Variable-rate applications of soil-applied herbicides in corn and grain sorghum

by

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B.S., Kansas State University, 2015

A THESIS

submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

Department of Agronomy
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2018

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Abstract

Field experiments were conducted in 2016 and 2017 across nine locations in Kansas to develop and evaluate a procedure for variable-rate applications (VRA) of soil-applied herbicides in corn and grain sorghum based on soil properties. Soil electrical conductivity (EC) and soil organic matter (SOM) data were collected at each location using a Veris MSP3. Soil EC was correlated to soil texture and herbicide algorithms were developed for two different tank-mixes for corn and for grain sorghum. Three algorithms were evaluated in the field for each tank-mix based only on SOM (alg-SOM), SOM and soil texture (alg-SOMtex), