions in SD change dramatically from dry, rolling hills in the west to relatively wet, flat areas in the east. Yield goals in dry, unirrigated land may be only 6000 kg/ha, but yield goals of over 13000 kg/ha are common in the far-eastern areas of SD. Further, SD native soil fertility changes across the state as well. For example, native K fertility is considered high across the state except for the far-eastern counties where K-deficient soils are more common (Ward and Carson, 1975). Due to an increase in precipitation, soluble salt levels have also increased on the soil surface which has led to a pH increase in the central part of the state (Millar, 2003). Furthermore, crop rotations in central and western SD may include more drought tolerant crops such as sorghum, wheat, and oats while no-till and cover crop use may be necessary to prevent erosion. Due to the environmental diversity in SD, fertilizer recommendations that change based on climate and soil conditions may better correlate with yield responses. Fertilizer recommendation accuracy may be improved if soil indicators that quantify the diverse climate and management practices of SD can be correlated with yield responses to fertilizer applications.

1.3 SOIL HEALTH

1.3.1 What is Soil Health and Why is it Important?

Soil health is defined as the continued capacity of soil to function as a vital living ecosystem that sustains plants, animals, and humans (Karlen et al., 1997). A soil said to have good soil health will be able to sustain microbial and plant life, effectively cycle nutrients, suppress diseases and pests, and promote environmental quality (Doran and

Zeiss, 2000). However, decades of management practices such as intensive tillage, excessive chemical use, and monocropping have severely reduced soil health through erosion, loss of organic matter, chemical contamination, and salinity increases (Lehman et al., 2015; Swift et al., 2008). Due to an increased understanding of how management practices impact long term sustainability, renewed emphasis has been placed on practices that build soil health rather than degrade it. Improvements in soil health correlate to better nutrient cycling (Rosolem and Calonego, 2013), reduced erosion (Jian et al., 2021) and pest suppression (Creamer et al., 1996). Soil health is generally improved by the adoption of conservation management practices that include reduced tillage (Nunes et al., 2018), cover cropping (Dapaah and Vyn, 1998), and diverse crop rotations (Aziz et al., 2011). Increased adoption of these management practices in recent years has led to discussions on how to quantify improvements in soil health. Although current fertilizer recommendations only use soil fertility measurements, emerging soil health measurements can potentially improve our understanding of yield responses to fertilizer applications.

Improving soil health is not only important for agricultural sustainability but has implications for many other areas of human life. For example, nutrient pollution is one of the primary problems effecting surface water in the U.S. (Carpenter et al., 1998). Soil health improvements can reduce erosion, preventing nutrients from reaching the water supply (Jian et al., 2021; Shaxson and Kassam, 2015). Management practices such as reduced tillage and cover crops which improve soil health indicators can hold the soil together resulting in reduced offsite movement of nutrients and chemical contaminants during rainfall events (Langdale et al., 1991; Laloy and Bielders, 2010).

Improvements in soil health may also be useful in reducing greenhouse gas emissions and sequestering carbon. For example, cover crops can reduce soil moisture content when allowed to grow for extended periods of time during wet periods (Sias et al., 2021). When soil moisture is reduced from field capacity, soil conditions become unfavorable for denitrification, and nitrous oxide emissions are reduced (Clough et al., 2004). Cover crops can also act as carbon banks by holding high amounts of carbon in their biomass instead of releasing it into the atmosphere (Sainju et al., 2007). Carbon sequestration has become an important topic as the ability of soil to hold carbon has become better understood. Although practices that reduce erosion and increase soil carbon have seen increased adoption, their impact on the other nutrients (e.g., P and K) is not well understood. Therefore, better understanding of correlations between plant available nutrients, soil health, and yield responses to fertilizers have the potential to reduce fertilizer applications when soil health improvements are made.

1.3.2 Soil Health Measurements

Soil health is said to be ideal when certain chemical, biological, and physical indicators are in “suitable” ranges (Karlen et al., 1997). Suitable ranges for soil health indicators maximize crop yields, nutrient availability, and sustainability while decreasing nutrient losses and erosion (Karlen et al., 1997). Generally, soil health indicators relate to processes and functions that occur in most soils. Soil health measurements include physical indicators (compaction, water holding capacity, and aggregate stability), chemical indicators (pH, CEC, and nutrient levels), and biological indicators (enzymes, active carbon, and soil respiration) (Moebius-Clune, 2016).

Soil health indicators can generally be improved by switching to conservation management practices. Although some soil health indicators, such as compaction, influence many soil processes, others, such as enzymes, relate to a single process in the soil (Feng et al., 2003; Eivazi and Tabatabai, 1977). Regardless, all soil health indicators are useful in quantifying the quality and sustainability of a soil. Some researchers use multiple measurements to form an overall soil health score, although they emphasize that individual tests are more important than an overall score (Andrews et al., 2004; Moebius-Clune et al., 2016). Because soil health indicators are useful in understanding many different soil functions and nutrient transformations, they may be helpful for understanding why or why not crop yield increases with fertilizer applications.

1.3.3 Soil Physical Indicators

Soil physical health is the ability of a given soil to meet plant and ecosystem requirements for water, aeration, and strength over time and to resist and recover from processes that might diminish that ability (McKenzie et al., 2011). A soil that has poor physical health has poor water infiltration, poor aeration, excessive water runoff, poor root penetration, and poor workability (Dexter, 2004). All of these deficient physical health indicators relate back to one problem: poor soil structure. A soil’s physical health and structure is highly dependent on the management practices used, especially tillage (Ramzan et al., 2019). Past management practices such as intensive tillage and crop monocultures can lead to poor soil structure, and in turn, poor soil health (Nunes et al., 2020; Munkholm et al., 2013). Farmers desire soils that ensure maximum nutrient retention, have improved structural quality, limit compaction, and increase water retention (Are, 2019). Reduced tillage has led to improved soil structure and increases in microbial biomass (Pagliai et al., 2004; Mathew et al., 2012), although conventional tillage increases aeration and lowers bulk density (Khan, 1996). However, over extended periods of reduced or no-till management (>5 years), significant improvements in soil physical quality indicators such as structure and aggregate stability has been observed (Aziz et al., 2013).

Most physical indicators can change relatively quickly compared to chemical and biological indicators. For example, a single pass with heavy machinery can increase bulk density while decreasing porosity and infiltration rate (Brandhuber et al., 2004). Some indicators change slowly over time. More than five years of diverse cover crops on a sandy loam soil increased both water and air infiltration (Folorunso et al., 1992). Soil physical characteristics can relate to nutrient availability as well. For example, soils with good structure can improve root growth which leads to higher uptake of key nutrients from lower in the soil profile (Passioura, 1991). Soil with good structure typically have higher fungal populations that form beneficial relationships with plants by supplying them with some nutrients (Feng et al., 2003; Kabir et al., 1998). Improvements in soil physical characteristics such as soil structure have therefore led to higher nutrient availability for P and K (Essington and Howard, 2000; Vyn and Janovicek, 2001). If nutrient availability and cycling can be improved by long-term physical soil quality improvements, then nutrient applications may be able to be reduced. Additionally, the predictability of crop response to fertilization may also be improved by using soil physical indicators along with traditional soil nutrient level tests.

1.3.4 Soil Chemical Indicators

Another aspect of soil health includes chemical measurements of the soil. Chemical soil health relates to the presence of elements and compounds in the soil that are important for soil processes and functions. Chemical health indicators include soil pH, soil nutrient levels, organic matter, and cation exchange capacity (CEC). Some soil chemical health indicators can be changed through application of soil amendments such as lime for pH adjustment (Anderson et al., 2013) and fertilizers to raise nutrient levels (Zhang et al., 2020). Fertilizer applications are important for building or maintaining nutrient levels in the soil. When nutrients are applied, both microbial activity and crop nutrient availability can be improved (Spohn and Schleuss, 2019; Passioura, 1991). A close relationship exists between soil nutrients and soil microbes. If management practices can increase microbial activity, then the soil may be able to supply more nutrients to a crop throughout the growing season. Therefore, soil biological health measurements along with chemical indicators listed below may improve our understanding of how corn yields respond to fertilizer amendments.

1.3.4.1 Soil Organic Matter and Cation Exchange Capacity

Soil organic matter (SOM) is both a chemical and biological health indicator. Classically, many people think of SOM as plant and animal matter in various stages of decay on the soil. Although correct, SOM has expanded to all plant, animal, and microbial biomass in the soil regardless of decomposition status (Fenton et al., 2008). Of particular importance to soil fertility, decaying organic material as well as soil microbes immobilize considerable amounts of nutrients that may otherwise be lost to the environment (Fenton et al., 2008). Due to the constant breakdown and release of nutrients from SOM, it effects all aspects of soil health: physical, chemical, and biological. For example, SOM helps hold soil particles together which increases aggregate stability, improves soil structure, and reduces soil erosion (Swift and Chaney, 1984). Not only are nutrients contained within SOM, but it also holds plant-usable cations in the soil profile, contributing highly to the total cation exchange capacity (CEC) of the soil. While clay soils can have CEC levels from 10-200 meq $100g^{-1}$, SOM can have CEC levels over 200 meq 100 g^{-1} (Parfitt et al., 1995). High CEC is usually associated with high clay, especially smectite, soils and high organic matter contents (Odom, 1984; Kaiser et al., 2008). A higher CEC means better nutrient retention of cations, especially K, which are important for plant growth. Many nutrients are also contained within SOM; estimates conclude that each percent of SOM in the top 15 cm of the soil profile releases up to 3 kg P ha^{-1} yr^{-1} (USDA NRCS, 2014). The ability of SOM to hold K ions while also immobilizing P makes it a strong candidate to be able to improve upon current P and K fertilizer recommendations.

Lastly, increased SOM can function as food for microbial communities. When plants die and organic matter is returned to the soil, microorganisms immediately begin the breakdown process. Strong relationships between SOM breakdown and soil microbial indicators such as respiration and enzymes in the soil are common (Dominy and Haynes, 2002; Matus et al., 2016). As microbes break down SOM, important nutrients are released into the soil solution in plant-available forms. If this flush of nutrients can be quantified, it could be of considerable importance when making fertilizer decisions. Therefore, along with biological activity, SOM could be an important indicator to improve correlations between corn yield responses and nutrient applications.

1.3.4.2 Soil pH, P, and K Levels

Nutrient levels in the soil can also be a measure of soil chemical health. Soil nutrient tests must correlate well with the actual availability of nutrients for the crops during the growing season, otherwise they cannot be correlated with yield and uptake. Most key nutrients are only plant available in certain forms. The forms of nutrients present in the soil are highly related to soil pH (Miller, 2016). For example, soil P's relation to pH was discussed earlier (Penn and Camberato, 2019). For K, low pH soils, which have relatively low CEC, reduce K availability due to reduced holding capacity by the soil (Miller, 2016; Jung et al., 2009). Plants can adjust the soil pH near root zones to make nutrients already in the soil more available to them (Youssef and Chino, 1989). However, if pH levels are extreme, nutrient applications may change to unavailable forms before plants have a chance to use them. Therefore, soil pH can be an important indicator of how plants respond to nutrient applications.

Soil pH also plays a role in the methodology used to test for soil P. There are several commonly used testing methods for plant available P: Bray-1, Mehlich-3, and Olsen (Bray and Kurtz, 1945; Mehlich, 1984; Olsen et al., 1954). In the calcareous, high pH soils present in much of SD, the Olsen test is recommended due to better correlations with plant-available P than Bray-1 or Mehlich-3 (Hooker et al., 1980; Ebeling et al., 2008). Many states have recommendations that build up soil P levels by applying fertilizers every year until a goal is met and then maintain P in the soil with timely applications. Despite this, P overapplication may not build up soil test levels in all soil types and can increase P losses in surface runoff (Fulford and Culman, 2018; Yuan et al., 2018). Although the Olsen test is an excellent indicator of soil inorganic P, it does not estimate organic P (Olsen et al., 1954). Therefore, the test underestimates total P in soils with high SOM and microbial biomass. Better understanding of how SOM mineralization can release nutrients (mainly N, P, and S) has been made in recent years (Sarker et al., 2018; Wood et al., 2018). However, few states have budgeted SOM nutrients into their fertilizer recommendations (e.g., Nebraska nitrogen recommendations use SOM percentages). Although SOM can indicate P that will become available throughout the growing season, Olsen P is still a robust indicator of how much plant-available P is currently in the soil. Therefore, Olsen P should still be used as an indicator to help us better understand yield responses to P fertilizer applications.

The ammonium acetate test for K estimates the amount of exchangeable K in the soil (Warncke and Brown, 1998). Exchangeable K is generally adsorbed to clay minerals although it can be released into the soil solution when exchanged with other cations. In the high pH soils of SD, an abundance of cations means they are constantly being replaced on the exchange sites. The K soil test measures exchangeable K, meaning that it tests for potential available K in the soil, not what is actively available in the soil solution. The amount of plant-available K is primarily related to soil moisture (Kuchenbuch et al., 1986; Brown and Zeng, 2000). As soil moisture increases, K is better mobilized and can reach plant roots. Plant-available K can also be impacted by soil microbes that can solubilize K (Das and Pradhan, 2016). Although soil K is used as the primary indicator of plant available K, studies have increasingly had problems trying to correlate soil K to yield responses (Mallarino et al., 1999; Boring et al., 2018). This indicates that soil processes that effect K availability need to be better understood.

Potentially, other indicators of soil K availability need to be found of developed to better correlate yield responses to K fertilizer applications.

1.3.4.3 Total Nitrogen and Carbon

Two important soil health tests involve the total N (TN) and C (TC) contents of the soil. While other N tests look for plant-usable forms of N, the TN test looks at all organic and inorganic N in the soil. While a soil may have thousands of kilograms of N in every hectare, only 1-4% becomes available during the growing season (Horneck et al., 2011). While TN is correlated to N fertilizer rates, it also correlates to other soil health indicators, especially organic carbon (Aula et al., 2016; Yang et al., 2015). Because total N correlates with other soil health indicators such as SOM and microbial biomass, it is also a good indicator of overall soil health (Yang et al., 2015; Wang et al., 2005). Management practices such as cover crops and reduced tillage have led to increases in total N content in the topsoil over prolonged periods (Mazzoncini et al., 2011; Sharma et al., 2018). Because of its relation to important soil health indicators and nitrogen fertilizer use, the TN test could be useful in determining why yields do or do not respond to fertilizer applications.

The total carbon test (TC) looks for all organic and inorganic carbon in the soil. Although sounding similar to the active carbon test mentioned later on, the TC test looks at carbon in all forms, including humic substances that are extremely slow to break down. The TC test is a long-term indicator of soil health as it relates to the slow increase in organic matter when conservation management practices are used (Lal et al., 2015; Blanco-Canqui and Lal., 2008). Over the past decades, TC measurements decreased as extensive tillage and organic matter removal reduced the carbon present in the soil (Dalal and Mayer, 1986). Due to climate change, a new emphasis on carbon sequestration has given new importance to the TC soil test (Schlesinger, 1999). While many soils in SD are degraded, conservation management practices promote carbon sequestration in the soil and can increase TC long term (Lal et al., 2015). Although total carbon does not immediately increase when conservation management practices are implemented, the TC test is an excellent long-term indicator of biological activity and biomass in the soil (Lal et al., 2015; Blanco-Canqui and Lal., 2008). Therefore, TC may be an important indicator of the long-term benefits of conservation management practices and could improve understanding of yield responses to fertilizer applications.

1.3.5 Soil Biological Indicators

The third aspect of soil health involves the biological health of the soil. Soil biological health encompasses all activities of microorganisms in the soil. In some texts, soil biological health has just been called “soil health” while soil physical and chemical properties are referred to as “soil quality” (Lehman et al., 2015). Many microbes in the soil are highly beneficial to plants (nitrogen-fixing bacteria, mycorrhizal fungi) while others may negatively impact plant health (pathogens). These microorganisms can be living inside plants, on plant roots, or in colonies in the soil (Lehman et al., 2015). Soil microbes are involved in many important processes for plants including facilitating organic matter turnover (Rao et al., 2019), building soil structure (Rillig and Mummey, 2006), and making nutrients available to plants (Azcon-Aguilar and Barea, 2015). Some recognized soil health tests that can indicate how well a soil can complete vital functions include soil enzymes, active carbon, soil respiration, and total soil protein. Soil biological health is highly dependent on management practices. Tillage practices that reduce soil breakup and compaction positively impact microbial communities, especially fungi (Feng et al., 2003; Kabir et al., 1998). Without disturbing the soil, microbial communities have time to grow and mature where they can reach their full potential for benefitting the soil.

One primary area of study has been nutrient turnover from organic matter that is catalyzed by microbial communities. As a large amount of nutrients are tied up in organic matter, destruction of microbial communities means that breakdown of organic matter is slowed (Tiessen et al., 1994). Of the primary nutrients, N is the most important for both microbial life and plants. Since N fertilizers need to be changed from either urea or ammonia to plant usable nitrate or ammonium by soil microbes, a reduction in soil microbes slows mineralization and immobilization (Craine et al., 2007; Schimel and Bennett, 2004). While the impact of soil microbes on nitrogen cycling has been the subject of many studies, the role of microbes in the cycling of P and K has been minimally discussed. As fertilizer prices continue to climb and conservation management adoption continues, a better understanding of soil microbial relationships to P and K availability needs to be determined that could result in improvements to fertilizer recommendations.

1.3.5.1 Enzymes

Soil enzymes are an important soil health indicator that link to the turnover of important nutrients for plants. To accomplish this, soil enzymes play a critical role in the breakdown of organic matter and subsequent release of nutrients (Lorenz et al., 2020). Generally, enzymes positively correlate to the amount of microbial activity going on in the soil (Dick, 1984; Sharma et al., 2013). As a soil becomes more biologically active, most soil enzyme levels tend to increase as well. The rise in enzyme activity helps cycle nutrients and carbon from SOM into plant usable forms (Dick and Bandick, 1999). Three of these enzymes, β-glucosidase, acid-phosphatase, and arylsulfatase, have shown the most potential in being related to nutrient cycling.

β-glucosidase (BG), an enzyme released by soil microbes, plays the final role in the breakdown of cellulose to glucose (Lorenz et al., 2020). Glucose can easily be taken up and used by soil microbes. As a result, increases in soil glucose have resulted in increased microbial growth (Reischke et al., 2014; Waldrop et al., 2000). Generally, an increase in organic carbon pools correlates to an increase in the need for BG enzymes to break it down (Turner et al., 2002). Soil BG levels are sensitive to changes in soil management practices and weather conditions, meaning BG testing is a good way to quantify the positive effects of management improvements. Management practices such as reduced tillage and cover cropping, generally increase BG levels in the short-term (Dick and Bandick, 1999; Lorenz et al., 2020). There are also strong correlations between BG and SOC (Eivazi and Tabatabai, 1990). Management practices such as reduced tillage and cover cropping that increase SOM can generally also result in BG increases. Due to a strong correlation to overall biological activity, BG is a robust indicator of the overall biological health of the soil and the ability to cycle nutrients for crops (Stott et al., 2009). Although BG is associated with the turnover of soil C, its correlation to overall microbial activity and SOM breakdown give it potential to quantify the rate at which other nutrients, such as P, are being mineralized from SOM. Therefore, BG could be useful for determining why yields may or may not respond to fertilizer applications.

A second enzyme, acid-phosphatase (AP), is involved in P cycling from SOM to plant-available forms. Most AP enzymes in the soil exist as either acid- or alkaline-phosphatase (Eivazi and Tabatabai, 1977). Given the names of these enzyme forms, pH plays a critical role in which form is dominant in a soil profile. When pH is more acidic, acid-phosphatase dominates the soil whereas neutral and alkaline soils have a dominating alkaline-phosphatase. (Eivazi and Tabatabai, 1977). Once in the soil, AP enzymes function to release P from SOM into plant usable forms. Therefore, AP levels have been linked to increases in overall SOM and other enzymes such as BG (Baldrian and Stursova, 2010). Soil AP levels have been positively correlated to tillage management and crop residues (Deng and Tabatabai, 1997). Also, AP can be released by the roots of some plants, not only soil microbes (Joner and Jakobsen, 1995). This may explain why cover crops dramatically increase AP (Karasawa and Takahashi, 2015). Fungi also play a large role in producing phosphatase enzymes. Fungal hyphae near plant roots produce AP enzymes that break down organic P and supply some to the host plant in a symbiotic relationship (Dighton, 1983). Due to the ability of AP to indicate the turnover of organic P, it may be useful in yield response prediction to P fertilization.

A third enzyme, arylsulfatase (AS), facilitates the cycling of sulfur from organic matter to soil solution S. Organic forms of sulfur account for upwards of 95% of total S in the soil (Scherer, 2009). Much like other organic nutrients, organic S is not usable for plants until it has undergone chemical processes. As its name suggests, AS has an important role in breaking down organic sulfur compounds and releasing SO_4 (Whalen and Warman, 1996). Once organic S has been turned into SO_4, it can be taken up by plants. The importance of AS to P and K fertilization is its ability to correlate to changes in SOM and, more importantly, management practices. As with many other enzymes, studies suggest management practices that don’t disturb the soil and promote microbial communities can result in increases in AS activity (Dick, 1984; Deng and Tabatabai, 1997). Liming and other practices that increase soil pH can also lead to increases in AS activity (Deng and Tabatabai, 1997). When soil organic matter is abundant, such as in cover-crop and reduced till systems, AS levels usually increase along with the biochemical cycling of S (Pariente and Li, 2003). Although S cycling isn't the focus of this paper, the ability of AS to indicate organic matter mineralization means it could relate to the release and availability of other nutrients such as P and K. Therefore, AS could be another helpful enzyme in predicting yield responses to fertilizer.

1.3.5.2 Active Carbon

Instead of measuring all carbon present in the soil, the active carbon soil test estimates labile carbon (Weil et al., 2003). Labile carbon is the most functional pool of carbon in the soil that is actively being broken down by microbes. Due to its role in providing available energy sources for the soil microbial community, active carbon can correlate well with the microbial breakdown of SOM (Moebius-Clune et al., 2016). Because of this, active carbon is highly related to organic matter contents and overall microbial biomass alike (Islam and Weil, 2000; Cambardella and Elliot, 1992). Since the active carbon soil test does not look at all forms of carbon in the soil, it does not always relate well with overall organic matter and usually responds to management changes years before SOM does (Nelson and Sommers, 1996; Moebius-Clune et al., 2016). Active carbon measurements can change rapidly based on soil management changes such as reduced tillage management (Pareja-Sanchez et al., 2017), cover cropping (Culman et al., 2013), and diversified crop rotations (Tiemann et al., 2015). Although the active carbon test measures easily degradable C, its direct relation to SOM turnover means it correlates with the release of nutrients from SOM (Calderon et al., 2017). Because of this, active carbon could be used to not only indicate the cycling of C but other nutrients as well. Therefore, the active carbon test could be used to better predict yield responses to fertilizer applications.

1.3.5.3 Soil Respiration

The soil respiration test directly measures the CO_2 released by soil microbes over a certain period of time. (Zibilske, 1994) This test attempts to quantify the overall microbial activity in the soil as microbes actively use carbon form organic sources and release CO_2. (Moebius-Clune et al., 2016). Because of its relationship to overall microbial activity, soil respiration is sensitive to both temperature and moisture content (Taylor and Lloyd, 1994; Azzalini and Diggle, 1994). The soil respiration test overcomes the environmental variability by incubating the soil at a certain moisture over a period of four days after which CO_2 output is obtained. A higher CO_2 content means increased microbial activity of the soil. Because soil respiration is so closely related to microbial activity, management practices that increase microbial biomass such as reduced tillage (Carpenter-Boggs et al., 2003), intensive crop rotations (Mnkeni and Gura, 2019), and cover crop treatments (Gucci et al., 2017) lead to higher soil respiration levels. Due to correlations between soil respiration and microbial activity, Soil respiration may be an important test for quantifying how management practices impact SOM turnover and subsequent release of nutrients. Therefore, the soil respiration test may also be helpful for predicting yield responses to fertilizer applications of P and K.

1.3.5.4 Total Protein

Another important soil biological indicator is known as the autoclaved citrate extractable (ACE) protein test. This test gained relevance when glomalin-related soil proteins were discovered in the 1990's (Wright and Upadhyaya, 1996). Glomalin proteins are mainly produced by arbuscular mycorrhizal fungi (AMF). Because AMF form symbiotic relationships with plants where they share nutrients, they have become an important topic relating to nutrient uptake (Giovannetti et al., 2007). These fungi can benefit plants in many ways including enhancing plant growth, increasing water stress tolerance, improving plant health, and facilitating nutrient cycling (Horii and Ishii, 2014). Although the glomalin that AMF produce is an important soil protein, a misconception is that the ACE protein test only extracts glomalin, however, it actually extracts all types of soil proteins (Hurisso et al., 2018). Soil proteins are important because they account for a large pool of N in the soil (Jones and Roberts, 2008). Protein levels are also involved in the mineralization and stabilization of soil nitrogen from SOM (Hurisso et al., 2018). The close relationship of soil proteins to N transformations has increased interest in using the ACE protein test as an overall indicator of soil biological health (Wright and Upadhyaya, 1996; Moebius-Clune et al., 2016).

The ACE protein test is sensitive to management practices and fertilizer amendments. Long term application of nitrogen has been shown to increase protein in the soil (Wu et al., 2011) while reduced tillage has resulted in increased fungal activity and related proteins (Yang et al., 2020). Because of its sensitivity to management practices, soil protein content, along with the ACE test, is becoming an important factor in soil health assays such as CASH (Moebius-Clune et al., 2016). Although not directly related to P or K in the soil, the ACE protein test does indicate a rise in beneficial organisms and microbial biomass (Moebius-Clune et al., 2016). Of importance to nutrient availability is that increases in soil proteins relate to better uptake of P, K, and other nutrients (Miransari et al., 2009). The enhanced uptake of P and K by buildup of soil proteins mean that the ACE protein test could be beneficial in determining whether or not corn yields will respond to fertilizer applications.

1.3.6 Soil Health Assays

As soil health indicators have become an important tool to show the benefits of sustainable agriculture, there have been attempts to create a soil health “score”. The two most well-known soil health assays are the Soil Management Assessment Framework (SMAF) and Cornell’s Comprehensive Assessment of Soil Health (CASH) which both use soil health measurements that they have determined to be the most influential at determining a soil’s overall health (Wienhold et al., 2009; van Es et al., 2008). Both tests select a variety of soil physical, chemical, and biological measurements and utilize them to quantify the ability of soil to perform critical soil processes and functions.

The SMAF evaluation was created to determine how management practices and land-use effect soil quality. The SMAF uses soil quality indicators from a bank of 80 different tests (Andrews et al., 2004). Before any soil tests are run, users fill out a survey of land management goals which includes three primary goals: productivity, waste recycling, and environmental protection (Andrews et al., 2004). For each of the three goals, the database refers to several soil functions that are vital for the goal chosen. After this, the SMAF database further narrows down selected indicators based on climate, crop rotation, tillage practice, assessment purpose, and inherent soil properties (Andrews et al., 2004). Once indicators are chosen, soil tests are run and are graded on a scoring curve given by the program. The program then changes the value to a score of zero to one. A one represents the highest possible score and means that the indicator is non-limiting to soil functions and properties (Andrews et al., 2004). An optional final step is to get an overall score by adding together all individual indicator scores, dividing by the number of indicators, and multiplying by 10. This gives an overall soil health score of the selected indicators between 0 and 10. The SMAF scores have been effective at quantifying the effects of management practices on soil functions (Karlen et al., 2006; Jokela et al., 2009). Individual indicator SMAF scores may be a useful tool for evaluating how management practices impact soil health indicators and could be a useful tool for soil fertility recommendations.

Another soil health assessment is Cornell's CASH. When the CASH protocol was developed, a pool of 42 potential physical, chemical, and biological indicators were evaluated to see their relevance to key soil processes, response to management, complexity of measurement, and overall cost (Moebius-Clune et al., 2016). After evaluation, four physical indicators (available water capacity, surface hardness, subsurface hardness, and aggregate stability), four biological indicators (organic matter, soil protein, soil respiration, and active carbon), and several soil chemical indicators (soil pH and nutrient levels) were chosen for the assessment. Similar to SMAF, the CASH output scores each indicator based on a curve that was developed from testing and gives an output of 0 to 100 (Moebius-Clune et al., 2016). An indicator's score is then put into a class of very low, low, medium, high, or very high. Most physical and biological tests are given higher scores for higher measured values, but some are given higher scores for lower values (surface and subsurface hardness). Chemical indicators are given a score for being in the optimum range for the selected soil type. Scoring functions for several indicators also change based on textural class. In 2016, adjustments were made that developed curves based on the NRCS major land resource area (MLRA) because differences were found in the mean indicator values for a majority of the indicators (Moebius-Clune et al., 2016).

An overall soil health score can be obtained although Cornell advises giving attention to individual indicators. Although CASH has not been used for direct fertilizer recommendations, it does indicate changes in soil health indicators that influence nutrient availability such as SOM, pH, active carbon, and soil respiration. Although both SMAF and CASH can give overall soil health scores, both assays explain that more emphasis on individual soil test scores and not the overall score (Andrews et al., 2004; Moebius-Clune et al., 2016). Therefore, for this study, we decided to place more emphasis on individual soil parameters that may influence the predictability of crop responses to fertilizer applications.

1.4 SOIL MANAGEMENT PRACTICES

1.4.1 Soil Management Overview

As emphasized throughout the previous section, management practices have profound impacts on almost all soil health indicators. However, conventional management practices that create desirable planting conditions, improve plant emergence, and control weeds and pests generally degrade soil health over time (Nunes et al., 2020; Osterholz et al., 2021). Conventional management practices are used because they are generally cost effective and are assumed by farmers to produce the highest yields. However, research contrary to these conceptions indicates high crop performance and effective weed control can still be achieved by adoption of practices that promote soil health rather than degrade it (Carrera et al., 2004; Kapusta et al., 1996; Munoz et al., 2014). For example, farmers have been slow to adopt cover crops, a soil health improving practice, due to the perceived risks of taking water and nutrients from crops. However, research shows effective termination timing and method can both control water use by the cover crop as well as add easily mineralizable nutrients to the soil (Sainju and Singh, 2001; Wortman et al., 2012). Although many misconceptions have been discredited and numerous benefits from management practices such as reduced tillage, cover cropping, and diverse crop rotations have been discovered, farmers are still slow to adopt a new practice that may not produce immediate, economic results. Further, although connections have been made between soil management decisions and soil health, overall knowledge of how soil health can impact fertility decisions is lacking.

Currently, there are no direct tests that can quantify how a management practice increases nutrient use and availability for plants. Links between soil health and nutrient availability that directly lead to reduced fertilizer rates could increase adoption of soil health building management practices. Farmers that see the financial benefit of better management decisions will be quicker to adopt them. Therefore, quantifying the soil health benefits of conservation management practices and using them to make fertilizer decisions may improve adoption of practices such as reduced tillage, cover cropping, and diverse crop rotations.

1.4.2 Reduced Tillage

A primary soil health building practice is to reduce tillage intensity of the soil. Conventional tillage (CT) has many practical benefits to farmers such as a prepared seed bed, nutrient incorporation, and reduced weed populations. However, conventional tillage breaks apart soil aggregates, destroys microbial communities, and creates plow pans in the subsoil (Kasper et al., 2009; Mathew et al., 2012; Allmaras et al., 1998). Switching from CT to reduced till (RT) can increase weed pressure and reduce yields in the short-term (Dickey et al., 1983; Wrucke and Arnold., 1985). This has led to misconceptions about the long-term goals of RT and has prevented adoption by some farmers. Longer-term studies found conflicting results compared to short-term research: yields can remain stable, weed pressure reduced, and water holding capacity be improved (Kumar et al., 2012; Kapusta et al., 1996; Hyde et al., 2016).

While a common claim of RT is high nutrient retention and cycling, few studies have been able to show this. Despite this, RT has been linked to improvements in many soil health tests which can indicate high organic matter turnover and subsequent release of plant available nutrients. Switching from CT to RT has also been linked to significant increases in SOM, total N and C, enzyme activity, active carbon, soil respiration and total protein (Thomas et al., 2007; Lal et al., 2015; Mazzoncini et al., 2011; Dick, 1984; Pareja-Sanchez et al., 2017; Carpenter-Boggs et al., 2003; Yang et al., 2020). Using RT also increases microbial diversity in the soil, especially mycorrhizal fungi (Brito et al., 2012). Mentioned earlier, AMF can associate with plant roots and can trap nutrients, including P and K that may otherwise be out of the root zone. (Bowles et al., 2016; Marschner and Dell; 1994). For most areas of SD, reduced tillage is a viable practice for reducing erosion and improving soil biological health. If misconceptions such as yield drag and weed control issues could be transformed, farmers may be more inclined to switch to RT practices. Because correlations exist between RT and many soil health measurements, switching to RT could improve nutrient turnover and SOM breakdown which could lead to reduced fertilizer rates to maintain high yields.

1.4.3 Cover Cropping

Another conservation management practice, cover cropping, has become increasingly adopted in SD in recent years. Of SD farmers surveyed in 2018, nearly half answered they had tried planting cover crops (Wang, 2020). Cover cropping previously referred to planting crops to protect the soil during periods when no cash crops were present with the goal of erosion reduction. In recent years, the discovery of soil health benefits to cover cropping have resulted in improved adoption rates. Benefits of cover crop introduction include improved pest management, better nutrient recycling, and recovered soil structure (Creamer et al., 1996; Wang et al., 2008; Dapaah and Vyn, 1998). Cover cropping also reduces erosion and therefore offsite movement of nutrients into bodies of water (Langdale et al., 1991; Gantzer et al., 1989).

Cover crops impact several major soil processes and soil health indicators. For example, cover crop roots can reduce soil compaction and subsurface hardness that can result from years of intensive cropping (Dapaah and Vyn, 1998; Williams and Weil, 2004). Of particular interest to soil fertility researchers are claims that cover crops can improve nutrient immobilization and cycling for use in subsequent crops. Studies involving differing nitrogen rates and cover crops have provided mixed results with lowering N rates (Bielenberg et al, 2021; Adeyemi et al., 2020), but P and K have not been largely examined. In research involving cover crops and P management, results varied based on cover crop species. While winter grasses such as vetch and oats did not increase soil P levels, they did significantly increase P uptake by corn plants (Dube et al., 2014). A study in California found neither legumes nor cereal cover crops increased P soil tests although legumes increased phosphatase activity (Maltais-Landry et al., 2014). When it comes to K, deep rooted cover crops (e.g., ruzigrass) can reduce K losses to the environment (Calonego and Rosolem, 2013) while a mix of broadleaves and grasses may increase soil test K levels over time (Steiner et al., 2012).

Cover crops impact biological indicators in the soil as well. Long-term cover cropping results in increasing SOM, CEC, Total N and C, enzyme activity, active carbon, soil respiration, and total protein (Ding et al., 2006; Sharma et al., 2018; Poeplau and Don, 2015; Dick and Bandick, 1999; Culman et al., 2013; Gucci et al., 2017; Nunes et al., 2018). Some cover crop combinations, such as buckwheat, may also increase P solubility near the root zone (Possinger et al., 2013). If improvements in soil health and nutrient cycling can be correlated to cover crop usage, then cover crop adoption in SD may also necessitate updated fertilizer recommendations.

1.4.4 Crop Rotations

A third management practice with significant influence on soil health indicators is diversified crop rotations. Although corn-soybean rotations are common in SD, government policy has led to an increase in corn demand and price. This has resulted in abandonment of diverse rotations to more profitable corn-corn rotations. However, yield gaps are possible when comparing mono-cropped corn to rotated corn (Seifert et al., 2017). Even though corn-soybean rotations are better for soil health than corn-corn, it may not be diverse enough. Some studies indicate that corn-soybean rotations can lead to declines in organic C, reduction in soil N, and loss of aggregate stability (Sarrantonio et al., 1998; Hall et al., 2019; Villamil et al., 2015). In addition to the soil physical and chemical downfalls with a corn-soybean rotation, bacterial and fungal diversity and richness in the soil decrease as well (Li et al., 2015; Jiang et al., 2017). These soil shortfalls result in increased reliance on herbicides and fertilizer inputs to maintain high yields. Diverse crop rotations that include both grasses and broadleaves can reduce optimum N rates for corn (Feng et al; 2021; Gaudin et al., 2015; Stanger and Lauer, 2008). Integration of soybean or alfalfa can supply N to future crops, with N credits being reflected in most states' fertilizer recommendations. Although studies have concluded legume-included crop rotations can reduce N applications in corn, few have considered more intensive crop rotations along with cover cropping that could reduce other nutrient applications such as P and K. (Decker et al., 1994).

Simple crop rotations have led to a reduction in aboveground biological diversity which has led to concerns of reduction in belowground diversity. Many intensive crop rotations also involve cover cropping and animal grazing which provides further benefits to the soil (Tobin et al., 2016; Nunes et al., 2018). Intensive crop rotations can improve soil health indicators compared to corn-corn or corn-soybean rotations. Diversified crop rotations can lead to increased SOM, Total C and N, enzyme activity, active carbon, soil respiration, and total protein (Janzen et al., 1992; King and Blesh, 2018; Van Eerd et al., 2014; Nath et al., 2020; Aziz et al., 2011; Gonzalez-Chavez et al., 2010). These improvements can immobilize excess nutrients in the soil for use in later years. Although little research exists, certain crop rotations can better immobilize P and K in the soil and have the potential to reduce fertilizer applications (Sassenrath et al., 2016; Rosolem and Calonego, 2013). Therefore, adoption of diversified rotations relationship to soil health and fertility needs to be better understood and may result in reduced fertilizer rates for diverse rotations.

1.5 OBJECTIVES FOR RESEARCH

The adoption of conservation management practices such as reduced tillage, cover cropping, and diverse crop rotations has led to improvements in soil health indicators across SD. These changes in soil health indicators and likely the associated changes in P and K availability provide evidence that current fertilizer recommendations need to be evaluated. Therefore, the objectives of this study were to 1) evaluate the accuracy of the critical value of current P and K fertilizer recommendations and 2) determine if soil health indicators can be used with soil fertility measurements to improve the accuracy of SD fertilizer application recommendations. Chapter two will compare the Olsen P soil test to relative yield by building a response curve to determine the critical value for P recommendations. Physical, chemical, and biological indicators will also be analyzed to determine if they correlate to yield responses to P fertilization. Chapter three will correlate the ammonium acetate K soil test to yield responses while also determining if relationships exist between other soil indicators and yield responses to K fertilization. For both chapters, variable importance will be determined for P and K recommendations, respectively, and determine which, if any, soil health variables may be used to improve fertilizer recommendations. Results from this study will help farmers better understand the role of soil health and demonstrate its relevance for use in nutrient management decisions.

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CHAPTER 2: CAN SOIL HEALTH AND FERTILITY MEASUREMENTS BE USED TO IMPROVE THE ACCURACY OF YIELD RESPONSE TO P FERTILIZER PREDICTIONS?

2.1 ABSTRACT

Researchers have pointed to changes in climate and land management practices to justify the need to reevaluate the accuracy of current South Dakota (SD) corn (*Zea mays* L.) P fertilizer recommendations. Also, an increase in soil health understanding has created the potential for soil health measurements to be used to improve the accuracy of these recommendations. The objectives for this study were to 1) evaluate the current P critical value and 2) determine the effect of including soil health indicators on fertilizer recommendation accuracy. This project was conducted throughout central and eastern SD from 2019-2021 at 97 experimental areas that varied in management, landform, and soil type. A fertilizer addition treatment of 112 kg P_2O_5 ha^{-1} was compared to a control with no P fertilizer. Soil health and fertility samples (0-15 cm) were collected before fertilization and analyzed for physical, chemical, and biological characteristics. Positive yield responses to P fertilization were observed at many soil test P (STP) levels beyond the current critical value of 16 mg kg^{-1}, indicating a critical value of 20 mg kg^{-1} would better fit our dataset. However, there was no change in RSE (0.145) and model accuracy was only improved by 1%, meaning there was not sufficient evidence to merit a critical value change. Random forest variable importance methods found differences among variables, although they were not significant. Decision tree analysis found several variables (Olsen P, CEC, soil respiration, and clay content), that when split using a decision tree, improved prediction accuracy to 74% compared to 63% when using Olsen

P alone. These results demonstrate that soil health indicators along with soil fertility testing improves the accuracy of our yield response predictions to P fertilizer.

2.2 INTRODUCTION

Corn (*Zea mays* L.) is the highest valued crop in South Dakota (SD), worth nearly three billion dollars in 2020 (USDA NASS, 2020). In 2017, corn was grown on more than two million hectares with an average yield of over 9000 kg ha^{-1}, a significant jump over the 5700 kg ha^{-1} yields from 2012 (USDA NASS, 2017). As yields increase, fertilizers are often used in increasing amounts to supplement the nutrient needs of corn. Among the essential nutrients needed by corn plants, phosphorus (P) has been identified as one of the most important for overall plant growth and health. Phosphorus is involved in vital plant functions including photosynthesis and nucleic acid formation (Veneklaas et al., 2012). Because of this, P deficiencies can cause significant reductions in corn yields if supply does not equal demand. Plants supply their P needs by taking it from the soil. Although naturally occurring P may be present in the soil, intensive crop production can quickly deplete soil P levels and result in an insufficient amount to optimize corn production. One method to overcome P deficiencies is to apply inorganic fertilizers when necessary. In 2019, SD farmers applied P-containing, inorganic fertilizers to 88% of corn hectares (USDA ERS, 2019). However, the overapplication of fertilizer can reduce profitability, change soil chemical properties, and result in excess nutrients in the soil where rainfall runoff can carry them to waterways (Scharf, 2001; Zhang et al., 2017; Yuan et al, 2018). Appropriate management of P fertilization can improve corn yields, reduce input costs, and protect waterways.

In SD, rates of fertilization for major crop nutrients are provided in the SD Fertilizer Recommendation Guide (Gerwing et al., 2005). For P, a soil testing approach using the Olsen P or Bray-1 methods of extraction is utilized to establish the abundance of P already available in the soil and determine if fertilization is necessary (Bray and Kurtz, 1945; Olsen et al., 1954). When developing P fertilizer recommendations, a sufficiency goal is established by determining a soil test P (STP) level where increased fertilization no longer increases yield, otherwise known as a critical value (Drescher et al., 2021; Reed et al., 2021). However, research in SD that determined the current fertilizer recommendations was conducted many years ago and the data from past calibration trials has been lost. Since developing the recommendations, yields have nearly doubled resulting in recommendations that may not meet nutrient removals or plant needs. Further, changes in both climate and management practices over the last decade may have impacted the accuracy of the current recommendations.

The climate of SD has changed in recent decades as increased temperatures have resulted in longer growing seasons. Also, increased rainfall in drier areas of Central SD has led to corn production in areas where it was previously unfeasible (EPA, 2016). Further, environmental awareness and policy has led to increased adoption of conservation management practices including reduced tillage, cover cropping, and diversified cropping rotations (USDA NRCS, 2019; Wang, 2020; Wang, 2022). The shift in management practices changes soil processes that impact the dynamics of plant-available P in the soil. For example, no-till management in some soils results in the stratification of P in the surface layer of the soil (Robbins and Voss, 1991). Because most forms of P are immobile in the soil, plant roots that extend downwards may not have access to this source of P (Mackay et al., 1987). Another management practice being adopted in SD, cover-cropping, causes changes in the organic matter fraction of the soil, which is a large pool of soil P (Torbert et al., 1996). While growing, cover crops generally immobilize P that may have otherwise been lost to the environment. Once the cover crop dies, P contained within the organic matter is recycled by soil microbes where it can be made plant-available again (Bünemann, 2015). Further, cover cropping has been associated with increases in mycorrhizal fungi that aid with plant uptake of P (Hallama et al., 2019). Management practices clearly play a large role in the cycling and uptake of soil P. Therefore, the adoption of management practices such as reduced-till, cover cropping, and diverse crop rotations provides evidence that the current P critical value needs to be reevaluated.

Currently, the only soil measurement used to aid in fertilizer recommendations in SD is the Olsen P soil test. However, only accounts for plant-available P that is currently available in the soil and does not account for the organic forms of P that are mineralized by soil microbes throughout the growing season (McDowell et al., 2001). There is a complex web of soil physical, chemical, and biological processes that all impact the availability of P to plants. As these soil processes became better understood, soil testing methods were improved and new tests were developed to quantify their overall impact on soil health (Moebius-Clune et al., 2016) (Table 2.1). These new soil health measurements may be able to help us better quantify P availability to plants throughout the growing season, thus being a potential indicator of yield responses to P fertilizer.

Soil health has been defined as the continued capacity of soil to function as a vital living ecosystem that sustains plants, animals, and humans (Karlen et al., 1997). Soil health has been broken down into physical, chemical, and biological measurements that all interact with each other. While some soil health tests look to specific biological processes (e.g., acid-phosphatase and the breakdown of organic P), other are broad and may correlate to overall microbial activity (e.g., soil respiration) (Eivazi and Tabatabai, 1977; Zibilski, 1994). Some research has attempted to generate an overall health score, although they have still placed emphasis on individual soil tests (Moebius Clune et al., 2016; Andrews et al., 2004). Many of these soil health tests have been correlated to soil functions (e.g., soil respiration and active carbon to organic matter mineralization and stabilization, respectively) that impact nutrient availability (Haney et al., 2008; Hurisso et al., 2016), and, therefore, may be helpful for improving the accuracy of fertilizer recommendations.

The availability of P has been related to many of the same soil health indicators as N. Similarly to N, breakdown of SOM by microbes releases a significant amount of plant-available P throughout the growing season (NRCS, 2014, Reddy, 1983). Soil respiration, which measures the overall microbial activity in the soil, is an effective indicator of SOM mineralization (Haney et al., 2015). Therefore, it can be assumed that as SOM is being mineralized, P is released into the soil solution where it is made available to plants (Moebius-Clune et al., 2016). Another soil health measurement, acid-phosphatase, refers to a vital enzyme in the breakdown of organic P (Eivazi and Tabatabai, 1977). Both plants and microbes produce acid-phosphatase enzymes to help solubilize organic P and may be a useful indicator of P availability (Tarafdar et al., 2001). Soil P is also affected by soil physical and chemical properties. For example, sandy soils may lose P to the environment more quickly than clay soils (O'halloran et al., 1985). Clay soils with a high CEC and non-optimal pH levels may fix P into plant-unusable forms (Penn and Camberato, 2019). Because of the connections between soil P and physical, chemical, and biological soil factors, the inclusion of more of these soil tests have the potential to improve current predictions of crop yield response to P fertilizer.

To this point, research has mainly been conducted with N in an attempt to use soil health measurements to better predict if a site will respond to N fertilizer. Research conducted in North Carolina attempted to quantify N mineralization throughout the growing season using soil respiration to predict an economically optimum N rate (EONR) (Franzluebbers, 2018). As soil respiration increased, both yield response to N and EONR decreased, indicating that including soil respiration testing better determined whether a yield response would occur to N fertilization. This was similar to a finding from a study across the US Midwest that showed both soil respiration and the Haney overall health score accounted for most of the variation in EONR (Yost et al., 2018). Other U.S.Midwest studies found that while anaerobic potentially mineralizable N is a weak indicator of yield response to N fertilization, the addition of soil texture as an indicator improved EONR predictions by 15% (Clark et al., 2019). Research conducted in New York used SOM along with a soil nitrate test to better determine if a site would respond to additional N fertilization beyond a starter application (Klapwyk and Ketterings, 2006). Some states, such as Nebraska, have included SOM in their N fertilizer recommendations (Shapiro et al., 2019), but this has not been attempted for P. Overall, these studies identified that interactions among soil physical, chemical, and biological indicators can be used to understand why a field may or may not respond to N fertilizer.

Similar studies are needed to determine the potential of using soil health tests in improving current P fertilizer recommendations. Given recent research attempts to include soil health measurements in N recommendations, this study explored whether the same can be done for P. The objectives of this research were to 1) evaluate the accuracy of the critical value of current P fertilizer recommendations and 2) determine if soil health indicators can be used with soil fertility measurements to improve the accuracy of SD P fertilizer recommendations.

2.3 MATERIALS AND METHODS

2.3.1 Research Sites and Experimental Design

Research trials were conducted at 28 locations across central and eastern SD from 2019-2021 (Figure 2.1) Locations varied in management practices, landforms, and soil types and are shown in Table 2.2. The goal of using diverse locations was to embody a range of growing conditions and fertility levels to build a dataset that represents the diverse growing conditions of SD. Location selection also only included fields that had not been fertilized with P or K the previous fall or were flagged to avoid P or K application in the spring. In 2019, trials were located at different locations in a single field, each one being referred to as a "stamp" from here on out, resulting in an absence of replication. Each location had between two and four stamps.

In 2020 and 2021, stamps were located within a randomized complete block design of several other studies and were generally located within 50 meters of each other. Each stamp ranged from 6.1-18.3 m. wide to 7.6-15 m. long, providing a surface area between 148-278 m^2. For fertilization treatments, each stamp was divided into four equal treatment areas (37.2 m^2 to 69.7 m^2). The upper-left quadrant was labeled the control and received no P, K, or S fertilizer (Figure 2.2). Fertilizer treatments were applied by hand to the other three quadrants. Fertilizer treatments were as follows: 1) control; 2) 112 kg ha^{-1} of P_2O_5 applied as triple super phosphate (460 g P_2O_5 kg^{-1}; 0-46-0); 3) 112 kg ha^{-1} of K_2O applied as potash (600 g K_2O kg^{-1}; 0-0-60); and 4) 28 kg ha^{-1} of S applied as ammonium sulfate (210 g N kg^{-1} and 240 g S kg^{-1}; 21-0-0-24). To balance all treatments for the N supplied to treatment four by the ammonium sulfate, an additional 25 kg N ha^{-1} as SUPER-U (460 g N kg^{-1}; 46-0-0) (Koch Agronomic Services, LLC, Wichita, KS) was applied to quadrants 1-3. Nitrogen was then applied to all treatments based on the farmer's usual rate of N.

2.3.2 Sampling and Laboratory Analyses

Soil samples were taken at each stamp in the spring before planting or fertilization. After treatments were flagged, eight cores (3.175 cm i.d.) were taken at random spots within each stamp for soil health analysis. Cores were divided into two depths (0-5 cm and 5-15 cm) and composited into one sample for each depth. Samples were put into plastic bags and immediately put into a cooler to keep them out of the sun and heat. Once out of the field, samples were stored in a cooler until the next step could be completed. When time was allowed, 0-5 cm and 5-15 cm samples were taken from the cooler, passed through an 8 mm sieve, and organic matter was removed using a forceps for a consistent time of four minutes per sample. Once four minutes had passed, samples were resealed in bags, and sent to either the USDA-ARS Soil and Water Quality Lab in Columbia, MO (2019-2020) or Ward Laboratories in Kearney, NE (2021). Analyses conducted included β-glucosidase, acid-phosphatase, arylsulfatase, active carbon, soil respiration, and ACE protein. Descriptive statistics of each measurement and the corresponding method citation are provided in Table 2.1.

To determine basic soil fertility measurements (pH, SOM, Olsen P, K, S, Total C, and Total N) from the top 0-15 cm, a portion of the soil health samples based on the depth of each sample was put in a separate bag and analyzed using the methods in Table 2.1. Soil profile characterization and sub-soil fertility were assessed at the center of each stamp by obtaining a soil core using a hydraulic probe (4.5 cm i.d.) to a depth of 60 cm. A single core was taken, split into different depths (0-15 cm, 15-30 cm, and 30-60 cm), broken up, and sealed in a plastic bag. Samples were air dried until constant moisture and analyzed for subsoil fertility (same as above) and texture analysis (sand, silt, and clay) following the methods from Table 2.1.

2.3.3 Harvest and Yield Analysis

Plants were harvested in the fall by hand or plot combine. If harvested by hand, the center 11.15 m^2 (2019-2020) or 9.3 m^2 (2021) area was picked and full ears were weighed in the field. Once out of the field, a subsample of eight ears was taken, weighed, and then dried down to obtain moisture content at harvest. Overall weight was multiplied by 0.88 to eliminate cob weight. If a plot combine was used, the center two rows of each plot were harvested. Grain weight from hand and combine harvesting methods were adjusted to 155 g kg^{-1} moisture. Relative yield was obtained by dividing each treatment plot by the control plot. For example, if a relative yield was calculated as 110%, then the treatment yielded 10% higher than the control plot.

2.3.4 Data Management and Statistical Analyses

Data was analyzed using R programming language with R version 4.1.2 (R Core Team, 2022). Linear plateau analysis was calculated using functions from R package *minpack.lm*, with the goal of finding a relationship between relative yield and STP up until a critical value (Whittemore and Fawcett, 1976; Elzhov et al., 2016). The critical value was considered the joint point between the linear and plateau portion of the model. This critical value is the STP level where continued application of P fertilizer no longer increases yield. Confidence intervals for model parameters were calculated using the *contfint2* function from the package nlstools (Baty et al., 2021). Other methods for determining a critical value involved grouping stamps by intervals of STP 4 mg kg^{-1} (0-4, 4-8, etc.) and averaging yield change or response frequency within each interval. Stamps with a positive (RY ≥ 105%), negative (RY ≤ 95%), and constant (95% ≤ RY ≤ 105%) yield response to fertilization were quantified within each P interval and presented as a percentage of the total number of sites within each interval. The yield change was calculated as the yield difference between the P treated plot and the control. If yield change was negative, then the control plot yielded higher than the treatment. The point where yield change became negative or the negative response frequency was higher than the positive response frequency was determined as a critical value. Cate-Nelson analysis was also used to find the point in the dataset that maximized the points that responded below and minimized the points that respond above a critical value (Cate and Nelson, 1971) This analysis was completed using the function *CateNelsonFixedY* in the package rcompanion (Mangiafico, 2015).

For objective two, the machine learning technique, random forest, was used to determine variables what were the most important at predicting yield response to P fertilizer. Random forest has been used in other studies to find and include variables in yield response to fertilizer predictions (Ransom et al., 2019; Mohapatra et al., 2017). Instead of using random forest to run a regression model on the dataset, a classification random forest was used to determine if one of two things happened: response (RY ≥ 105%) or no response (RY < 105%). Random forest was run using the *train* function from the R package Caret (Kuhn et al., 2021). Because the data set was small, all rows of data were included for training. The R package RandomForestExplainer was used to build graphs to evaluate variable importance (Paluszynska, 2017). The three methods of variable importance used for this project were mean decrease in accuracy (MDA), mean decrease in Gini (MDG), and mean minimal depth (MMD) (Breiman, 2001; Han et al., 2016; Ishwaran et al., 2008). For both MDA and MDG, a higher value means the variable was more important to predicting yield responses to P fertilizer. For MMD, a lower value means a variable was closer to the root of the tree, meaning it was a better predictor than the variables higher in the decision tree. After random forest was run, decision trees were made using the R package rpart.plot (Milborrow, 2021). Decision trees were split using the best available variable from the list in Table 2.1. The model given by the decision tree was then compared to the observed responses from the study and a model accuracy and error were determined. The accuracy is the percentage of stamps that the model correctly predicted if they would respond while the error is the percentage the model predicted incorrectly.

2.4 RESULTS AND DISCUSSION

2.4.1 General Results

The 0-15 cm pre-plant Olsen P levels across all stamps ranged from 3.6 to 106.7 mg kg^{-1} with the average being 17.1 mg kg^{-1}. In all, 59 of the 97 stamps were below the current SD critical value for P recommendations of Olsen P 16 mg kg^{-1}. When split into the thresholds according to the SD Fertilizer Recommendation Guide, the 59 insufficient sites were considered very low (2 stamps, 0-4 mg kg^{-1}), low (33 stamps, 4-8 mg kg^{-1}), medium (16 stamps, 8-12 mg kg^{-1}), or high (8 stamps, 12-16 mg kg^{-1}) (Table 2.3). Of the stamps that were sufficient in STP (38 stamps, >16 mg kg^{-1}), 16 had Olsen P levels between 16 and 20 mg kg^{-1} while 22 stamps had higher than 20 mg kg^{-1} STP.

Overall control plot grain yields ranged from 2187 to 16331 kg ha^{-1} while averaging 10406 kg ha^{-1}. Plots treated with P fertilizer had yield ranges from 2808 to 17797 kg ha^{-1} with an average of 10832 kg ha^{-1}. Across all stamps, P fertilization significantly increased ($P = 0.05$) yields by an average of 426 kg ha^{-1} or about a 5% increase from the control. Out of the 97 stamps, applying P fertilizer increased grain yields by at least 5% (RY > 105%) at 53 (54%) and decreased it (RY < 0.95) at 24 stamps (25%). Yield was considered constant at 20 stamps (21%) if RY was between 95% and 105% of the control yield.

2.4.2 Phosphorus Critical Value

Both linear plateau and Cate-Nelson regression techniques showed a relationship between corn grain response to P fertilization and STP (Figure 2.3; Table 2.4). Generally, increases in corn yield with P fertilization were greatest at the lowest STP levels and decreased as STP increased until plateauing at higher STP values. Using linear plateau, a critical value of 24 mg kg^{-1} was determined where grain yield no longer increased with added P fertilizer. According to the linear plateau model, when STP was at 0 mg kg^{-1}, treatment yields were 11% higher than the control yields. Relative yield then decreased as STP increased until reaching the critical value. When at the critical value of 24 mg kg^{-1}, RY was approximately 100% and stayed constant as STP increased. Linear plateau models have also been used in other studies to determine critical values of STP for both corn yields and turfgrass quality (Cox, 1992; Johnson et al., 2003).

Another method for determining critical values, Cate-Nelson (1971), calculates a critical value that maximizes the points that responded below the critical value and points that did not respond beyond it. Cate-Nelson analysis has been a useful tool for determining critical values for P tissue percentage to corn grain yield in other studies (Gagnon et al., 2020; Redi et al., 2016). Cate-Nelson testing gave several possible STP critical values (19, 19.1, 15.6, 18, and 18.1 mg kg^{-1}) when an initial parameter of a 5% yield increase (RY = 105%) was used to determine if a positive yield response occurred (Table 2.4). Of the five best critical values, the one that best explained our data set was at 19 mg kg^{-1} which had a 64% accuracy (model predicted correctly) and 36% error (model predicted incorrectly). This new critical value was only marginally better than the current critical value of 16 mg kg^{-1} which had 63% accuracy and 37% error. A critical value of 19 mg kg^{-1} also had a slightly lower Pearson-*P* (0.017) than the current critical value (0.028).

Both the linear plateau (24 mg kg^{-1}) and Cate-Nelson (19 mg kg^{-1}) techniques suggest that positive yield responses to P fertilization occur at higher STP than the current critical value of 16 mg kg^{-1}, indicating that the current critical value may be too low. Although these methods indicate that the critical value likely needs to increase, the new critical values only slightly differ from the current value. For example, the residual standard error for the linear plateau model was 0.135 (RY %) when the critical value was 24 mg kg^{-1} (Figure 2.3), which was identical to when the critical value was forced to 16 mg kg^{-1}. Also, the confidence interval (P = 0.68) for the new linear plateau critical value overlapped the current STP critical value (lower = 8 mg kg^{-1}, upper = 40 mg kg^{-1}). Although both tests indicated the critical value likely needs to increase, neither method gave a critical value that was significantly different than the current critical value. For example, when compared to a linear plateau model where the critical value was set at 16 mg kg^{-1}, the new linear plateau model with a critical value of 24 mg kg^{-1} was not significantly different (P = 0.38). Likewise, Cate-Nelson's critical value of STP 19 mg kg^{-1} only improved the model by 1% and both had significant Pearson P-values (Table 2.4). Other methods of determining critical values could be helpful in validating what linear plateau and Cate-Nelson found.

Another potential way of determining a critical value may be to relate the STP level to the change in yield when P fertilizer is applied (Figure 2.4). Generally, as STP increased, the yield change decreased until it plateaued at STP 24 mg kg^{-1}. By applying the same response threshold used in previous methods (RY = 105%), a minimum yield change of +50 kg ha^{-1} occurred at STP 21 mg kg^{-1}, which was similar to both the Cate-Nelson and linear plateau methodologies. The similar critical value produced by this method further indicates the potential need for an increase in the STP critical value in SD.

A fourth method for calculating critical values is to evaluate the frequency of yield responses to P fertilization at different STP levels. This relationship indicated that as STP increased, the percentage of data points where yield increased with added P decreased (Figure 2.5). The yield response frequency, although not a direct method for finding critical values, has been used before to indicate when responses are no longer likely to occur (Drescher et al., 2021). The positive yield response frequency (RY ≥ 105%) had a strong, negative linear relationship (R^2 = 0.79) to STP. When STP was at 0 mg kg^{-1}, 77% of stamps positively responded (RY = 105%) to P fertilizer applications. However, when STP increased to 20 mg kg^{-1}, only 40% of stamps positively responded. The positive yield frequency reached 0% when STP was approximately 42 mg kg^{-1} or higher. In contrast, negative yield response frequency (RY ≤ 95%) followed a moderate, positive linear relationship (R^2 = 0.65). As STP increased, the negative response frequency to P fertilization increased. When STP was 0 mg kg^{-1}, there was only a 5% chance that application of P fertilizers would decrease yield. However, as STP increased to 20 mg kg^{-1}, a 40% negative response frequency was observed and continued increasing as STP levels rose. The no response frequency (95% ≤ RY ≤ 105%) regression line followed very closely to the negative response frequency (R^2 = 0.65) line and increased as STP rose. Since an STP of 20 mg kg^{-1} was where there was an equal chance of seeing a positive or a negative response, this point could be used as a critical value.

All four methods of determining critical values calculated values within 5 mg kg^{-1} of one another (19 to 24 mg kg^{-1}). These critical values are slightly higher than the Olsen P or Bray-1 equivalent values of the surrounding states of ND, MN, NE, and KS which are all approximately 16 mg kg^{-1} (Franzen, 2018; Kaiser et al., 2020; Shapiro et al., 2017, Leikam et al., 2003). However, our calculated critical values are closer to the Iowa P critical value of 19 mg kg^{-1} (Mallarino, 2013). Although linear plateau indicated a critical value of STP 24 mg kg^{-1} should be used, the line plateaued at 100% RY meaning no increase in yield occurred from P fertilization. If a reasonable increase of 5% (RY = 105%) would be used to determine the critical value, then the linear plateau critical value would be slightly lower (STP 16-20 mg kg^{-1}). By using a RY of 105% as a sufficient increase in yield to merit fertilization, all four potential critical value tests determined a critical value of approximately 20 mg kg^{-1} as opposed to the current 16 mg kg^{-1} value.

Confidence intervals of critical values determined with linear plateau models are not commonly reported in the literature as they are computationally intensive to derive (Nigon 2020), but they do provide a better understanding of how variable critical values may be, as some research has identified (Cox, 1992). For example, a 68% confidence interval of the linear plateau model showed critical values could range from 8 to 40 mg kg^{-1}, which includes the old and potentially new critical values (16 and 20 mg kg^{-1}, respectively) discussed in this paper. Further, even when using an updated critical value of STP 20 mg kg^{-1}, a 36% error rate still occurred when using the Cate-Nelson methodology (e.g., yield did not respond when below the critical value or did respond when above it) (Table 2.4). Since the error rate did not alter much when critical values were changed, the error may be coming from environmental or soil parameters that are not accounted for in current SD fertilizer recommendations. Studies have found that management practices (e.g., fertilization methods) and soil factors (e.g., soil type and pH) can affect corn yield response to P fertilization (Fernández and White, 2012; Yan et al., 2021). These studies along with our results provide evidence that more than an updated STP critical value is likely needed to substantially improve the predictability of corn response to P fertilization.

2.4.3 Variable Importance and Selection

The random forest machine learning technique identified variables that could be used as predictors of corn grain yield response to P fertilization. A random forest model was built using all variables from Table 2.1 except for Total N and C, which were highly correlated to SOM, and ACE protein, which lab results had not yet been received. Random forest has been used by researchers in recent years due to its ability to find important variables even in small datasets (Mohapatra et al., 2017). Variables from the model were ranked by importance using several criteria including the mean decrease in accuracy with variable permutation, the mean decrease in Gini, and the mean minimal depth in the tree (Archer and Kimes, 2007).

The mean decrease in accuracy, predicts the overall change in accuracy when a variable's value is randomly permutated. For example, if overall accuracy of the model is 70% and, by randomly changing the values for that variable, accuracy drops to 60%, then the decrease in accuracy is 10%. Doing this to all trees (n = 1000) and taking the average gets the MDA. Using the MDA measurements, the best variables were specified as tillage practice, soil respiration, and Olsen P (MDA > 5%) which was considerably higher than any of the other variables (MDA <5%) (Figure 2.6). It should be noted that because tillage only has two options (CT or NT), its mean decrease in accuracy may be overestimated by the model because the only random permutations it can choose are one or two.

The MDG is the sum of the decreases in node purity when a certain variable is used to split the tree divided by the number of trees. By using MDG, the three variables with the highest values were soil respiration, Olsen P, and active carbon. While these three were identified as the most important variables using MDG, all variables had MDG values that were similar (3 < MDG > 5) except for tillage which was remarkably lower (MDG = 1.8). By using both MDA and MDG, variables that had the highest values for both tests were considered to be the most important. Both soil respiration and Olsen P were near the top of both charts, meaning they should be considered for use in the decision tree.

The MMD is the mean depth of the variable (root = 0) across all trees. The variables with the lowest MMD were acid-phosphatase, arylsulfatase, and soil respiration (Figure 2.7). Although ranked in order of importance, it should be noted that the MMD for variables only ranged from 3.62 to 3.77, meaning all variables were ranked nearly the same by this method. Only soil respiration matched the results of the MDA and MDG methods as being one of the most important variables by being ranked high in MDA (2nd), MDG (1st), and MMD (3rd). Although some variable importance measurements agreed among which variables were more important, others varied depending on measurement. Differences between variables were not large enough to confidently rule any of them out. Therefore, all variables were included in the building of the decision tree.

The decision tree made splits based on soil respiration, clay, acid-phosphatase, and CEC (Figure 2.8). At the root of the tree, soil respiration was split by a value of 125 mg CO_2 kg^{-1}. When soil respiration was higher than 125 mg CO_2 kg^{-1}, corn grain yield only responded 42% of the time with added P. The points with high soil respiration were split again by a clay percentage of 55. When clay was below 55%, stamps only responded to P fertilization at 37% of stamps, but when clay was above 55%, stamps had a much higher chance of responding (86%). On the other side of the tree, where soil respiration was below 125 mg CO_2 kg^{-1}, stamps had a 74% chance of responding to P application. This was then split by acid-phosphatase 139 μg p-nitrophenol g soil^{-1} hr^{-1}. When acid-phosphatase was above 139 μg p-nitrophenol g soil^{-1} hr^{-1}, the node split again by a CEC of 25 meq 100g^{-1}. When CEC was above 25 meq 100g^{-1}, stamps only had a 20% chance of responding to P fertilization, but when above, they responded 71% of the time. Going back up to the previous node, when acid-phosphatase was below 139 μg p-nitrophenol g soil^{-1} hr^{-1}, stamps had a 94% chance of responding.

Due to the complexity and cost of additional soil tests, the decision tree is only practical if a considerable increase in accuracy of predicting yield response to P fertilization was made. To test this, the decision tree model was applied to our dataset. Of the 97 stamps, the model predicted that 41 would and 56 would not respond compared to 53 stamps that did and 46 that did not respond to P fertilization (Figure 2.9). These results mean the model underestimated the number of stamps that did respond by 12 and overestimated the stamps that did not. Despite this, an accuracy of 71% was achieved compared to the 63% using only an Olsen P critical value of 20 mg kg^{-1}.

Most notably, this decision tree did not include STP, although the random forest technique identified Olsen P as one of the top predictors for yield response to P fertilization (Figure 2.6). Because both yield change (R^2 = 0.95) and positive yield response frequency (R^2 = 0.79) correlated well with STP (Figures 2.4 and 2.5), a decision tree including Olsen P should considerably improve accuracy. To manually test the use of STP in the decision tree, the data set was split into STP $\geq$ 20 and STP < 20, which would be used as the first split in the decision tree.

For stamps above the Olsen P critical value, the decision tree only included a split at CEC 19 meq $100g^{-1}$ (Figure 2.10). When CEC was above 19 meq $100g^{-1}$, yield only responded at 7% of stamps compared to 86% of stamps when CEC was below 19 meq $100g^{-1}$. For stamps below the Olsen P critical value (STP < 20 mg kg^{-1}), the decision tree included soil respiration and clay content, which was similar to the decision tree using all variables (Figure 2.8). When soil respiration was greater than 124 mg CO_2 kg^{-1}, the tree split again at 55% clay (Figure 2.10). When clay was below 55%, yield only responded to P fertilization 42% of the time compared to 86% of stamps when above 55% clay. When soil respiration was below 124 mg CO_2 kg^{-1}, the model predicted yield would respond, which it did at 80% of stamps.

When combining the two decision trees, the model predicted that yield would increase at 53 and decrease at 44 stamps (Figure 2.11). This prediction was identical to the number of stamps where yield was observed to increase or decrease in our study. The decision tree that manually added Olsen P had an overall accuracy of 74% compared to 71% for the tree that did not include Olsen P and 63% when Olsen P was used alone. Although both decision trees used many of the same variables (e.g., clay, soil respiration, CEC), the decision tree that manually included Olsen P excluded acid-phosphatase, reducing the number of soil health tests needed to improve P response predictability. Fewer soil health tests needed would reduce overall soil testing costs and was more accurate than more complex decision trees.

The results from the random forest and decision tree variable importance methodologies support the adoption of additional variables to improve SD P fertilizer recommendations. By using decision trees that included additional variables (Figures 2.8

and 2.10), model accuracy was 71% and 74%, respectively, which was higher than simply using Olsen P with a critical value of 20 mg kg^{-1} (63%). Additional variables provided by random forest techniques showed soil respiration, active carbon, arylsulfatase, and acid-phosphatase all have the potential to be useful predictors for yield responses to P fertilization (Figures 2.6 and 2.7). Also, both decision trees utilized soil respiration as a predictor indicating overall microbial activity has a role in how plants respond to P additions. These results support the general hypothesis that soil microbial communities play a role in P availability and can be used to better understand yield responses to P fertilization. (Snapp et al., 2005; Gonzalez-Chavez et al., 2010; Bünemann et al., 2008; Hallama et al., 2019; Khan et al., 2007).

2.5 SUMMARY AND CONCLUSIONS

This study assessed the current SD P fertilizer recommendations by first investigating the current STP critical value, and then, searching for additional soil health variables that could improve the accuracy of our yield response to P fertilizer predictions. By using linear plateau and Cate-Nelson methodologies along with yield change and yield response frequency graphs, an increase in the STP critical value from 16 to Olsen P 20 mg kg^{-1} improved the P fertilizer response prediction accuracy and better explained why positive yield responses were still observed in areas that had STP values between 16 and 20 mg kg^{-1}. Using random forest and decision tree methodologies, the addition of physical (clay), chemical (CEC), and biological (soil respiration, acid-phosphatase, active carbon) soil measurements were determined as important variables for predicting yield response to P fertilization. Among these, soil respiration, Olsen P, CEC, and clay content were determined to be the most beneficial when used in a decision tree, increasing accuracy (74%) when compared to Olsen P alone (63%). These results show that additional soil health variables, especially soil respiration, may be useful for predicting yield response to P fertilization. Further, adoption of soil health-improving practices such as no-till, cover cropping, and diverse crop rotations that generally increase soil respiration could correlate to reducing P fertilizer rates. While this study demonstrates that changes are warranted to the SD P fertilizer recommendations in corn, economics need to be considered to justify if an increase in prediction accuracy is worth the additional soil tests needed. Studies will be needed to validate the models presented here and calibrate required P fertilizer rates to optimize corn yield under varying soil health and STP levels. Further research in the area of quantifying soil health changes with various soil management practices (or change in management practices) would also be helpful to better understand how management practices would likely affect yield response to fertilizer applications.

2.6 LITERATURE CITED

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2.7 TABLES AND FIGURES

Table 2.1. Descriptive statistics and references of the soil physical, chemical, and biological tests analyzed as potential variables to correlate to yield response to P fertilization. Total C and N were not used in the random forest model due to a high correlation to soil organic matter.

Analyses[A]	Unit	Min.	Max	Median	S. Dev[B]	Citation
Soil Physical Properties						
Sand	%	7	61	25	12	Gee and Bauder, 1979
Silt	%	20	53	40	9	Gee and Bauder, 1979
Clay	%	12	62	31	10	Gee and Bauder, 1979
Soil Chemical Properties						
pH		5.0	8.3	6.4	0.9	Soil Survey Staff, 2014
SOM	g kg^{-1}	24	62	4	1	Broadbent, 1965
P (Olsen)	mg kg^{-1}	4	107	11	17	Olsen et al., 1954
K	mg kg^{-1}	99	613	238	148	Warncke and Brown, 1998
CEC	meq 100 g $soil^{-1}$	12	43	21	7	Ross and Ketterings, 2011
S	mg kg^{-1}	4	672	10	85	Hoeft et al., 1973
Total C	g kg^{-1}	12	37	23	5	Nelson and Sommers, 1996
Total N	g kg^{-1}	1.2	3.3	2.0	0.1	Bremner, 1965
Soil Biological Properties						
β-Glucosidase	µg p-nitrophenol g $soil^{-1}$ hr^{-1}	32	165	72	31	Deng and Popova, 2011
Acid-phosphatase	µg p-nitrophenol g $soil^{-1}$ hr^{-1}	60	280	163	54	Tabatabai and Bremner, 1969
Arylsulfatase	µg p-nitrophenol g $soil^{-1}$ hr^{-1}	15	144	42	29	Tabatabai and Bremner, 1970
Active Carbon	mg C kg $soil^{-1}$	328	1631	1029	381	Weil et al., 2003
Soil Respiration	mg CO_2 released kg $soil^{-1}$	61	245	135	39	Zibiliske et al., 1994
ACE Protein	mg protein kg $soil^{-1}$	2.3	7.1	3.7	1.2	Wright et al., 1996

[A] SOM = Soil organic matter; CEC = Cation exchange capacity; ACE Protein = Autoclaved citrate-extractable protein

[B] S. Dev = Standard deviation

Table 2.2. Location information for each site from 2019-2021. Included are county in South Dakota, soil series, previous crop, tillage practice, row width, planting date, average control yield, and average relative yield for the P fertilized plots for that location.

Location[A]	Year	County	Soil Series[B]	Previous Crop	Tillage Practice[C]	Row Width	Planting Date[D]	Control Yield	RY[E]
						cm		kg ha^{-1}	%
1	2019	Brookings	Lenona-Swenoda	Soybean	CT	76.2	U	11189	102
2	2019	Minnehaha	Nora-Crofton	Soybean	NT	76.2	U	12270	99
3	2019	Minnehaha	Obert	Soybean	CT	76.2	U	13399	113
4	2019	Minnehaha	Nora-Crofton	Soybean	NT	76.2	U	14078	108
5	2019	Roberts	Esmond-Heimdal-Sisseton	Soybean	CT	76.2	U	12127	111
6	2019	Roberts	Hamerly-Tonka	Soybean	CT	76.2	U	12877	103
7	2020	Clay	Egan-Clarno-Trent	Soybean	NT	76.2	29-Apr	12159	102
8	2020	Edmunds	Williams-Bowbells	Cover Crop Mix	NT	76.2	15-May		
9	2020	Kingbury	Poinsett-Waubay	Soybean	NT	76.2	27-May	14550	101
10	2020	Minnehaha	Nora-Crofton	Corn	NT	76.2	U	12725	104
11	2020	Potter	Agar	Wheat	NT	76.2	11-May	11466	111
12	2020	Tripp	Millboro	Wheat	NT	152.4	29-Apr	7520	117
13	2020	Tripp	Millboro	Wheat	NT	76.2	29-Apr	10704	100
14	2021	Aurora	Houdek-Dudley	Sunflower	NT	50.8	U	3162	124
15	2021	Brookings	Brandt	Soybean	CT	76.2	U	7254	95
16	2021	Codington	Kranzburg-Brookings	Wheat	NT	76.2	U	11702	106
17	2021	Davison	Houdek-Prosper	Wheat	NT	76.2	U	6148	96
18	2021	Hand	Houdek-Prosper	Fallow	NT	76.2	4-May	11232	111
19	2021	Hutchinson	Hand-Bonilla	Soybean	CT	76.2	1-May	7496	118
20	2021	Lincoln	Wentworth-Chancellor	Soybean	CT	76.2	27-Apr	8434	95
21	2021	Minnehaha	Blendon	Corn	CT	76.2	3-May		
22	2021	Minnehaha	Moody-Nora	Corn	CT	76.2	U	10285	98
23	2021	Potter	Agar	Cover Crop Mix	NT	76.2	4-May	11471	101
24	2021	Potter	Agar-Mobridge	Wheat	NT	76.2	5-May	5745	110
25	2021	Roberts	Peever	Soybean	CT	76.2	28-Apr	12553	101
26	2021	Tripp	Millboro	Wheat	NT	76.2	3-May		
27	2021	Turner	Egan-Ethan	Soybean	CT	76.2	1-May	7578	107
28	2021	Yankton	Clarno-Crossplain-Davison	Soybean	CT	76.2	U	11706	93

[A] Locations 8, 21, and 26 were lost due to poor stands, weather damage, or other environmental problems that severely impacted some plots

[B] Soil series from WebSoilSurvey

[C] CT = conventional tillage; NT = no tillage

[D] U = unknown

[E] RY = relative yield; Average of P treated plots divided by the average of the control plots at each location. A value greater than 100 means yield was increased at that location by applying P fertilizer

Table 2.3. Mean yield information for soil test P in intervals of 4 mg kg^{-1}. Table includes the number of stamps where yield increased, decreased, or didn't respond to P fertilizer within a predetermined interval. Also shown are mean control yield, mean treatment yield, mean relative yield, mean yield change, and the mean yield increase response frequency.

Soil Test P Interval	Number of stamps				Mean Olsen P Soil test	Mean Control Yield	Mean Treatment Yield	Mean Relative Yield	Mean Yield Change[A]	Mean Yield Increase Response Frequency[B]
	n	Yield Decrease[C]	No Response[D]	Yield Increase[E]						
mg kg^{-1}					mg kg^{-1}	kg ha^{-1}		%	kg ha^{-1}	%
0-3	2	0	1	1	3.7	9609	10635	111	1026	50
4-7	33	6	5	22	6.2	10512	11123	106	611	67
8-11	16	5	1	10	10.0	9967	10659	107	692	63
12-15	8	2	1	5	14.1	8840	9314	105	473	63
16-19	16	4	4	8	18.4	12002	12459	104	457	50
20-23	4	1	2	1	22.4	11613	11637	100	24	25
24-27	5	3	1	1	25.5	8919	8578	96	-342	20
28-31	2	0	1	1	29.8	8288	8266	100	-22	50
32-35	4	1	2	1	34.1	8874	8890	100	16	25
36+	7	2	2	3	66.4	11128	10922	98	-205	43

[A] Mean treatment yield – mean control yield

[B] Percentage of stamps in each increment where yield increased (RY ≥ 105%) with P fertilizer application

[C] Number of sites where yield decreased (RY ≤ 0.95) with P fertilizer application

[D] Number of stamps where yield did not response (0.95 < RY < 1.05) to P fertilizer application

[E] Number of stamps where yield increased (RY ≥ 1.05) with P fertilizer application

Table 2.4. Top five critical values using Cate-Nelson analysis results when Y was forced at 1.05 (RY = 105%). A critical x =16 is shown to represent the current critical value of soil test P of 16 mg kg^{-1} and its accuracy.

Critical X	**Critical Y**	**Model**[A]	**Error**[B]	**Pearson *P***[C]
			%	
19	1.05	62	35	0.017
19.1	1.05	62	35	0.017
15.6	1.05	61	36	0.026
18	1.05	61	36	0.031
18.1	1.05	61	36	0.031
Previous Critical Value				
16	1.05	61	36	0.028

[A] Number of stamps (n = 97) the model correctly predicts
[B] Number of stamps the model incorrectly predicts
[C] Pearson chi-square *P*-value

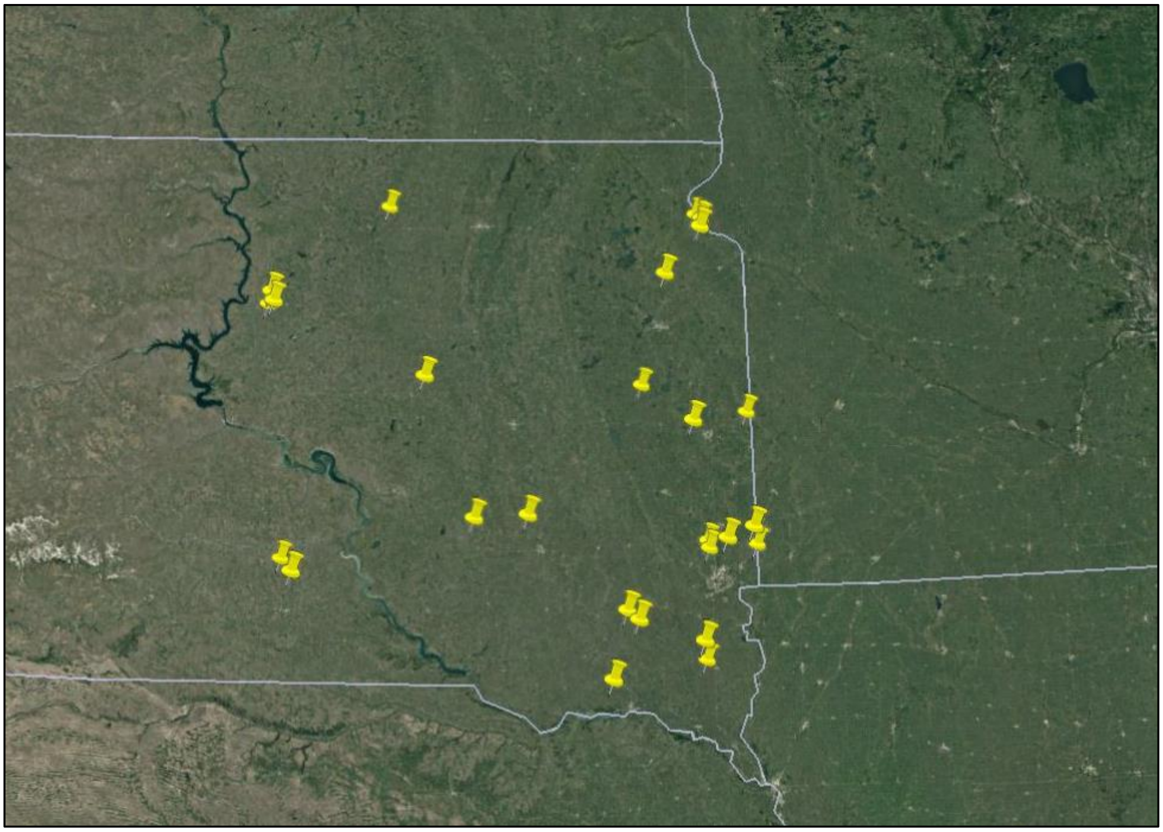

Figure 2.1. Research locations from the 2019-2021 growing seasons. Image from Google Earth

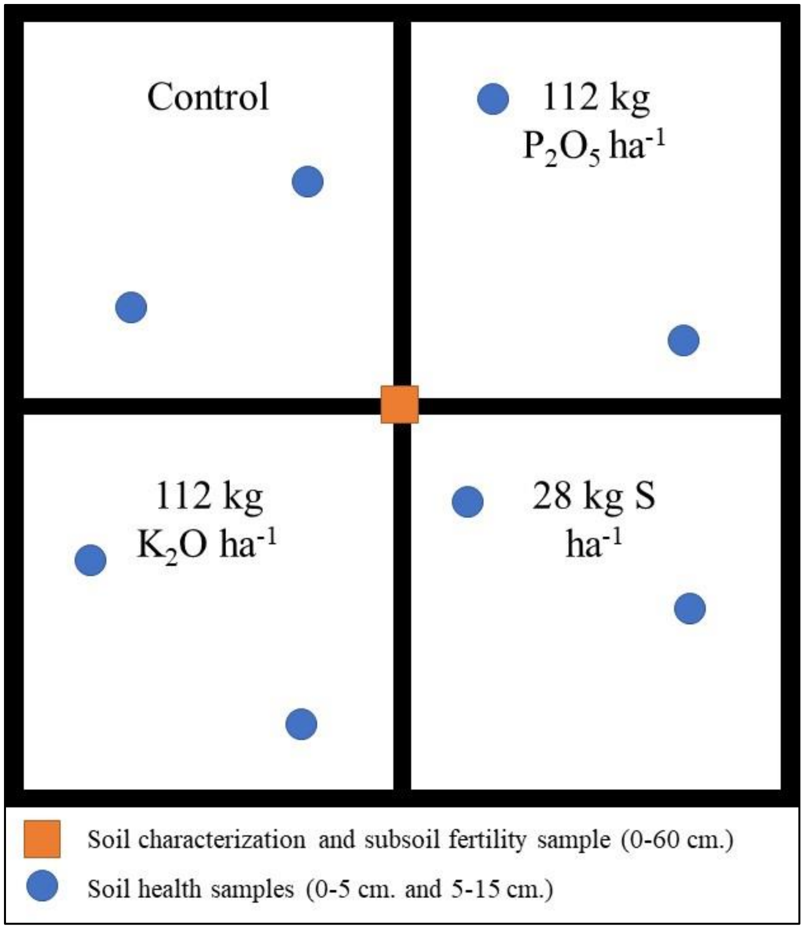

Figure 2.2. Treatment layout of each stamp. The orange square represents the single deep core (0-60 cm) used for soil characterization and subsoil fertility measurements. Blue circles represent the randomized sampling of the soil health cores

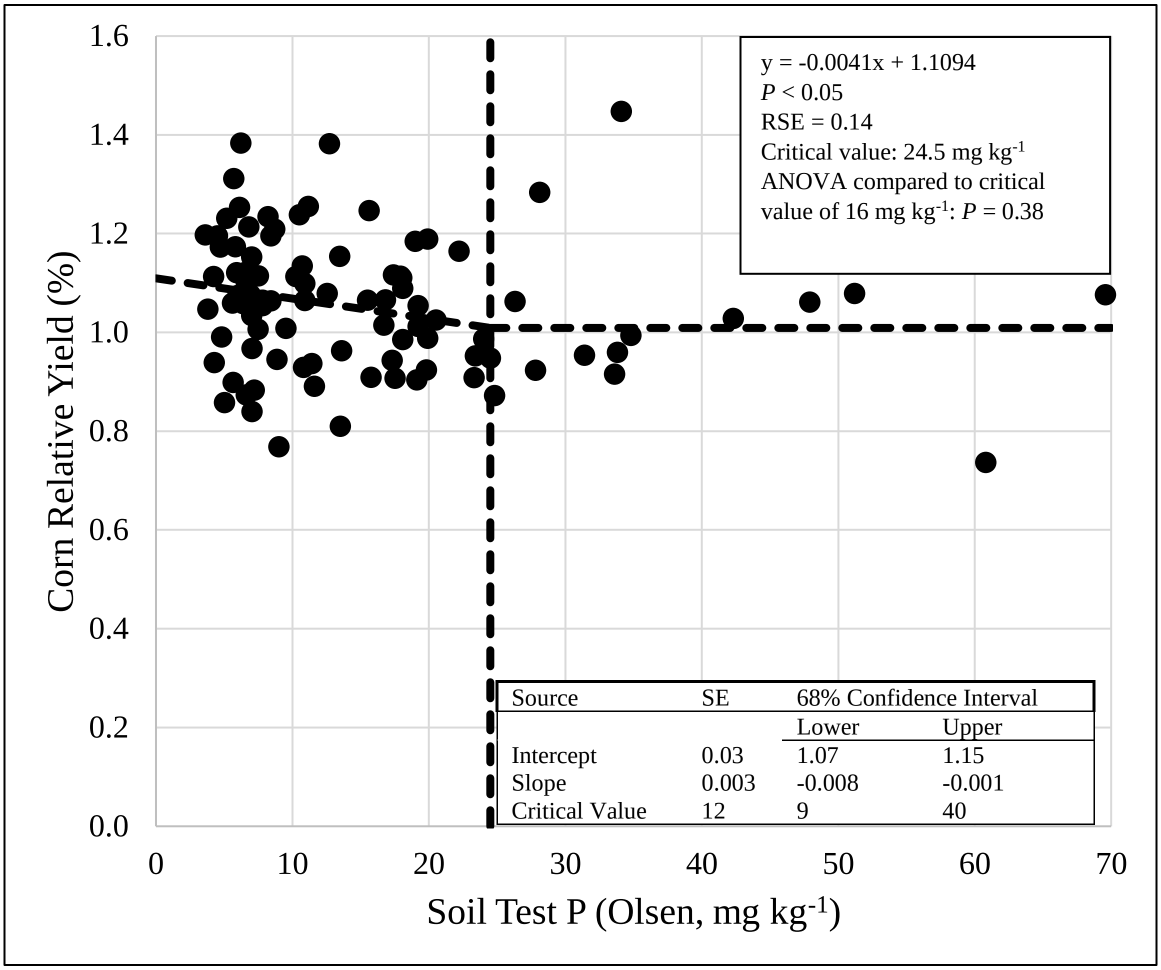

Figure 2.3. Relative yield response to P fertilization as a function of soil test P (0-15 cm) across 97 stamps from 2019-2021. Corn relative yield was calculated by dividing the treatment yield by the control yield. When relative yield was >1, yield increased with P fertilizer application. The table in the bottom-right shows the standard error and confidence intervals of the model components. The box in the top-right shows the regression equation and its *P*-value, RSE, critical value from the linear plateau model, and the ANOVA comparing the new critical value to the old one of soil test P of 16 mg kg^{-1}

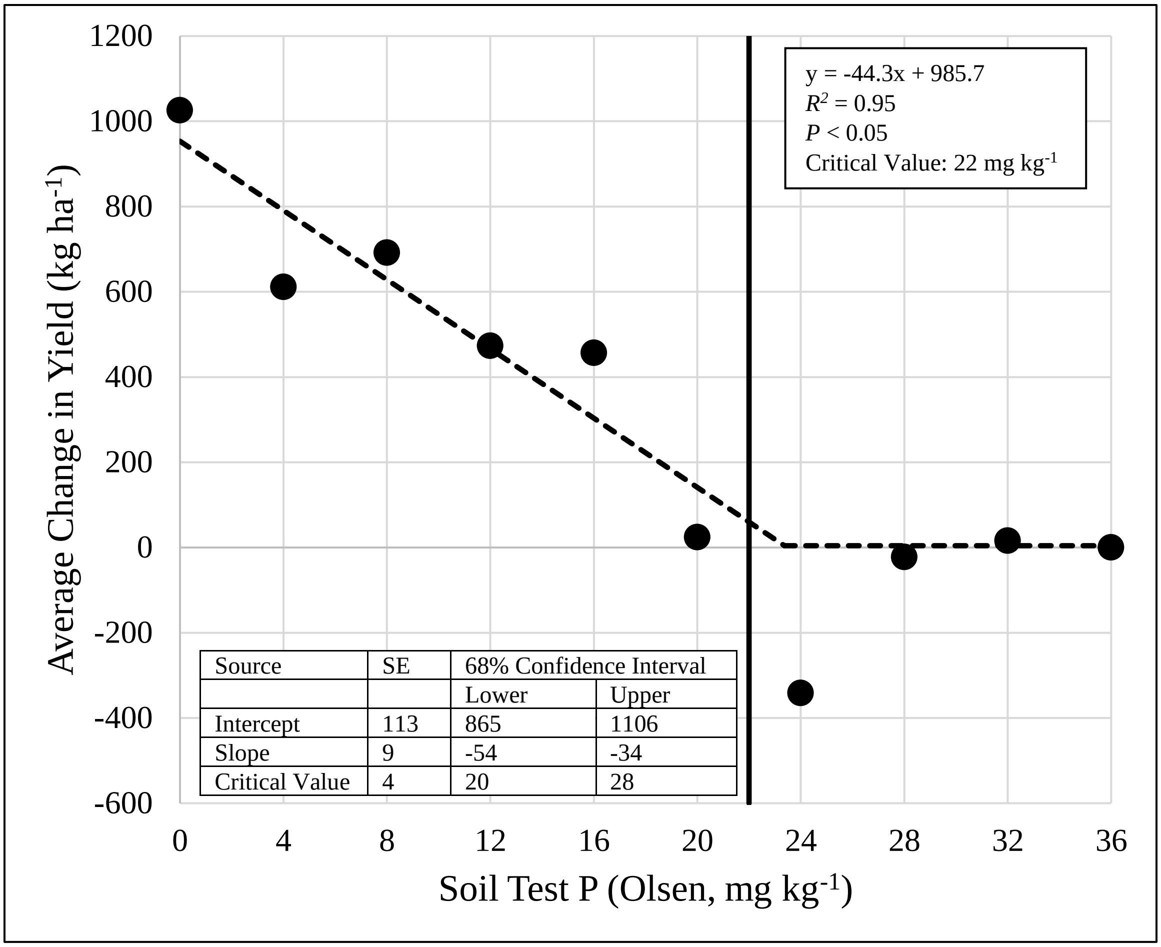

Figure 2.4. Average yield change when P fertilizer was applied as a function of soil test P (0-15 cm) across 97 stamps from 2019-2021. Change in yield was calculated averaging the treatment yield of all the points within grouped intervals of soil test P of 4 mg kg^{-1} and dividing by the average of the control. The critical value was determined where the yield increase dropped below 5% of the maximum (+50 kg ha^{-1}) giving a critical value of approximately 22 mg kg^{-1}. The table in the bottom-left shows the standard error and confidence intervals of the model components.

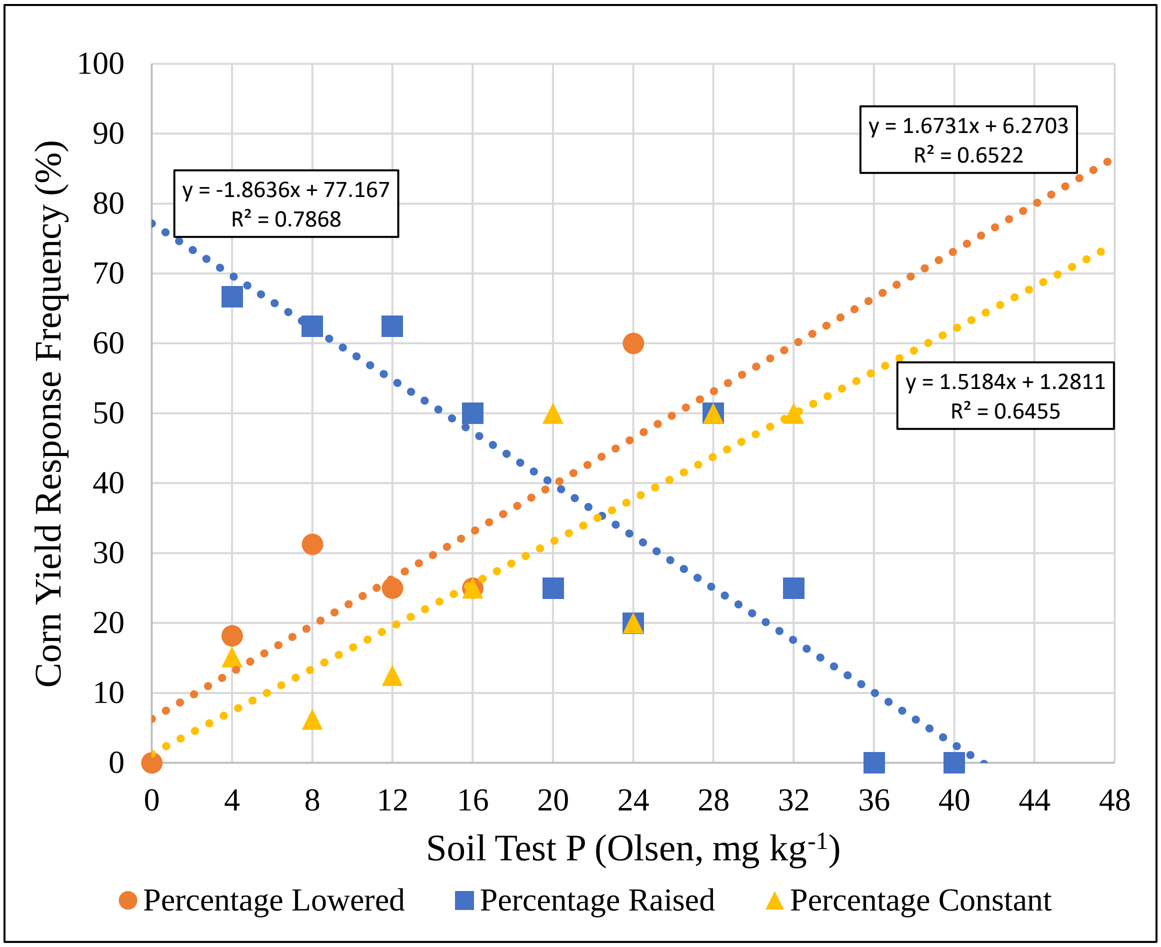

Figure 2.5. Positive, negative, and constant yield response frequency to P fertilization as a function of soil test P (0-15 cm) in intervals of 4 mg kg^{-1} across 97 stamps from 2019-2021. Regression equations and R^2 are shown in boxes nearest their corresponding regression line.

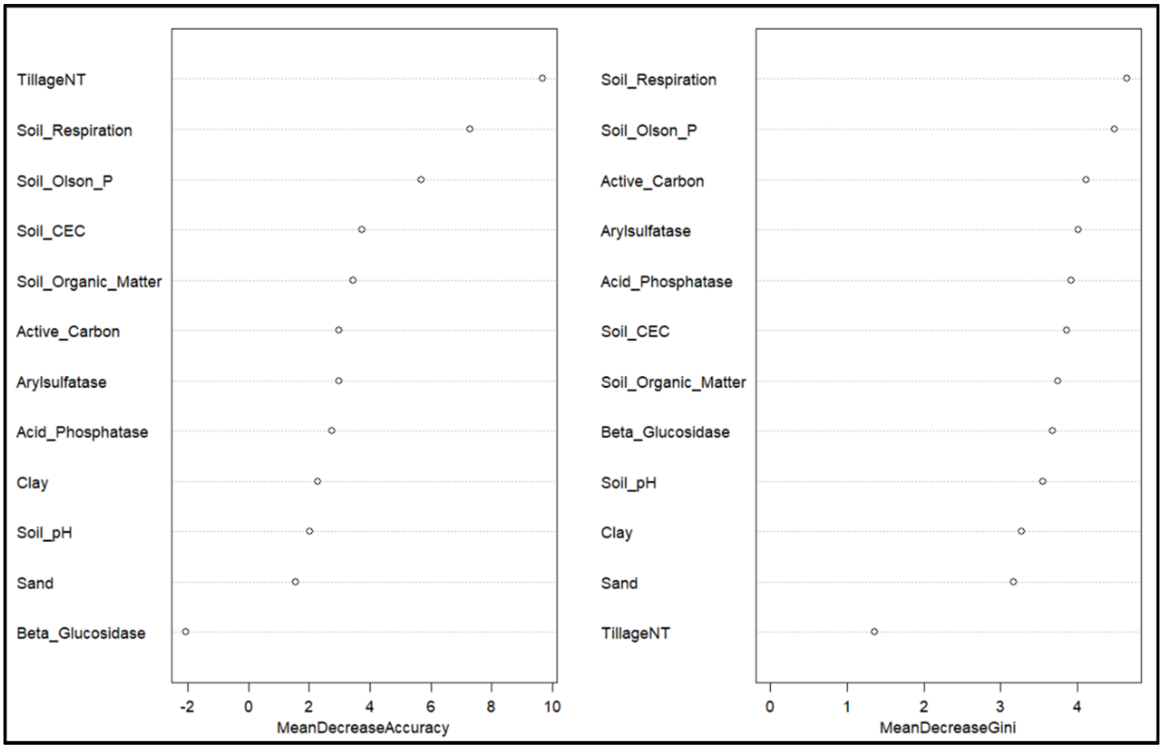

Figure 2.6. Plot from random forest output ranking variables based on two tests. The mean decrease in accuracy puts a random permutation in place of that variable and determines how much the accuracy of the model decreased. The mean decrease in Gini is the average of a variable’s decrease in node impurity which is weighted by the proportion of samples reaching that node. A higher mean decrease in accuracy and mean decrease in Gini means a variable was more important to the model.

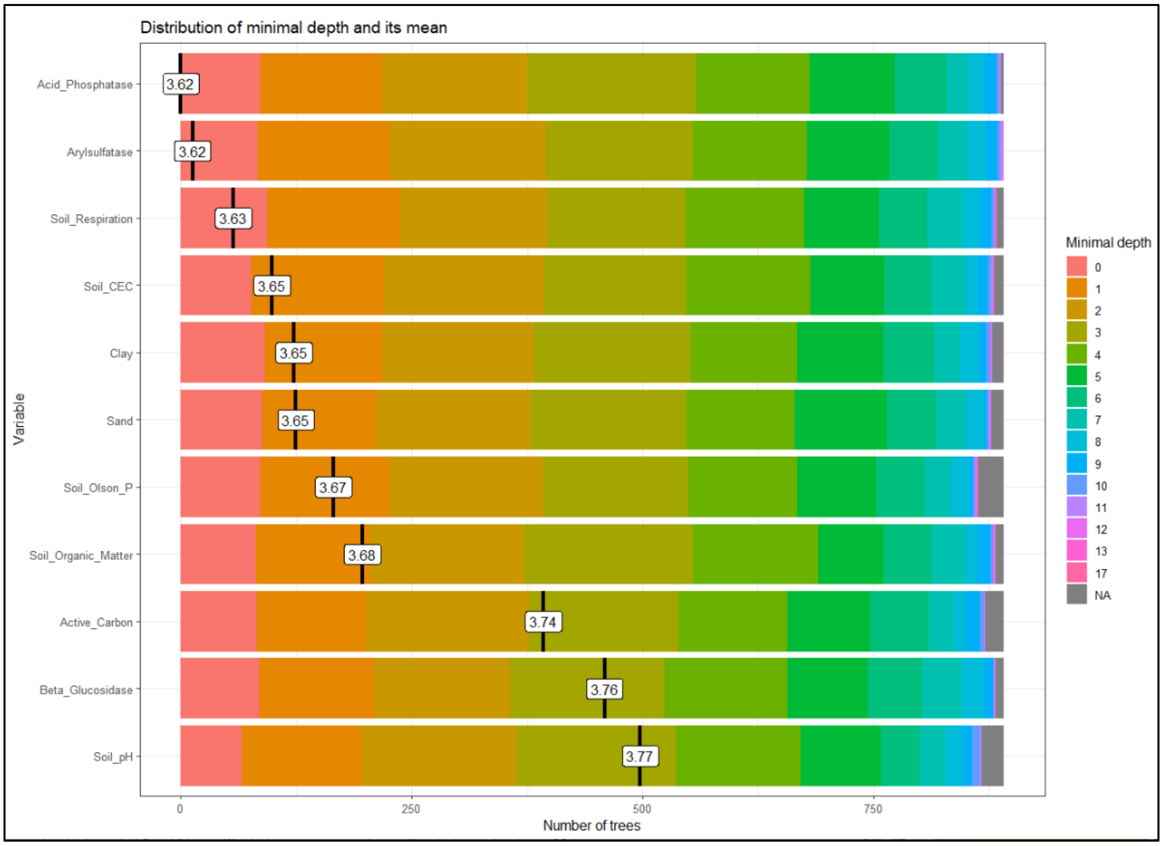

Figure 2.7. Random forest output ranking variables by the number of trees each variable is present in (n = 1000 trees) and what the mean minimum depth was in the tree. The more trees the variable was included in, the more important that variable was. A variable that had a lower mean minimum depth was closer to the root of the tree on average. The colors represent the minimum depth of that variable in each decision tree.

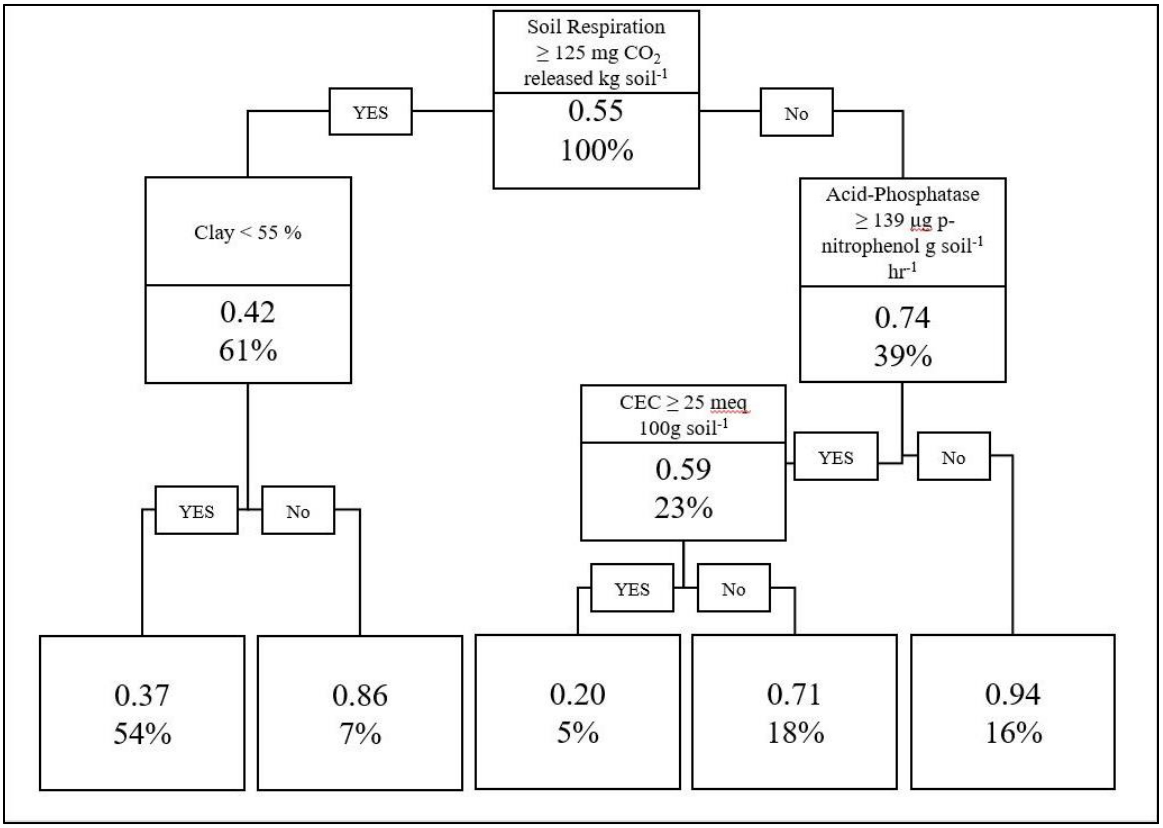

Figure 2.8. Decision tree using chosen soil parameters and their calculated critical value to predict yield response to P fertilization. The top number in each box was the percentage of sites in that node that positively responded (RY ≥ 1.05) to P fertilization. The second number was the percentage of total stamps (n = 97) that were located within that node. The bottom number was a critical value for that variable that split the node. For example, the first node split the data using soil respiration. If soil respiration was above 125 mg CO_2 kg soil^{-1}, a stamp had a 42% chance of positively responding and 61% of stamps were included in that node. If soil respiration was less than 125 mg CO_2 kg soil^{-1}, a stamp had a 74% chance of positively responding and 39% of stamps were included in that node. The bottom level adds up to 100% of all stamps.

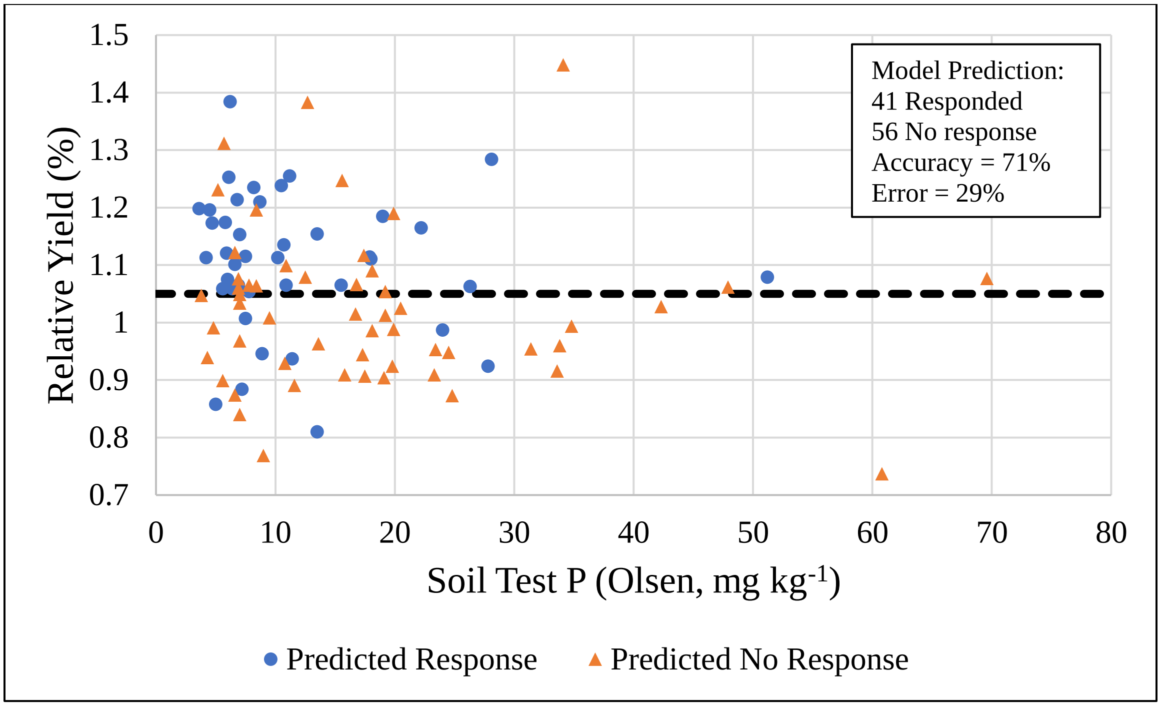

Figure 2.9. Decision tree (Figure 2.8) accuracy in determining if corn grain yield responded to P fertilization. Points in blue were predicted to respond to P fertilization while orange triangles were predicted not to respond. The more predicted response points above and predicted no-response points below the response line (RY ≥ 105%), the more accurate the model was for our dataset. The accuracy is the percentage of orange points that are below and blue points that are above the black dotted line, meaning the model predicted them correctly.

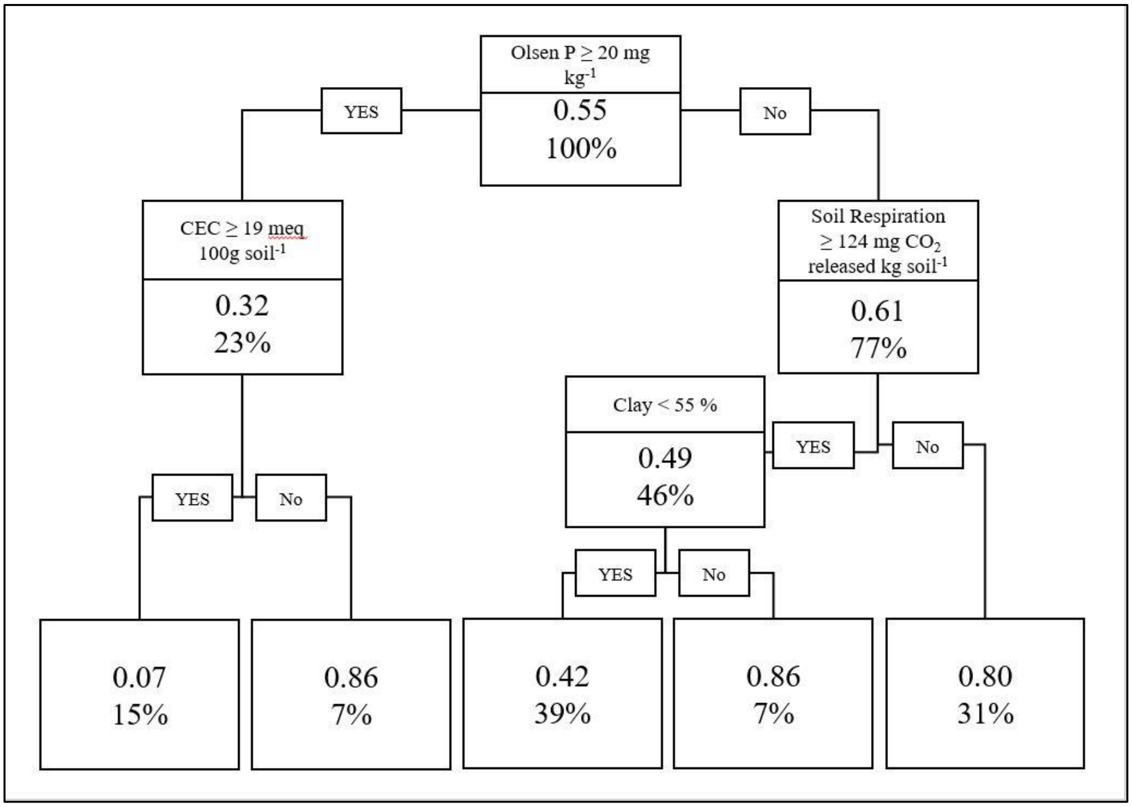

Figure 2.10. Decision tree using chosen soil parameters and their calculated critical value to predict yield response to P fertilization. The top number in each box was the percentage of sites in that node that positively responded (RY ≥ 1.05) to P fertilization. The second number was the percentage of total stamps (n = 97) that were located within that node. The bottom number was a critical value for that variable that split the node. For example, the first node split the data using Olsen P. If Olsen P was above 20 mg kg^{-1}, a stamp had a 32% chance of positively responding and 23% of stamps were included in that node. If Olsen P was less than 20 mg kg^{-1}, a stamp had a 61% chance of positively responding and 77% of stamps were included in that node. The bottom level adds up to 100% of all stamps.

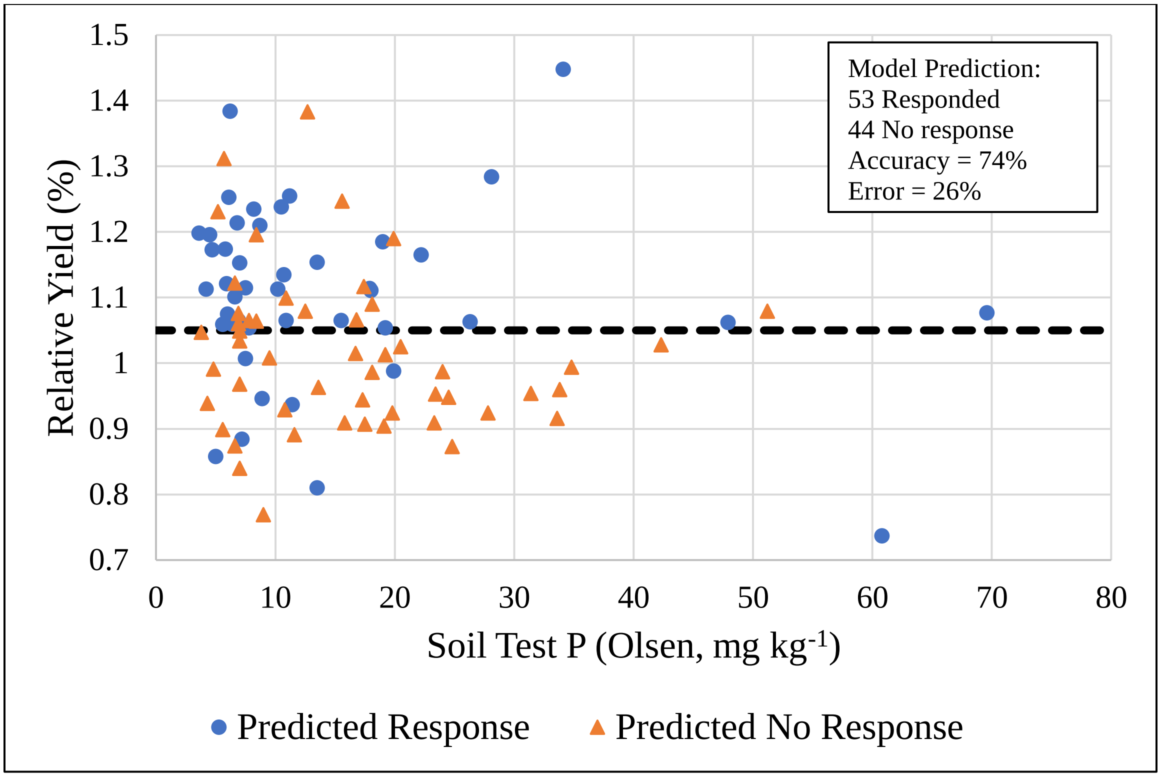

Figure 2.11. Decision tree (Figure 2.10) accuracy in determining if corn grain yield responded to P fertilization. Points in blue were predicted to respond to P fertilization while orange triangles were predicted not to respond. The more predicted response points above and predicted no-response points below the response line (RY ≥ 105%), the more accurate the model was for our dataset.

CHAPTER 3: CAN SOIL HEALTH AND FERTILITY MEASUREMENTS BE USED TO IMPROVE THE ACCURACY OF YIELD RESPONSE TO K FERTILIZER PREDICTIONS?

3.1 ABSTRACT

Researchers have pointed to changes in climate and land management practices to justify the need to reevaluate the accuracy of current South Dakota (SD) corn (*Zea mays* L.) K fertilizer recommendations. Also, an increase in soil health understanding has created the potential for soil health measurements to be used to improve the accuracy of these recommendations. The objectives for this study were to 1) evaluate the current K critical value and 2) determine the effect of including soil health indicators on fertilizer recommendation accuracy. This project was conducted throughout central and eastern SD from 2019-2021 at 97 experimental areas that varied in management, landform, and soil type. A fertilizer addition treatment of 112 kg K_2O ha^{-1} was compared to a control with no K fertilizer. Soil health and fertility samples (0-15 cm) were collected before fertilization and analyzed for physical, chemical, and biological characteristics. Positive yield responses were only observed at 27% of sites, likely because only 33% of sites had soil test K values below the current critical value of 160 mg kg^{-1}. Modeling showed the critical value could be lowered (140 mg kg^{-1}), but the model significance was never below 0.05, meaning more data points or different modeling approaches are needed before any change in the current critical value should be made. Random forest variable importance methods found differences among variables, but these differences were not significant. Decision tree analysis found several variables (soil test K, tillage practice, and pH), that when used to split a decision tree, improved prediction accuracy to 77%

compared to 63% when using soil K alone. These results demonstrate that soil health indicators along with soil fertility testing improves the accuracy of our yield response predictions to K fertilizer.

3.2 INTRODUCTION

Corn (*Zea mays* L.) is the highest valued crop in South Dakota (SD), worth nearly three billion dollars for the SD economy in 2020 (USDA NASS, 2020). In 2017, corn was grown on more than two million hectares with an average yield of over 9000 kg ha^{-1}, a significant jump over the 5700 kg ha^{-1} yields from 2012 (USDA NASS, 2017). As yields increase, fertilizers are often used in increasing amounts to supplement the nutrient needs of corn. Among the essential nutrients needed by corn plants, potassium (K) has been identified as one of the most important for overall plant growth and health. Potassium is involved in several vital plant functions including the balancing of turgor pressure, uptake of water, and photosynthesis (Hasanuzzaman et al., 2018). Because of this, K deficiencies can cause significant reductions in corn yields if supply does not equal demand. Plants supply their K needs by taking it from the soil. In SD, naturally occurring K is abundant in most soils, however, intensive crop production has slowly reduced this source of K (Gerwing et al., 2001). One method to overcome K deficiencies is the application of inorganic fertilizers when necessary. In 2018, SD farmers applied K-containing, inorganic fertilizers to 60% of corn hectares, a significant increase of 21% from 2000 (USDA ERS, 2019). However, the overapplication of fertilizer can reduce profitability, change soil chemical properties, and result in excess nutrients in the soil where rainfall runoff can carry them to waterways (Scharf, 2001; Zhang et al., 2017; Wang et al, 2002). Appropriate management of K fertilization can improve corn yields, reduce input costs, and protect offsite nutrient movement.

In SD, rates of fertilization for major crop nutrients are provided in the SD Fertilizer Recommendations Guide (Gerwing et al., 2005). For K, a soil testing approach using the ammonium acetate K method of extraction is utilized to establish the abundance of K already available in the soil and determine if fertilization is necessary (Warncke and Brown, 1998). When developing K fertilizer recommendations, a sufficiency goal is established by determining a soil test K (STK) level where increased fertilization no longer increases yield, otherwise known as a critical value (Drescher et al., 2021; Reed et al., 2021). However, research in SD that determined the current fertilizer recommendations was conducted years ago and changes in both climate and management practices over the last decade may have impacted the accuracy of the current recommendations.

The climate of SD has changed in recent decades as increased temperatures have resulted in longer growing seasons. Also, increased rainfall in drier areas of Central SD has led to corn production in areas where it was previously unfeasible (EPA, 2016). Further, environmental awareness and policy has led to increased adoption of conservation management practices including reduced tillage, cover cropping, and diversified cropping rotations (USDA NRCS, 2019; Wang, 2020; Wang, 2022). The shift in management practices changes soil processes that impact the dynamics of plant-available K in the soil. For example, no-till management and some crop rotations results in the stratification of K in the surface layer of the soil when it is surface applied (Robbins and Voss, 1991; Holanda et al., 1998). Plant roots may not have access to this source of K, especially during dry years when roots extend further downwards (Vyn et al., 2002). Tillage, which is used by many farmers to dry the soil surface, may also impact K fixation. Research on calcareous soils found that constant wetting and drying cycles in the soil increase K fixation that reduces its availability to plants (Shakeri and

Abtahi, 2019; Mouhamad, 2015). Another management practice being adopted in SD, cover-cropping, can impact K availability through soil chemical changes or taking K up, making it unavailable to the corn crop (Tiecher et al., 2017). While growing, cover crops with large root zones can access K in the soil that the corn roots may not have found. When stored in plant biomass, soil K cannot be fixed to soil colloids or lost to the environment (Calonego and Rosolem, 2013) When the cover crop is terminated, this K is released back into the soil where it can be taken up by corn during the growing season. Further, cover cropping has been associated with increases in microbial communities that aid with the release of fixed K from clay minerals (Bahadur et al., 2016). These research results demonstrate that management practices can impact the cycling and uptake of soil K. Therefore, the increased adoption of management practices such as reduced-till, cover cropping, and diverse crop rotations provides evidence that the current K critical value needs to be reevaluated.

Currently, the only soil measurement used to aid in fertilizer recommendations in SD is the ammonium acetate K soil test. However, this soil test may overestimate the amount of available K in the soil by including a fraction of fixed K (Cassman et al., 1990). This causes a problem for STK use in fertilizer recommendations as it cannot accurately predict K that is plant available, which is exacerbated by the naturally high-K soils of SD that contain large amounts of unavailable K (Ward and Carson, 1975; Schindler et al., 2005). There is a complex web of soil physical, chemical, and biological processes that all impact the availability and form of K in the soil. Some researchers have concluded that soil testing for K is not a reliable method to use in K recommendations as there are too many other factors impacting K availability (Khan et al., 2014; Barbagelata, 2006). Although the ammonium acetate method of K extraction has not been improved, soil testing methods developed in recent years (active carbon, clay mineralogy) have attempted to quantify different soil characteristics or processes that may impact nutrient availability (Yuan et al., 2021; Franzen et al., 2019). Perhaps, these new soil health measurements may be able to help us better quantify K availability to plants throughout the growing season, thus being a potential indicator of yield responses to K fertilization.

Soil health has been defined as the continued capacity of soil to function as a vital living ecosystem that sustains plants, animals, and humans (Karlen et al., 1997). Soil health has been broken down into physical, chemical, and biological measurements that all interact with each other. While some soil health tests look to specific biological processes (e.g., β-glucosidase and the breakdown of organic C), others are broad and may correlate to overall microbial activity (e.g., soil respiration) (Eivazi and Tabatabai, 1988; Zibilski, 1994). Some research has attempted to generate an overall health score, although they have still placed emphasis on individual soil tests (Moebius Clune et al., 2016; Andrews et al., 2004). Many of these soil health tests have been correlated to soil functions (e.g., soil respiration and active carbon to organic matter mineralization and stabilization, respectively) that impact nutrient availability (Haney et al., 2008; Hurisso et al., 2016), and, therefore, show potential for improving the accuracy of fertilizer recommendations.

The availability of K has been related to some soil processes. For example, different clay types have the ability to fix more K between layers. Research conducted on montmorillonite, a type of clay widely found in SD, showed it fixed a considerable amount of K (Inoue, 1983). A study on vermiculite found it also fixed a significant amount of K with up to 50% of K applied becoming non-exchangeable and, therefore, not usable by plants (Rees, 2015). Cation exchange capacity (CEC), which is affected by clay type, may also play a role in potassium levels in the soil. Research has demonstrated that CEC correlates well with potassium fixation (Bloom et al., 1991). A higher CEC along with increasing K fertilizer rates increased K fixation in the soil. Although soils with higher CEC can hold more K, most of it is unavailable as it is fixed to clay minerals where it is unavailable to plants. Availability of K may also be impacted by pH. At high pH levels like those present in much of SD, Ca^{2+} competes with K^+ on exchange sites, releasing more K into the soil solution, increasing K availability (Xie et al., 2021) However, some have hypothesized that first-year applications of K may increase yields even on high K soils because the Cl^- may increase the dissolved cations in the soil solution (Jakobsen, 1993). Also, overabundance of K may have an antagonistic relationship to uptake of other cations, especially Mg^{2+} (Xie et al., 2021). The complex physical and chemical processes that impact K availability are poorly understood. However, research that can determine which soil processes impact yield response to K fertilizers can help us understand factors that can be used to determine why corn does or does not respond to K fertilization.

In recent years, improvements in soil health have been related to potassium availability in the soil. For example, some bacteria and fungi species can solubilize K from soil minerals (Bahadur et al., 2016). Researchers have isolated several bacterial species that significantly improved the assimilation of K by corn (Singh et al., 2010). Research conducted by Maurya et al. (2014) found that bacteria decreased the pH around them which subsequently released K into the soil solution. Others discovered fungal strains that increased soluble K in the soil and biomass K in young corn plants (Barin et al., 2017). Because correlations were made between microbial activity and K availability, the use of soil biology measurements could improve the accuracy of predicting yield responses to K fertilization.

To this point, research has mainly been conducted with N in an attempt to use soil health measurements to better predict if a site will respond to N fertilizer. Research conducted in North Carolina attempted to quantify N mineralization throughout the growing season using soil respiration to predict an economically optimum N rate (EONR) (Franzluebbers, 2018). As soil respiration increased, both yield response to N and EONR decreased, indicating that including soil respiration testing better determined whether a yield response would occur to N fertilization. This was similar to findings from other studies across the US Midwest that showed both soil physical and biological measurements could improve EONR predictions (Yost et al., 2018; Clark et al., 2019). Research conducted in New York used SOM and soil nitrate to better determine if a site would respond to additional N fertilization beyond a starter application (Klapwyk and Ketterings, 2006). Some states, such as Nebraska, have included SOM in their N fertilizer recommendations (Shapiro et al., 2019), but this has not been attempted for K. Overall, these studies identified that interactions among soil physical, chemical, and biological indicators can be used to understand why a field may or may not respond to N fertilizer.

Similar studies are needed to determine the potential of using soil health tests in improving current K fertilizer recommendations. Given recent research attempts to include soil health measurements in N recommendations, this study explored whether the same can be done for K. The objectives of this research were to 1) evaluate the accuracy of the critical value of current K fertilizer recommendations and 2) determine if soil health indicators can be used with soil fertility measurements to improve the accuracy of SD K fertilizer recommendations.

3.3 MATERIALS AND METHODS

3.3.1 Research Sites and Experimental Design

Research trials were conducted at 28 locations across central and eastern SD from 2019-2021 (Figure 3.1) Locations varied in management practices, landforms, and soil types and are shown in Table 3.2. The goal of using diverse locations was to embody a range of growing conditions and fertility levels to build a dataset that represents the diverse growing conditions of SD. Location selection also only included fields that had not been fertilized with P or K the previous fall or were flagged to avoid P or K application in the spring. In 2019, trials were located at different locations in a single field, each one being referred to as a “stamp” from here on out, resulting in an absence of replication. Each location had between two and four stamps.

In 2020 and 2021, stamps were located within a randomized complete block design of several other studies and were generally located within 50 meters of each other. Each stamp ranged from 6.09-18.29 m. wide to 7.6-15 m. long, providing a surface area between 148.65-278.71 m^2. For fertilization treatments, each stamp was divided into four equal treatment areas (37.2 m^2 to 69.7 m^2). The upper-left quadrant was labeled the control and received no P, K, or S fertilizer (Figure 3.2). Fertilizer treatments were applied by hand to the other three quadrants. Fertilizer treatments were as follows: 1) control; 2) 112 kg ha^{-1} of P_2O_5 applied as triple super phosphate (460 g P_2O_5 kg^{-1}; 0-46-

0); 3) 112 kg ha^{-1} of K_2O applied as potash (600 g K_2O kg^{-1}; 0-0-60); and 4) 28 kg ha^{-1} of S applied as ammonium sulfate (210 g N kg^{-1} and 240 g S kg^{-1}; 21-0-0-24). To balance all treatments for the N supplied to treatment four by the ammonium sulfate, an additional 25 kg N ha^{-1} as SUPER-U (460 g N kg^{-1}; 46-0-0) (Koch Agronomic Services, LLC, Wichita, KS) was applied to quadrants 1-3. Nitrogen was then applied to all treatments based on the farmer's usual rate of N.

3.3.2 Sampling and Laboratory Analyses

Soil samples were taken at each stamp in the spring before planting or fertilization. After treatments were flagged, eight cores (3.175 cm i.d.) were taken at random spots within each stamp for soil health analysis. Cores were divided into two depths (0-5 cm and 5-15 cm) and composited into one sample for each depth. Samples were put into plastic bags and immediately put into a cooler to keep them out of the sun and heat. Once out of the field, samples were stored in a cooler until the next step could be completed. When time was allowed, 0-5 cm and 5-15 cm samples were taken from the cooler, passed through an 8 mm sieve, and organic matter was removed using a forceps for a consistent time of four minutes per sample. Once four minutes had passed, samples were resealed in bags, and sent to either the USDA-ARS Soil and Water Quality Lab in Columbia, MO (2019-2020) or Ward Laboratories in Kearney, NE (2021). Analyses conducted included β-glucosidase, acid-phosphatase, arylsulfatase, active carbon, soil respiration, and ACE protein. Descriptive statistics of each measurement and the corresponding method citation are provided in Table 3.1.

To determine basic soil fertility measurements (pH, SOM, Olsen P, K, S, Total C, and Total N) from the top 0-15 cm, a portion of the soil health samples based on the depth of each sample was put in a separate bag and analyzed using the methods in Table 3.1. Soil profile characterization and sub-soil fertility were assessed at the center of each stamp by obtaining a soil core using a hydraulic probe (4.5 cm i.d.) to a depth of 60 cm. A single core was taken, split into different depths (0-15 cm, 15-30 cm, and 30-60 cm), broken up, and sealed in a plastic bag. Samples were air dried until constant moisture and analyzed for subsoil fertility (same as above) and texture analysis (sand, silt, and clay) following the methods in Table 3.1.

3.3.3 Harvest and Yield Analysis

Plants were harvested in the fall by hand or plot combine. If harvested by hand, the center 11.15 m^2 (2019-2020) or 9.3 m^2 (2021) area was picked and full ears were weighed in the field. Once out of the field, a subsample of eight ears was taken, weighed, and then dried down to obtain moisture content at harvest. The overall weight of the ears was multiplied by 0.88 to eliminate the weight of the cobs. If a plot combine was used, the center two rows of each plot were harvested. Grain weight from hand and combine harvesting methods were adjusted to 155 g kg^{-1} moisture. Relative yield was obtained by dividing each treatment plot by the control plot. For example, if a relative yield was calculated as 110%, then the treatment yielded 10% higher than the control plot.

3.3.4 Data Management and Statistical Analyses

Data was analyzed using R programming language with R version 4.1.2 (R Core Team, 2022). Linear plateau analysis was calculated using functions from R package *minpack.lm*, with the goal of finding a relationship between relative yield and STK up until a critical value (Whittemore and Fawcett, 1976; Elzhov et al., 2016). The critical value was considered the joint point between the linear and plateau portion of the model.

This critical value is the STK level where continued application of K fertilizer no longer increases yield. Confidence intervals for model parameters were calculated using the *contfint2* function from the package nlstools (Baty et al., 2021). Other methods for determining a critical value involved grouping stamps by intervals of STK 40 mg kg^{-1} (80-120, 120-160, etc.) and averaging yield change or response frequency within each interval. Stamps with a positive (RY ≥ 105%), negative (RY ≤ 95%), and constant (95% ≤ RY ≤ 105%) yield response to fertilization were quantified within each K interval and presented as a percentage of the total number of sites within each interval. The yield change was calculated as the yield difference between the K treated plot and the control. If yield change was negative, then the control plot yielded higher than the treatment. The point where yield change became negative or the negative response frequency was higher than the positive response frequency was determined as a critical value. Cate-Nelson analysis was also used to find the point in the dataset that maximized the points that responded below and minimized the points that respond above a critical value (Cate and Nelson, 1971) This analysis was completed using the function *CateNelsonFixedY* in the package rcompanion (Mangiafico, 2015).

For objective two, the machine learning technique, random forest, was used to determine variables what were the most important at predicting yield response to K fertilizer. Random forest has been used in other studies to find and include variables in yield response to fertilizer predictions (Ransom et al., 2019; Mohapatra et al., 2017). Instead of using random forest to run a regression model on the dataset, a classification random forest was used to determine if one of two things happened: response (RY ≥ 105%) or no response (RY < 105%). Random forest was run using the *train* function from the R package Caret (Kuhn et al., 2021). Because the data set was small, all rows of data were included for training. The R package RandomForestExplainer was used to build graphs to evaluate variable importance (Paluszynska, 2017). The three methods of variable importance used for this project were mean decrease in accuracy (MDA), mean decrease in Gini (MDG), and mean minimal depth (MMD) (Breiman, 2001; Han et al., 2016; Ishwaran et al., 2008). For both MDA and MDG, a higher value means the variable was more important to predicting yield responses to K fertilizer. For MMD, a lower value means a variable was closer to the root of the tree, meaning it was a better predictor than the variables higher in the decision tree. After random forest was run, decision trees were made using the R package rpart.plot (Milborrow, 2021). Decision trees were split using the best available variable from the list in Table 3.1. The model given by the decision tree was then compared to the observed responses from the study and a model accuracy and error were determined. The accuracy is the percentage of stamps that the model correctly predicted if they would respond while the error is the percentage the model predicted incorrectly.

3.4 RESULTS AND DISCUSSION

3.4.1 General Results

The 0-15 cm pre-plant STK levels across all stamps ranged from 99 to 613 mg kg^{-1} with the average being 278 mg kg^{-1}. In all, only 32 of the 97 stamps were below the current SD critical value for K recommendations of ammonium-acetate K 160 mg kg^{-1}. When split into the thresholds according to the SD Fertilizer Recommendation Guide, the 32 insufficient stamps were considered medium (6 stamps, 80-119 mg kg^{-1}) or high (26 stamps, 120-159 mg kg^{-1}) (Table 3.3). Notably, no stamps were located on soils testing in the “very low” (0-39 mg kg^{-1}) and “low” (40-79 mg kg^{-1}) categories as they are not highly present in SD, a similar problem that other potassium-related studies in SD have determined (Ward and Carson, 1975; Schindler et al., 2005). Of the stamps that were sufficient in STK (65 stamps, >160 mg kg^{-1}), 23 had STK levels more than 2.5 times higher than the critical value (>400 mg kg^{-1}).

Overall control plot grain yields ranged from 2187 to 16331 kg ha^{-1} while averaging 10406 kg ha^{-1}. Plots treated with K_2O fertilizer had yield ranges from 1734 to 17139 kg ha^{-1} with an average of 10065 kg ha^{-1}. Across all stamps, K fertilization slightly decreased yields by an average of 339 kg ha^{-1} or about a 2% decrease from the control yields. Of the 97 stamps, applying K fertilizer increased grain yield by at least 5% (RY ≥ 105%) at 26 (27%) and decreased it (RY ≤ 0.95) at 40 stamps (41%). Yield was considered constant at 31 stamps (32%) when RY was between 95% and 105% of the control yield.

3.4.2 Potassium Critical Value

Both linear plateau and Cate-Nelson regression techniques found a weak relationship ($P > 0.05$) between corn grain yield response to K fertilization and STK (Figure 3.1; Table 3.4). The weak relationship may have been caused by a lack of low STK stamps (< 100 mg kg^{-1}). Having lower STK locations could have improved our ability to calculate a critical value as it would have likely resulted in more sites that positively responded to K fertilization. However, even at relatively low STK values (<160), corn yield negatively responded to K fertilization more often (13 stamps) than it positively responded (8 stamps) (Table 3.3). This is contrary to the thought that the only economic downside of overapplying fertilizer is the cost of the fertilizer itself. Using linear plateau, a critical value of STK 137 mg kg^{-1} was determined (slope *P*: 0.63; critical value *P*: 0.003) where grain yield no longer increased with added K fertilizer (Figure 3.3). According to the linear plateau model, when STK was at 0 mg kg^{-1}, treatment yields were 18% higher than the control yields. Relative yield then decreased as STK increased until reaching an STK of 137 mg kg^{-1}, where RY was approximately 98% and stayed constant as STK increased. Linear plateau models have also been used in other studies to determine critical values of STK for both corn yields and turfgrass quality (Mallarino and Barbagelata, 2012; Franzen et al., 2019; Johnson et al., 2003). Although the model determined 137 mg kg^{-1} to be a good critical value, RSE was unchanged (0.175). Additionally, the confidence interval (68%) for the linear plateau model overlapped the old critical value of 160 mg kg^{-1} (lower = 91 mg kg^{-1}, upper = 182 mg kg^{-1}). Further, when comparing the current and new critical values with ANOVA, they were not significantly different ($P = 0.65$). Other methods for determining critical values are needed to validate the linear plateau model.

Another method for determining critical values, Cate-Nelson, calculates a critical value that maximizes the points that responded below the critical value and points that did not respond beyond it. Cate-Nelson analysis has been a useful tool for determining critical values for STK to soybean or corn grain yield in other studies (Mallarino and Barbagelata, 2012; Fulford and Culman, 2017; Beegle and Oravec, 1990). Cate-Nelson testing gave several possible STK critical values (100, 103, 109, 104, and 108 mg kg^{-1}) when an initial parameter of a 5% yield increase (RY = 105%) was used to determine if a positive yield response occurred (Table 3.4). Of the five best critical values, the one that best explained our data set was at 100 mg kg^{-1} which had a 71% accuracy and 29% error.

This new critical value was better than the current critical value of 160 mg kg^{-1} which had 57% accuracy and 43% error. Although model accuracy was improved by 14% by using a 100 mg kg^{-1} critical value, none of the calculated critical values had a significant Pearson-p coefficient (Table 3.4). This was likely due to there being very few stamps (6) that had STK levels lower than 120 mg kg^{-1}.

Although these methods indicate that the critical value likely needs to decrease, both models become less predictive at lower STK values because very few stamps had STK levels below their calculated critical values. For example, the linear plateau model predicted a yield increase when STK was less than 137. From our observations, when STK was below 137, a stamp had a much stronger possibility of not responding (72%) than showing a positive response (28%). The issue effecting both critical value methods is the lack of stamps with low STK values. These problems persisted because at no point was there a STK level that definitively resulted in positive yield responses to K fertilization. Other methods of determining critical values could be helpful to compare the results from linear plateau and Cate-Nelson modeling.

Another potential way of determining a critical value is to relate the STK level to the change in yield when K fertilizer is applied (Figure 3.4). As STK increased, the yield change decreased linearly with added K fertilizer. At no point on the regression line was yield increased, even at low STK levels. According to the regression line, even when STK was 0 mg kg^{-1}, yield would be unchanged by adding K fertilizer, meaning application of K at any STK level would result in a slight yield decrease that was reduced more as STK increased. Although no critical value can be determined by this method, it does show that yield change decreases as STK increases, which favors a lower critical value rather than a higher one.

A fourth method for calculating critical values is to evaluate the frequency of yield responses to K fertilization at different STK levels. This relationship indicated that as STK increased, the percentage of stamps where yield increased with added K decreased (Figure 3.5). The yield response frequency, although not a direct method for finding critical values, has been used before to indicate when responses are no longer likely to occur (Drescher et al., 2021). The positive yield response frequency (RY ≥ 105%) had a weak, negative linear relationship (R^2 = 0.23) to STK. According to the regression line, if STK was at 0 mg kg^{-1}, approximately 45% of stamps would respond (RY ≥ 105%) to K fertilizer applications. However, when STK increased to 160 mg kg^{-1}, less than 30% of stamps would respond. The positive yield frequency reached 0% when STK was approximately 400 mg kg^{-1} or higher. In contrast, negative yield response frequency (RY ≤ 95%) followed a moderate, positive linear relationship (R^2 = 0.68). As STK increased, the negative response frequency to K fertilization increased. According to the regression line, if STK was 0 mg kg^{-1}, there was a 0% chance that application of K fertilizers would decrease yield. However, as STK increased to 160 mg kg^{-1}, a 45% negative response frequency was observed and continued increasing as STK levels increased further. The no response frequency (95% ≤ RY ≤ 105%) regression line (R^2 = 0.65) gradually increased as STK rose. Since a STK of approximately 120 mg kg^{-1} was where there was an equal chance of seeing a positive or a negative response, this point could be used as a critical value.

Three of the four methods of determining critical values calculated STK values between 100 and 140 mg kg^{-1}. The Cate-Nelson analysis gave several critical values near 100 mg kg^{-1}, but there were almost no points below those values meaning the critical values given by this methodology could not be trusted. The best option for a critical value came from the linear plateau model, which indicated a critical value of STK 137 mg kg^{-1} should be used. While slightly lower than the current critical value of STK 160 mg kg^{-1}, there were a fair number of points below 140 mg kg^{-1} in our dataset (23%) to support the accuracy of the linear plateau model. This critical value for STK is lower than those of the surrounding states of ND, MN, and IA which all have critical values higher than 160 mg kg^{-1} (Franzen et al., 2018; Kaiser et al., 2020; Mallarino et al., 2013). However, our calculated critical value is closer to the Nebraska and Kansas STK critical values of 125 and 130 mg kg^{-1}, respectively (Shapiro et al., 2017; Leikam et al., 2003).

Conclusions could be made that STK is not a good predictor of overall yield response to K fertilizer, but because no locations were used that had STK levels in the "very low" or "low" categories, this paper stops short of making such claims. Perhaps yield responses to K fertilization would be observed when STK levels are below 100 mg kg^{-1} as other studies have observed (Boring et al., 2018; Singh et al., 2019). Using the stamps we had, a decrease in critical value to 140 mg kg^{-1} increased the accuracy (+6%) of predictions of yield response to K fertilization. However, more locations at lower STK levels are needed before conclusions can be made.

Because only weak relationships were found between yield response to K fertilizer and STK in our study, other inherent factors may be impacting yield response. Because our study was set up at different locations across the state, weather conditions varied across the stamps. One hypothesis to explain the variability among yield responses may be differences in rainfall. For example, some hypothesize that soil moisture impacts K availability (Kuchenbuch et al., 1986; Sardi and Fulop, 1994), while others show correlations between pH and soil solution K (Magdoff and Bartlett, 1980). Method of K extraction (moist vs. oven-dry) also impacts the measured K in the soil (Mallarino and Barbagelata, 2012). Some also hypothesize that the ammonium-acetate K extraction procedure measures some fixed, plant-unavailable K and may overestimate plant available K (Hartz, 2007; Zebec et al., 2017). Further, other soil factors such as pH or CEC may impact yield responses to K application by fixing K to clay surfaces where it is largely unavailable to plants. Additionally, some have even shown that clay mineralogy may impact clay sorption of cations (Franzen et al., 2019). Soil health indicators may also be useful as some studies found relationships between soil microbes and plant-available K (Das and Pradhan, 2016; Verma et al., 2017). These studies along with our results provide evidence that more than an updated STK critical value is likely needed to substantially improve the predictability of corn response to K fertilization.

3.4.3 Variable Importance and Selection

The random forest machine learning technique identified variables that could be used as predictors of corn grain yield response to K fertilization. A random forest model was built using all variables from Table 3.1 except for Total N and C, which were highly correlated to SOM. Variables from the model were ranked by importance using several criteria including the MDA, MDG, and MMD which are all discussed in the methods section (Archer and Kimes, 2007).

The MDA predicts the overall change in accuracy when a variable's value is randomly permutated. Using the MDA measurements, the best variables were specified as soil pH, soil respiration, and arylsulfatase (MDA > 1%) which was higher than any of the other variables (MDA <1%) (Figure 3.6). Soil pH was considerably higher than the other variables (MDA = 4), meaning its importance is much greater than the other variables.

The MDG is the sum of the decreases in node purity when a certain variable is used to split the tree divided by the number of trees. By using MDG, the variables with the highest values were acid-phosphatase and soil respiration (MDG > 4). While these two were identified as the most important variables using MDG, all variables had MDG values that were similar (2 < MDG > 4) except for tillage which was remarkably lower (MDG = 0.3). By using both MDA and MDG, variables that had the highest values for both tests were considered to be the most important. Both soil respiration and soil pH were near the top of both charts, meaning they should be considered for use in the decision tree.

The MMD is the mean depth of the variable (root = 0) across all trees. The variables with the lowest MMD were acid-phosphatase, SOM, and soil respiration (Figure 3.7). Although ranked in order of importance, it should be noted that the MMD for variables only ranged from 3.2 to 4.34, meaning all variables were ranked nearly the same by this method (except for tillage). Only soil respiration matched the results of the MDA and MDG methods as being one of the most important variables by being ranked high in MDA (2nd), MDG (2st), and MMD (3rd). Soil pH was also near the top of all three tests and was ranked high in MDA (1st), MDG (4th), and MMD (3rd). Although some variable importance measurements agreed among which variables were more important, others varied depending on measurement. Because there was little difference within each method, no variables could be confidently ruled out. Therefore, all variables were included in the building of the decision tree.

The decision tree made splits based on soil pH, SOM, and arylsulfatase (Figure 3.8). At the root of the tree, soil pH was split by a value of 7.7. When soil pH was lower than 7.7, corn grain yield only responded 21% of the time with added K. The points with low pH were split again by a SOM of 29 g kg^{-1}. When SOM was above 29 g kg^{-1}, stamps responded to K fertilization 18% of the time, but when SOM was below 29 g kg^{-1}, stamps had a much higher chance of responding (60%). On the other side of the tree, where soil pH was above 7.7, stamps had a 50% chance of responding to K application. This was then split by arylsulfatase 60 μg p-nitrophenol g $soil^{-1}$ hr^{-1}. When arylsulfatase was above 60 μg p-nitrophenol g $soil^{-1}$ hr^{-1}, stamps had only a 31% chance to respond to K fertilizer. When arylsulfatase was below 60 μg p-nitrophenol g $soil^{-1}$ hr^{-1}, stamps then had an 86% chance of responding to K fertilization.

Due to the complexity and cost of additional soil tests, the decision tree is only practical if a considerable increase in accuracy of predicting yield response to K fertilization was made. To test this, the decision tree model was applied to our dataset. Of the 97 stamps, the model predicted that 15 would and 82 would not respond compared to 26 stamps that did and 71 that did not respond to K fertilization (Figure 3.9). These results mean the model underestimated the number of stamps that did respond and overestimated the stamps that did not by 11. Despite this, an accuracy of 78% was achieved compared to 63% using only a K critical value of 140 mg kg^{-1}.

Most notably, this decision tree did not include STK. The lack of stamps below the critical value may have caused random forest analysis to leave out STK as an important indicator. Also, once past the critical value, STK would be expected to no longer correlate well with yield responses. Although there was no relationship found in our study, numerous studies have correlated STK to yield responses (Boring et al., 2018; Singh et al., 2019; Franzen et al., 2019). Because of this, manipulating the decision tree to add STK may improve the accuracy while not opposing research that has found correlations between STK and yield responses to K fertilizer. To manually test the use of STK in the decision tree, the data set was split into STK $\geq$ 140 and STK < 140, which would be used as the first split in the decision tree.

This decision tree made splits based on STK, soil pH, and tillage practice (Figure 3.10). At the root of the tree, STK was manually split by a value of 140 mg kg^{-1}. When STK was lower than 140, corn grain yield only responded 27% of the time with added K. The points with insufficient STK were split again by tillage practice. When no-till was used, stamps responded to K fertilization 8% of the time, but with conventional tillage practices, stamps had a much higher chance of responding (56%). On the other side of the tree, where STK was above 140 mg kg^{-1}, stamps had a 27% chance of responding to K application. This was then split by soil pH of 7.7, similar to the first decision tree. When soil pH was below 7.7, stamps had only a 20% chance to respond to K fertilizer. When soil pH was above 7.7, stamps had a 64% chance of responding to K fertilization.

For the decision tree including STK, the model predicted that yield would increase at 20 and decrease at 77 stamps which was similar to the number of stamps where yield was observed to increase or decrease in our study (Figure 3.11). This resulted in the decision tree including STK to have an overall accuracy of 77% compared to 78% for the tree that did not include STK and 63% when the critical value (140 mg kg^{-1}) was used alone. Although both decision trees used soil pH, the decision tree that manually included STK excluded arylsulfatase and SOM, reducing the number of soil health tests needed to improve K response predictability while only being 1% less accurate. Fewer soil health tests needed would reduce overall soil testing costs and the accuracy was similar to that of more complex decision trees.

The results from the random forest and decision tree variable importance methodologies support the adoption of additional variables to improve SD K fertilizer recommendations. By using decision trees that included additional variables (Figures 3.8 and 3.10), model accuracy was improved (78% and 77%) and was higher than simply using STK with a critical value of 140 mg kg^{-1} (63%). Additional variables provided by random forest techniques showed soil pH, soil respiration, acid-phosphatase, and SOM all have the potential to be useful predictors for yield responses to K fertilization (Figures 3.6 and 3.7). Also, both decision trees utilized soil pH as a predictor, indicating pH levels have a role in how plants respond to K additions. These results support some hypotheses that high soil pH can reduce K availability by increased competition with other cations and increasing fixation to soil colloids (Magdoff and Bartlett, 1980; Shakeri and Abtahi, 2019). Also, the importance of soil respiration supports studies that claim soil microbes play a role in the release of K into the soil solution (Das and Pradhan, 2016; Verma et al., 2017)

3.5 SUMMARY AND CONCLUSIONS

This study assessed the current SD K fertilizer recommendations by first investigating the current STK critical value, and then, searching for additional soil health variables that could improve the accuracy of our yield response to K fertilizer predictions. Both the Cate-Nelson method and the yield response frequency graph provided evidence that an decrease in the critical value was necessary, although neither could determine how much. By using the linear plateau model, a decrease in the critical value from STK 160 mg kg^{-1} to 140 mg kg^{-1} improved the P fertilizer response prediction accuracy (+6%) and better explained why positive yield responses were not being observed in areas that had STK values less than 160 mg kg^{-1}. Using random forest and decision tree methodologies, the addition chemical (soil pH) and biological (soil respiration, SOM, and arylsulfatase) soil measurements were determined as important variables for predicting yield response to K fertilization. Also, tillage practice (CT vs. NT) was important for determining yield response to K fertilizer at low STK levels. Among the indicators, soil K, soil pH, and tillage practice were determined to be the most beneficial when used in a decision tree, increasing yield response to K fertilization accuracy (77%) when compared to STK alone (63%).

These results show that additional soil health variables, especially soil pH, may be useful for predicting yield response to K fertilization. Further, adoption of soil health-improving practices such as no-till may reduce K fertilizer needs. While this study demonstrates that changes are warranted to the SD K fertilizer recommendations in corn, economics need to be considered to justify if an increase in prediction accuracy is worth the additional soil tests needed. Studies will be needed to validate the models presented here and calibrate required K fertilizer rates to optimize corn yield under varying soil health and STK levels. Further research in the area of quantifying soil health changes with various soil management practices (or change in management practices) would also be helpful to better understand how management practices would likely affect yield response to fertilizer applications.

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3.7 TABLES AND FIGURES

Table 3.1. Descriptive statistics and references of the soil physical, chemical, and biological tests analyzed as potential variables to correlate to yield response to K fertilization. Total C and N were not used in the random forest model due to a high correlation to soil organic matter.

Analyses[A]	Unit	Min.	Max	Median	S. Dev[B]	Citation
Soil Physical Properties						
Sand	%	7	61	25	12	Gee and Bauder, 1979
Silt	%	20	53	40	9	Gee and Bauder, 1979
Clay	%	12	62	31	10	Gee and Bauder, 1979
Soil Chemical Properties						
pH		5.0	8.3	6.4	0.9	Soil Survey Staff, 2014
SOM	g kg^{-1}	24	62	4.1	1	Broadbent, 1965
P (Olsen)	mg kg^{-1}	4	107	11	17	Olsen et al., 1954
K	mg kg^{-1}	99	613	238	14	Warncke and Brown, 1998
CEC	meq 100g $soil^{-1}$	12	43	21	7	Ross and Ketterings, 2011
S	mg kg^{-1}	4	672	10	85	Hoeft et al., 1973
Total C	g kg^{-1}	12	37	23	5	Nelson and Sommers, 1996
Total N	g kg^{-1}	1.2	3.3	2.0	0.1	Bremner, 1965
Soil Biological Properties						
β-Glucosidase	µg p-nitrophenol g $soil^{-1}$ hr^{-1}	32	165	72	31	Deng and Popova, 2011
Acid-phosphatase	µg p-nitrophenol g $soil^{-1}$ hr^{-1}	60	280	163	54	Tabatabai and Bremner, 1969
Arylsulfatase	µg p-nitrophenol g $soil^{-1}$ hr^{-1}	15	144	42	29	Tabatabai and Bremner, 1970
Active Carbon	mg C kg-$soil^{-1}$	328	1631	1029	381	Weil et al., 2003
Soil Respiration	mg CO_2 released kg $soil^{-1}$	61	245	135	39	Zibiliske et al., 1994
ACE Protein	mg protein kg $soil^{-1}$	2.3	7.1	3.7	1.2	Wright et al., 1996

[A] SOM = Soil organic matter; CEC = Cation exchange capacity; ACE Protein = Autoclaved citrate-extractable protein

[B] S. Dev = Standard deviation

Table 3.2. Location information for each site from 2019-2021. Included are county in South Dakota, soil series, previous crop, tillage practice, row width, planting date, average control yield, and average relative yield for the K treated plots for that location.

Location[A]	Year	County	Soil Series[B]	Previous Crop	Tillage Practice[C]	Row Width	Planting Date[D]	Control Yield	RY[E]
						cm		kg ha^{-1}	%
1	2019	Brookings	Lenona-Swenoda	Soybean	CT	76.2	U	11189	97
2	2019	Minnehaha	Nora-Crofton	Soybean	NT	76.2	U	12270	99
3	2019	Minnehaha	Obert	Soybean	CT	76.2	U	13399	78
4	2019	Minnehaha	Nora-Crofton	Soybean	NT	76.2	U	14078	102
5	2019	Roberts	Esmond-Heimdal-Sisseton	Soybean	CT	76.2	U	12127	95
6	2019	Roberts	Hamerly-Tonka	Soybean	CT	76.2	U	12877	97
7	2020	Clay	Egan-Clarno-Trent	Soybean	NT	76.2	29-Apr	12159	97
8	2020	Edmunds	Williams-Bowbells	Cover Crop Mix	NT	76.2	15-May		
9	2020	Kingbury	Poinsett-Waubay	Soybean	NT	76.2	27-May	14550	102
10	2020	Minnehaha	Nora-Crofton	Corn	NT	76.2	U	12725	89
11	2020	Potter	Agar	Wheat	NT	76.2	11-May	11466	103
12	2020	Tripp	Millboro	Wheat	NT	152.4	29-Apr	7520	106
13	2020	Tripp	Millboro	Wheat	NT	76.2	29-Apr	10704	94
14	2021	Aurora	Houdek-Dudley	Sunflower	NT	50.8	U	3162	88
15	2021	Brookings	Brandt	Soybean	CT	76.2	U	7254	96
16	2021	Codington	Kranzburg-Brookings	Wheat	NT	76.2	U	11702	92
17	2021	Davison	Houdek-Prosper	Wheat	NT	76.2	U	6148	97
18	2021	Hand	Houdek-Prosper	Fallow	NT	76.2	4-May	11232	88
19	2021	Hutchinson	Hand-Bonilla	Soybean	CT	76.2	1-May	7496	104
20	2021	Lincoln	Wentworth-Chancellor	Soybean	CT	76.2	27-Apr	8434	112
21	2021	Minnehaha	Blendon	Corn	CT	76.2	3-May		
22	2021	Minnehaha	Moody-Nora	Corn	CT	76.2	U	10285	99
23	2021	Potter	Agar	Cover Crop Mix	NT	76.2	4-May	11471	88
24	2021	Potter	Agar-Mobridge	Wheat	NT	76.2	5-May	5745	98
25	2021	Roberts	Peever	Soybean	CT	76.2	28-Apr	12553	95
26	2021	Tripp	Millboro	Wheat	NT	76.2	3-May		
27	2021	Turner	Egan-Ethan	Soybean	CT	76.2	1-May	7578	107
28	2021	Yankton	Clarno-Crossplain-Davison	Soybean	CT	76.2	U	11706	94

[A] Locations 8, 21, and 26 were lost due to poor stand, weather damage, or other environmental problems that severely impacted some plots
[B] Soil series from WebSoilSurvey
[C] CT = conventional tillage; NT = no tillage
[D] U = unknown
[E] RY = relative yield; Average of K treated plots divided by the average of the control plots at each location. A value greater than 100 means yield was increased at that location by applying K fertilizer

Table 3.3. Mean yield information for soil test K in intervals of 40 mg kg^{-1}. Table includes the number of stamps where yield increased, decreased, or didn't respond to K fertilizer within a predetermined interval. Also shown are mean control yield, mean treatment yield, mean relative yield, mean yield change, and the mean yield increase response frequency.

Soil Test K Interval	Number of stamps				Mean K Soil test	Mean Control Yield	Mean Treatment Yield	Mean Relative Yield	Mean Yield Change[A]	Mean Yield Response Frequency[B]
	n	Yield Decrease[C]	No Response[D]	Yield Increase[E]						
mg kg^{-1}					mg kg^{-1}	kg ha^{-1}		%	kg ha^{-1}	%
80-119	6	1	3	2	103.8	12856.4	13047.2	1.01	190.79	33.3
120-159	26	12	8	6	136.5	11068.7	10511.3	0.95	-557.40	23.1
160-199	9	3	1	5	185.9	11865.3	12200.1	1.03	334.87	55.6
200-239	8	5	2	1	213.1	10179.9	9939.3	0.98	-240.66	12.5
240-279	6	3	2	1	253.2	12904.9	11303.9	0.88	-1600.99	16.7
280-319	6	1	4	1	311.0	10677.9	10578.8	0.99	-99.03	16.7
320-360	8	4	2	2	338.9	10102.0	9149.7	0.91	-952.25	25.0
360-399	5	2	1	2	371.6	9134.2	9095.4	1.00	-38.77	40.0
400+	24	9	8	6	498.6	8183.4	8065.5	0.99	-117.87	25.0

[A] Mean treatment yield – mean control yield

[B] Percentage of stamps in each increment where yield increased (RY ≥ 105%) with K fertilizer application

[C] Number of sites where yield decreased (RY ≤ 0.95) with K fertilizer application

[D] Number of stamps where yield did not response (0.95 < RY < 1.05) to K fertilizer application

[E] Number of stamps where yield increased (RY ≥ 1.05) with K fertilizer application

Table 3.4. Top five critical values using Cate-Nelson analysis when Y was forced at 1.05 (RY = 105%). A critical x = 160 is shown to represent the current critical value of soil test K of 160 mg kg^{-1} and its accuracy.

Critical X	**Critical Y**	**Model**[A]	**Error**[B]	**Accuracy**	**Pearson *P***[C]
				%	
100	1.05	69	28	71	0.95
103	1.05	68	29	70	0.68
109	1.05	68	29	70	1
104	1.05	67	30	69	0.51
108	1.05	67	30	69	0.51
Previous Critical Value					
160	1.05	55	42	57	0.97

[A] Number of stamps (n = 97) the model correctly predicts
[B] Number of stamps the model incorrectly predicts
[C] Pearson chi-square *P*-value

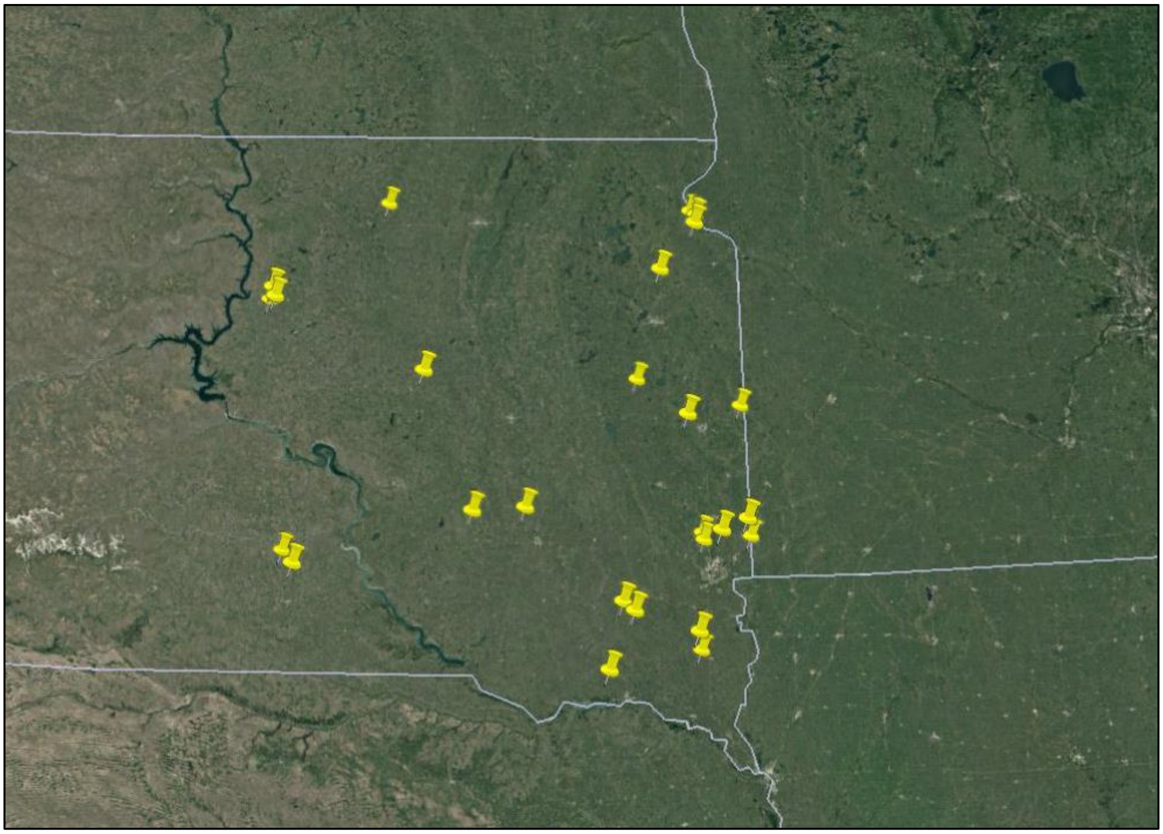

Figure 3.1. Research locations from the 2019-2021 growing seasons. Image from Google Earth

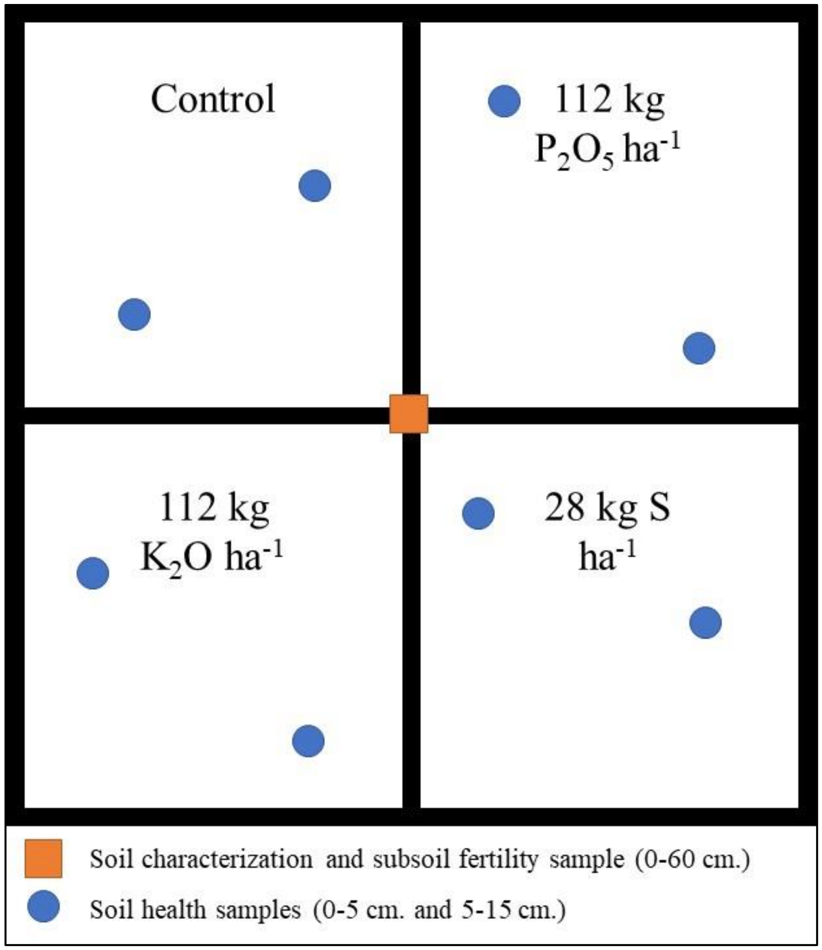

Figure 3.2. Treatment layout of each stamp. The orange square represents the single deep core (0-60 cm) used for soil characterization and subsoil fertility measurements. Blue circles represent the randomized sampling of soil health cores.

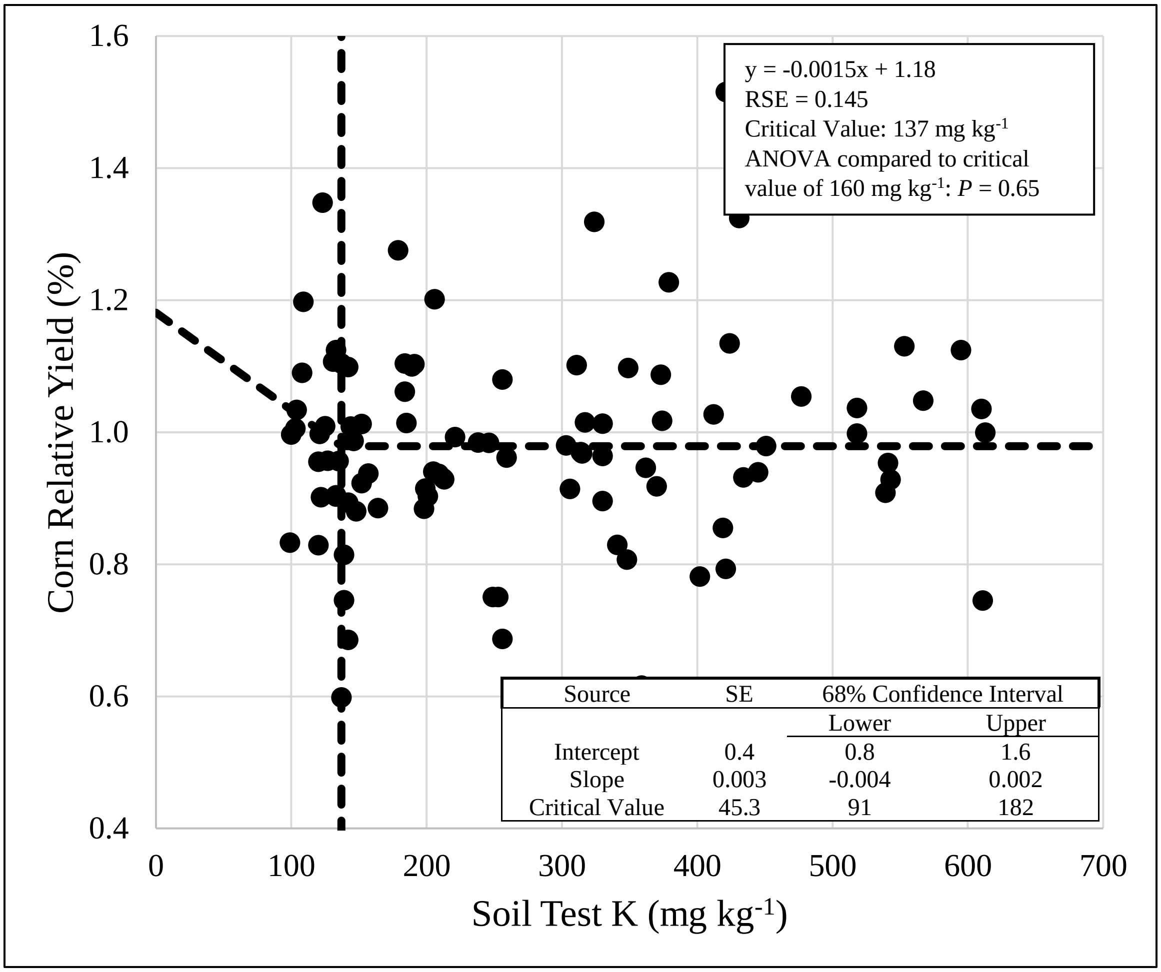

Figure 3.3. Relative yield response to K fertilization as a function of soil test K (0-15 cm) across 97 stamps from 2019-2021. Corn relative yield was calculated by dividing the treatment yield by the control yield. When relative yield was >1, yield increased with K fertilizer application. The table in the bottom-right shows the standard error and confidence intervals of the model components. The box in the top-right shows the regression equation and its *P*-value, RSE, critical value from the linear plateau model, and the ANOVA comparing the new critical value to the current one of soil test K 160 mg kg^{-1}.

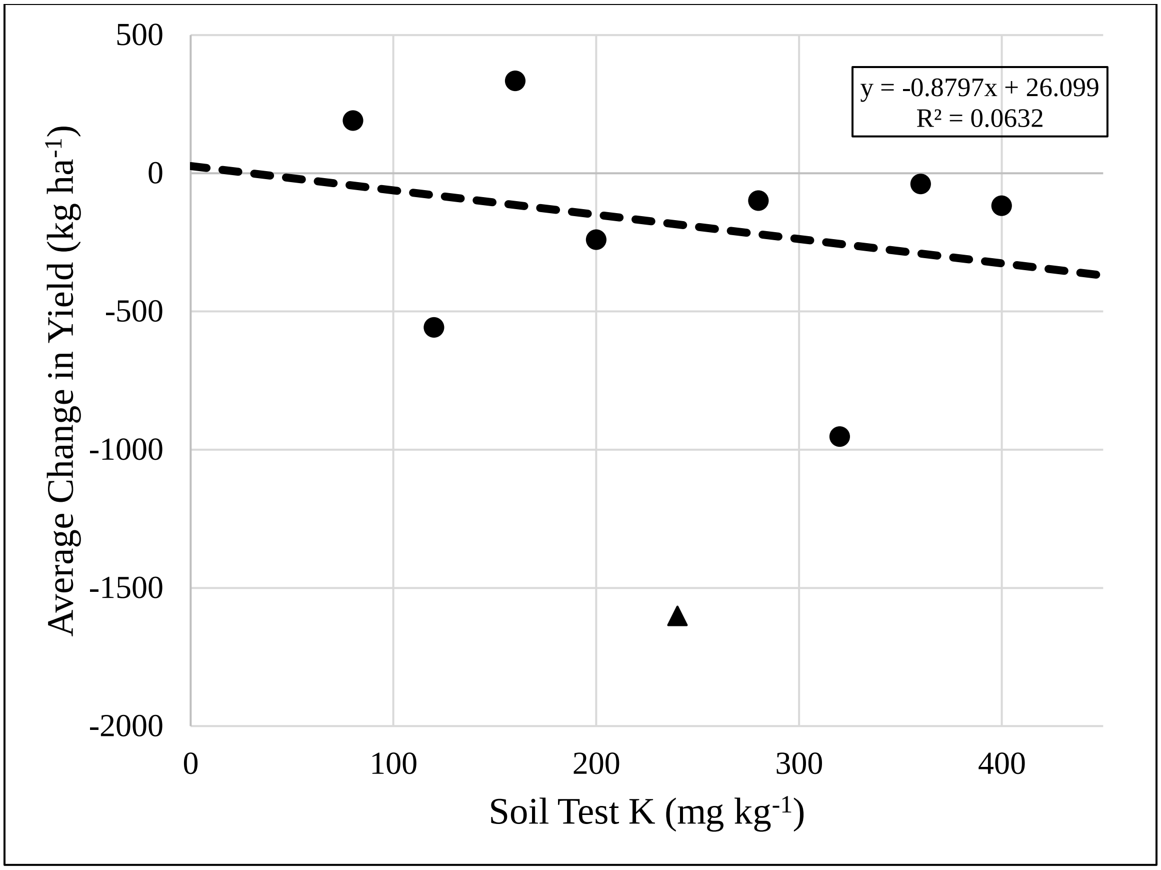

Figure 3.4. Average yield change when K fertilizer was applied as a function of soil test K (0-15 cm) in 97 K treatments from 2019-2021. Change in yield was calculated averaging the treatment yield of all points within grouped intervals of soil test K of 40 mg kg^{-1} and divided by the average of the control. The equation of the regression line is in the top-right corner along with the R^2 value. The ▲ point was not used in the regression line calculation because there were very few points between soil test K 240 and 280 mg kg^{-1}.

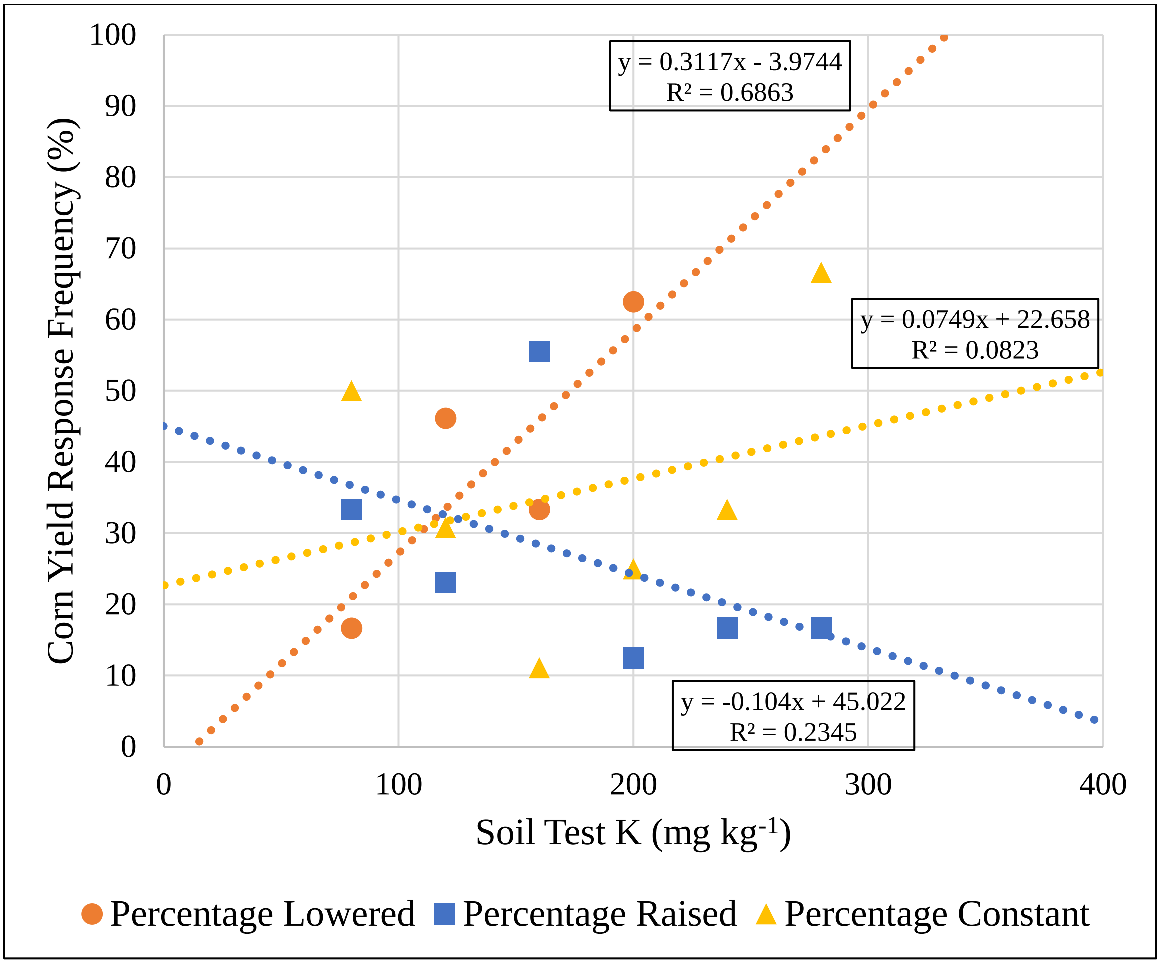

Figure 3.5. Positive, negative, and constant yield response frequency to K fertilization as a function of soil test K (0-15 cm) in intervals of 40 mg kg^{-1} across 97 stamps from from 2019-2021. Regression equations and R^2 are shown in boxes nearest their corresponding regression line.

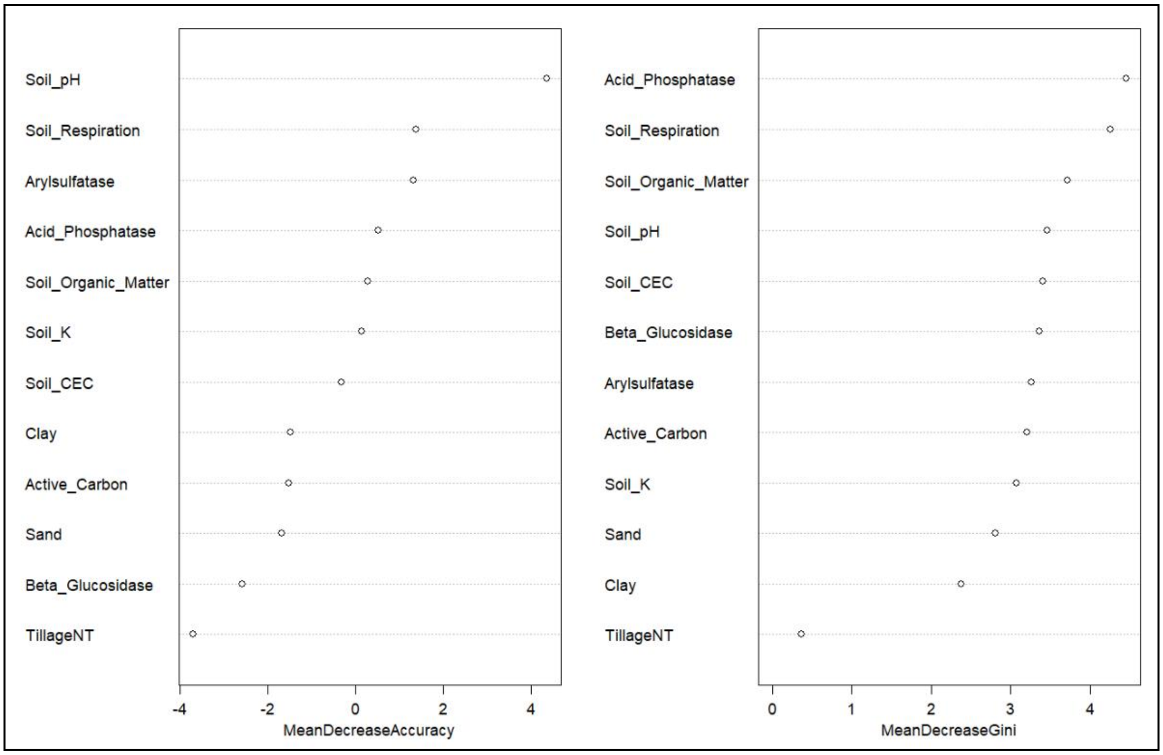

Figure 3.6. Plot from random forest output ranking variables based on two tests. The mean decrease in accuracy puts a random permutation in place of that variable and determines how much the accuracy of the model decreased. The mean decrease in Gini is the average of a variable's decrease in node impurity which is weighted by the proportion of samples reaching that node. A higher mean decrease in accuracy and mean decrease in Gini means a variable was more important to the model.

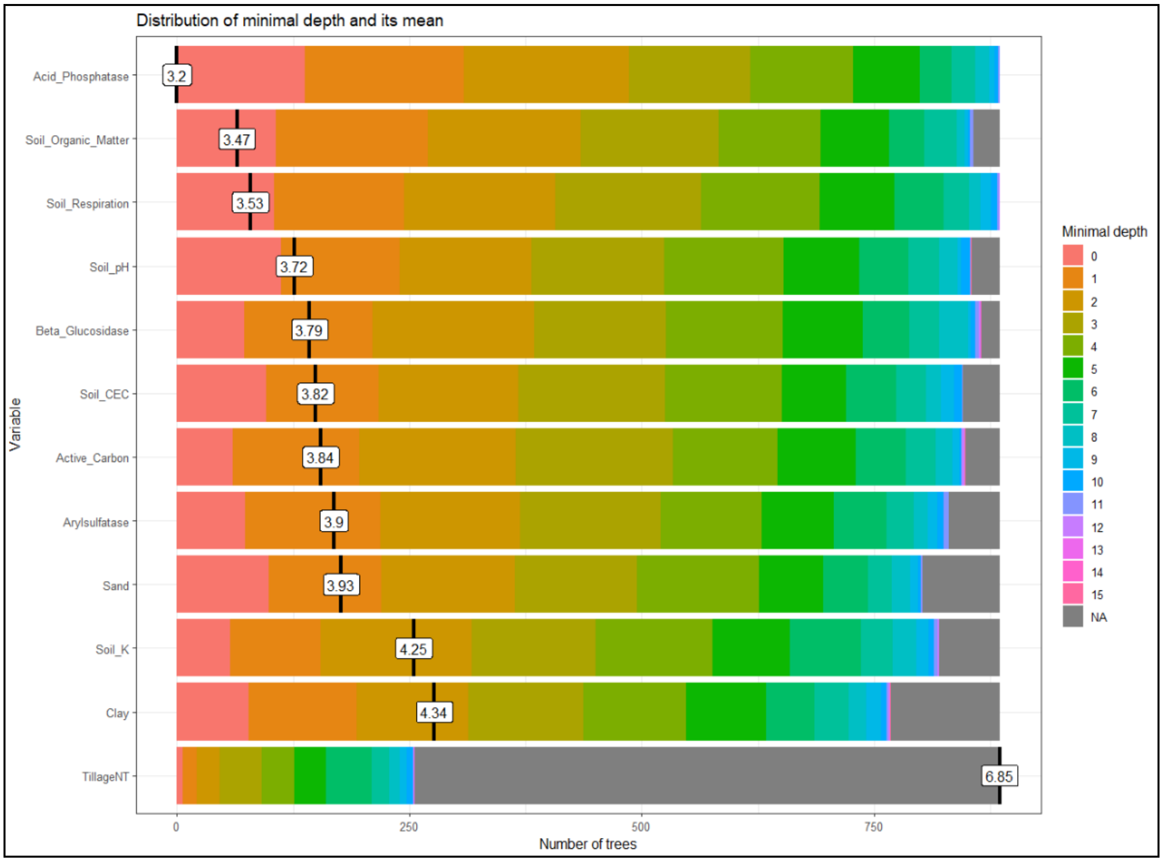

Figure 3.7. Random forest output ranking variables by the number of trees each variable is present in (n = 1000 trees) and what the mean minimum depth was in the tree. The more trees the variable was included in, the more important that variable was. A variable that had a lower mean minimum depth was closer to the root of the tree on average. The colors represent the minimum depth of that variable in each decision tree.

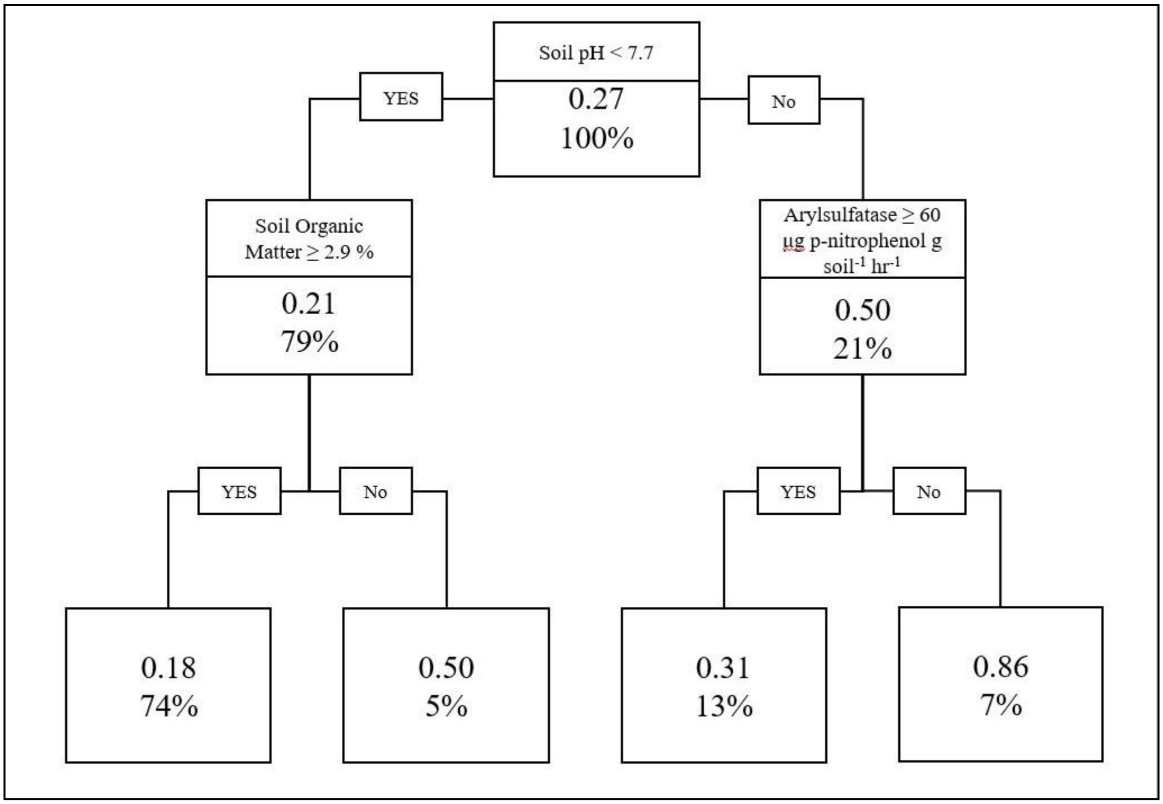

Figure 3.8. Decision tree using chosen soil parameters and their calculated critical value to predict yield responses to K fertilization. The top number in each box was the percentage of sites in that node that positively responded (RY ≥ 1.05) to K fertilization. The second number was the percentage of total stamps (n = 97) that were located within that node. The bottom number was a critical value for that variable that split the node. For example, the first node split the data using soil pH. If soil pH was below 7.7, a stamp had a 21% chance of positively responding and 79% of stamps were included in that node. If soil pH was more than 7.7, a stamp had a 50% chance of positively responding and 21% of stamps were included in that node. The bottom level adds up to 100% of all stamps.

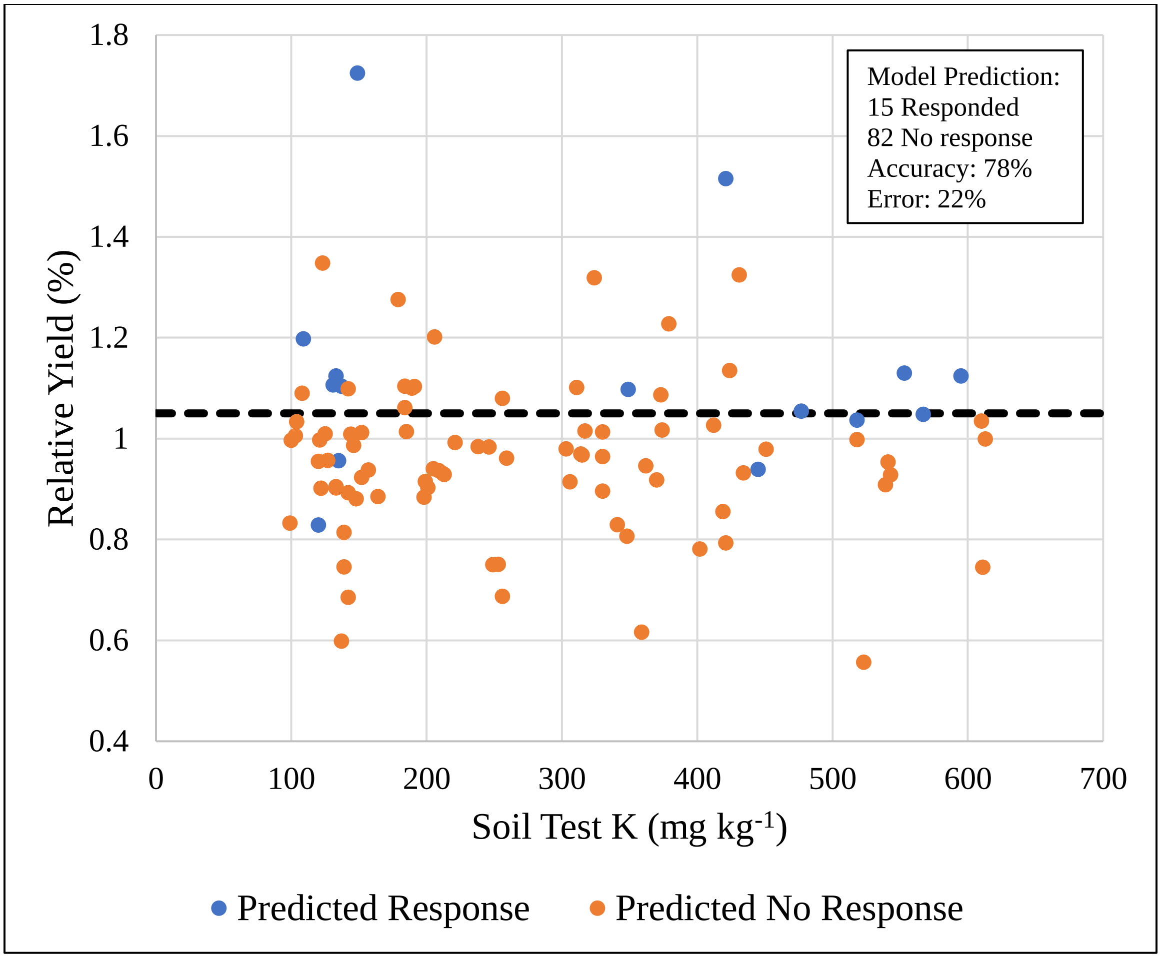

Figure 3.9. Decision tree (Figure 3.8) accuracy in determining if corn grain yield responded to K fertilization. Points in blue were predicted to respond to K fertilization while points in orange were predicted not to respond. The more predicted response points above and predicted no-response points below the response line (RY ≥ 105%), the more accurate the model was for our dataset. The accuracy is the percentage of orange points that are below and blue points that are above the black dotted line, meaning the model predicted them correctly.

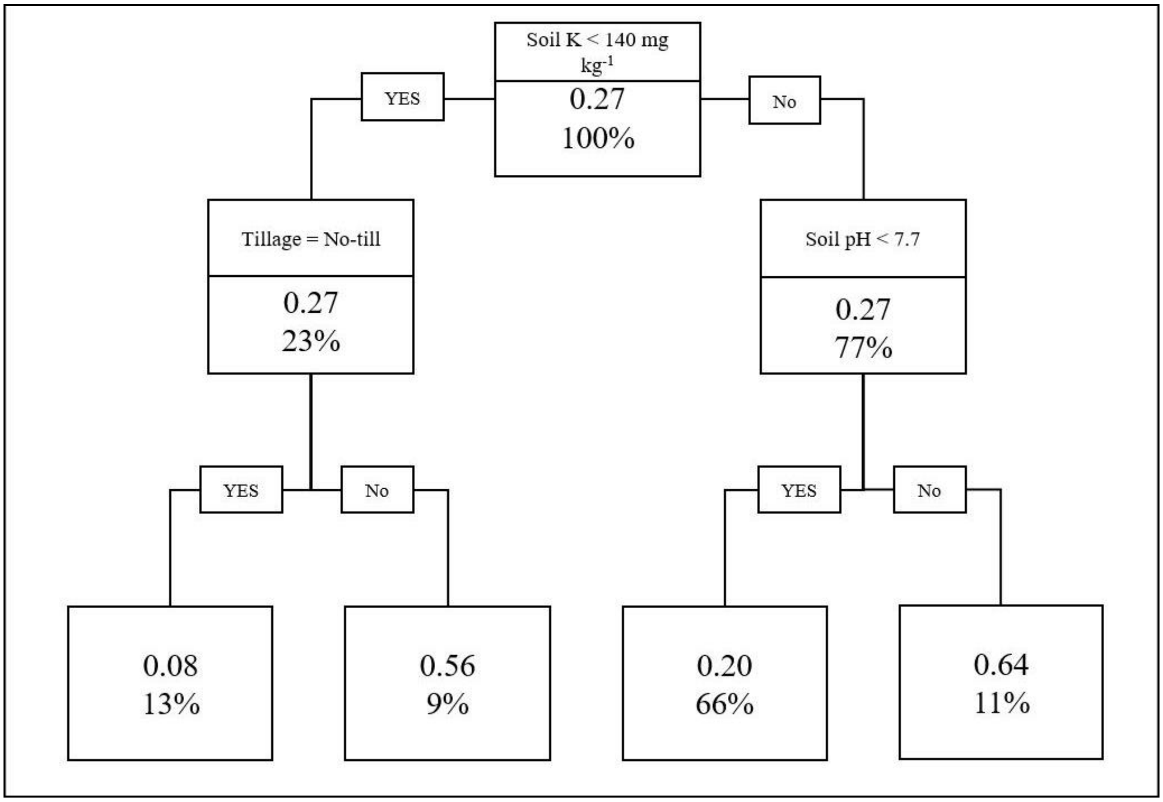

Figure 3.10. Decision tree using chosen soil parameters and their calculated critical value to predict yield response to K fertilization. The top number in each box was the percentage of sites in that node that positively responded (RY ≥ 1.05) to K fertilization. The second number was the percentage of total stamps (n = 97) that were located within that node. The bottom number was a critical value for that variable that split the node. For example, the first node split the data using soil test K. If soil test K was below 140 mg kg^{-1}, a stamp had a 27% chance of positively responding and 23% of stamps were included in that node. If soil test K was more than 140 mg kg^{-1}, a stamp had a 27% chance of positively responding and 77% of stamps were included in that node. The bottom level adds up to 100% of all stamps

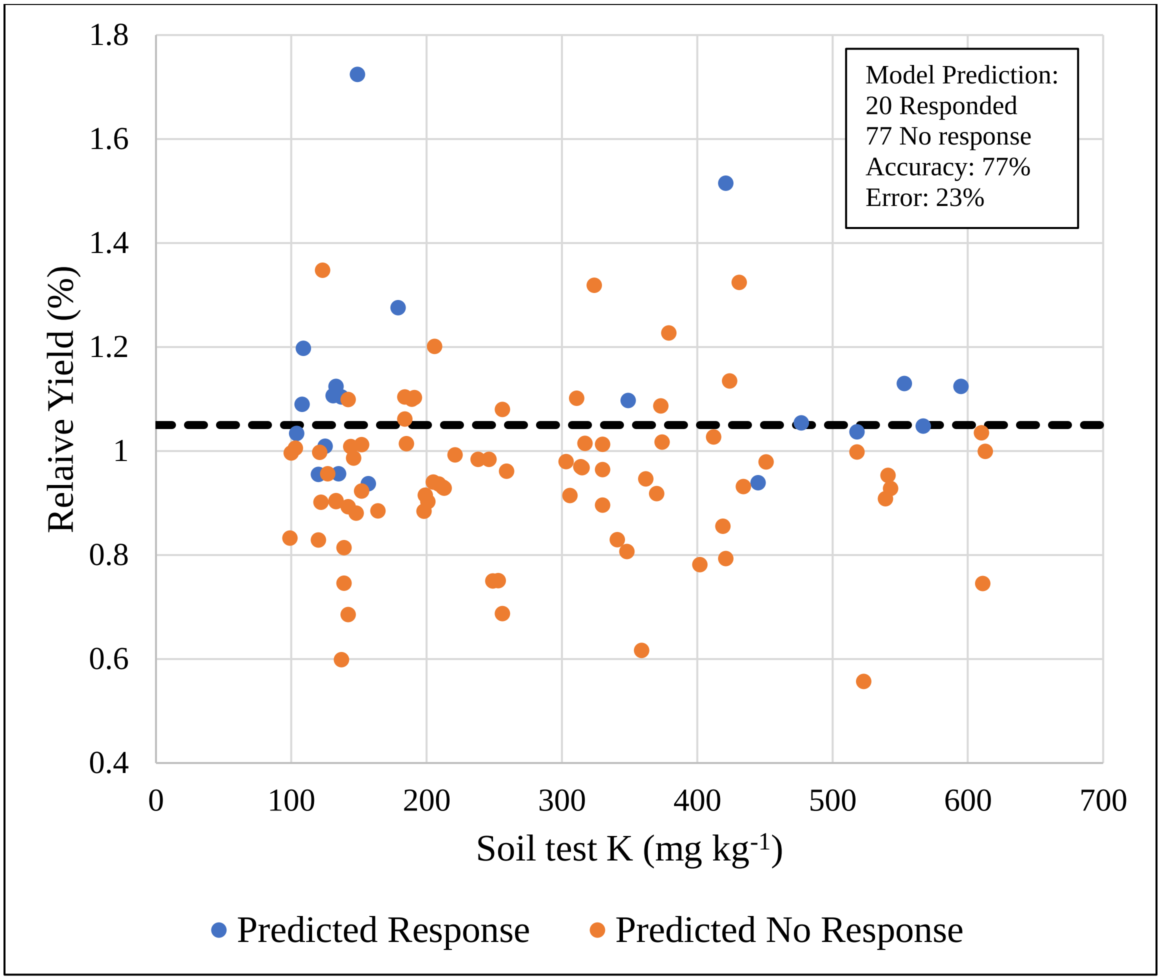

Figure 3.11. Decision tree (Figure 3.10) accuracy in determining if corn grain yield responded to K fertilization. Points in blue were predicted to respond to K fertilization while points in orange were predicted not to respond. The more predicted response points above and predicted no-response points below the response line (RY ≥ 105%), the more accurate the model was for our dataset.

CHAPTER 4: GENERAL DISCUSSION

4.1 ADVANTAGES AND LIMITATIONS

This study had many advantages compared to common fertilizer rate correlation and calibration studies. For example, many other studies are only conducted on several sites due to the number of treatments required in a correlation and calibration experimental design. Because our study only had three treatments, it was much easier to conduct this study in many areas of SD. Therefore, it took place at many different locations across central and eastern SD that had diverse soil fertility levels, soil types, and landscapes. The weather was also significantly different from year to year. For example, 2019 and 2020 were record-breaking wet years, while 2021 was one of the driest. Thus, our dataset was built using research sites that were distinct from one another, and our calculated critical value changes represent central and eastern SD.

While most other projects conduct both correlation and calibration studies simultaneously, we decided to look at only correlation for this study. One reason for this was that a calibration study may not be necessary if the determined critical values from a new study matched or were similar to the currently used critical value. Also, due to the soil health component of this study, our goal was to find sites that had a variety of soil health/fertility testing levels. Calibration studies are extensive and would have limited us to fewer sites each year than conducting a correlation study alone. Fewer sites would have reduced the range of soil testing levels we encountered and made correlating yield responses to soil health/fertility indicators more difficult. Further, findings from this study could be used to determine 1) if a calibration study is necessary and 2) what locations could be chosen for plots based on soil and climate attributes that we found to be most important.

To standardize yield across all locations, this study used relative yield calculations to better demonstrate how different yield levels are impacted by fertilizer treatments. This was necessary because yield levels change based on different areas of SD. If absolute yield was used, the higher yielding environments could have outweighed the lower-yielding areas in the model. The advantage of using relative yield means our findings can better associate to all corn-growing areas in the central and eastern part of SD. Our findings can also be correlated to what other states that conduct similar research may find.

Another advantage was the use of farmer's fields in addition to research farms. Conducting research on farmer's fields was an effective way to show that nutrient management decisions could be implemented by farmers, and fertilization wasn't always necessary to achieve the highest yields. For example, our study found that K applications did not improve yields when STK was considered high (120-160 mg kg^{-1}) even though current recommendations would have recommended K application. Farmers who have applied K fertilizer for years may now question whether K application is necessary and profitable at these soil test levels. Questions raised by farmers are important to break common misconceptions in agriculture. On-farm testing can be a useful tool to raise awareness to farmers that the way things have always been done is not necessarily the best.

The research we conducted may lead to management practice changes that can improve the soil health of many fields in SD. For example, our results indicate a correlation between soil respiration and yield responses to P fertilization; as soil respiration increased, yield responses to P fertilizer decreased. Long-term tillage and cover-cropping studies generally demonstrate increased soil respiration and organic matter. This indicates that switching to reduced tillage or planting cover crops may reduce P fertilization and save money for farmers. Insufficient K soils also rarely responded to K fertilizer in no-till fields, indicating farmers who switch to no-till may be able to reduce K fertilization rates. Therefore, switching to no-till may lead to reductions in both P and K fertilization in some situations. Future P and K correlation and calibration research could focus on management practices such as tillage, cover cropping, or crop rotations. If more research similar to ours would show direct economic benefits of improving soil health, more farmers may adopt conservation management practices.

While this study had many advantages, there were also limitations. Due to the nature of the experimental design, there was no replication during the first year of this study. Replication was not done during the first year because we wanted to maximize the number of different locations that we tested the treatments on. This idea was abandoned because of the Covid-19 pandemic and limited personnel which made driving long distances and conducting field operations at multiple locations difficult. In 2020 and 2021, this study was included in an RCBD with other studies which then resulted in replication at each location. However, replication was not considered in this study as each replication was treated as its own location during data analysis. The goal was not to compare correlations between soil test levels and yield responses in a single field but across all of central and eastern SD.

Another limiting feature is that soil health tests are constantly being modified and updated. Therefore, the tests we used may become outdated. However, continued research in the soil testing field will increase the likelihood of developing tests that better correlate to certain soil functions and processes. Even simple soil measurements such as STP have a variety of tests that can be used to determine P in the soil. This is further compounded by the inconsistent soil sampling depths that are used by researchers. Soil health measurements are also complicated by large changes based on sampling time, soil moisture, and soil temperature. While a soil testing lab may use the same method as other labs, uniform conditions cannot be guaranteed (e.g., time, room temperature, moisture). A standardization of soil testing depth, timing, and procedure once samples are taken could improve the accuracy of soil health tests, and findings could be better cross validated between studies.

This leads into another limitation of sampling time. Samples for this study were taken to see how soil health measurements can impact yield responses to fertilizer. To obtain this information, samples had to be taken before fertilizer was applied. However, more soil samples taken during periods after fertilization could be used to understand how fertilization impacts soil health measurements. While that was not an objective for this study, it would have opened the door for future research on how soil health is impacted by fertilization. For example, this study found that soil respiration can be used to better predict a yield response to P fertilization. Perhaps a farmer who had high soil respiration would proceed to withhold P fertilizer for several years. What if this absence of P fertilization reduced soil respiration levels and, consequently, resulted in the need for P fertilizer to improve yields? While we considered how soil health impacts yield responses to fertilization, I believe fertilization's impact on soil health measurements is also an important area of study.

Another limitation was the lack of low STK locations. To accurately develop response curves for yield as a function of STK, low testing sites are required. Although sites were found that had STK values below the current critical value (160 mg kg^{-1}), the lowest experimental area had a STK of 99 mg kg^{-1}, which is considered "medium" in the current recommendations. This caused problems for linear plateau and Cate-Nelson modeling functions because no STK levels were found where yield was consistently raised with K application. If lower testing sites were found and yielded positively to K fertilizer, then the models could better predict a critical value.

Lastly, this study did not follow the "limiting nutrient" approach to fertilization. This approach hypothesizes that yield is limited by the nutrient that is in the shortest supply to the plant. By using that approach, we could hypothesize that when yield was increased, it was because the treatment we used was the most limiting to the control, and when yield was decreased, it was because a different nutrient was more limiting than the nutrient we applied. While that method would explain why an experimental area would respond to fertilization at low STP or STK levels, it would not explain why yields were sometimes raised even when STP or STK were evidently abundant in the soil. I would hypothesize that most locations where yield negatively responded were not caused by the application of the nutrient itself, but by an external factor such as spatial yield variability or other limiting, nonmobile nutrients in the soil.

4.2 OVERALL CONCLUSIONS

This study examined the current fertilizer recommendations for P and K in SD to determine if 1) the current critical value was accurate and 2) if other variables could be used to improve the accuracy of predictions of yield responses to fertilizer. For P, soil respiration could improve the accuracy of the fertilizer recommendation, similar to what some have found with N. This verifies the relationship between biological activity and availability of P to plants. I hypothesize that many of the same soil processes that release considerable amounts of N into the soil, such as SOM mineralization, also release P. Therefore, soil biological health measurements should be considered to improve P fertilizer management.

Management practices that improve soil biological health should also be considered for research into P and K availability. Many studies have been conducted that correlate soil health measurements to different management practices such as tillage, cover cropping, and crop rotations. Future research should consider the variables we considered to be the most important to yield responses to fertilization and link them to management practices and yield responses. Perhaps adoption of cover cropping, which largely improves soil biological health and SOM contents, can lead to the reduction in reliance on inorganic P fertilizers. Maybe switching to no-till can increase K availability by holding more water and lead to decrease K fertilizer rates. Studies that can demonstrate economic advantages by switching to conservation management could increase the adoption of these practices.

For K, the relationship between yield responses and ammonium acetate STK were minimal. This study indicated that either 1) the critical value needs to be lowered or 2) there are other factors impacting yield responses to K fertilization more than STK. Random Forest and decision trees indicated that K is affected by soil physical and chemical processes (pH and tillage) much more than biological. However, both SOM and arylsulfatase were used in one of the decision trees for K indicating they likely play some role in K availability to plants. The relationship between pH and yield response to K was interesting because yield increasingly responded to K fertilization as pH rose, which is the opposite of literature that says K availability increases as pH increases. Perhaps K is in competition with other cations at high pH levels and plants struggle to uptake enough.

This study provided evidence that soil physical, chemical, and biological indicators play a role in grain yield responses to both P and K fertilization. Research correlating the indicators this study identified as the most important to yield responses would be the next natural step in determining if they should be incorporated into the recommendations. If calibration studies could determine and quantify the impact of these indicators while improving accuracy over STK alone, then they could be incorporated into fertilizer recommendations. This would help farmers better understand when to apply fertilizer and could reduce fertilizer costs and improve yields.

This study exposed me to a wide variety of misconceptions about agriculture that I may not have otherwise understood. For example, management practices such as no-till that I had only assumed were for erosion reduction also have many other benefits. Cover cropping, which I assumed stole water and nutrients from crops, also improves the cycling of nutrients within the soil. The overall importance of soil processes on the growth and development of corn was not well understood by me until I saw how corn yields reacted to different soil conditions used in our study. I also didn’t realize the wide range of benefits that can come from improving soil health such as carbon sequestration and nutrient retention. The ideas I learned from taking part in this study will help in my career as I hope to try to bring conservation management practices and sustainable agriculture to places that do not think they need it.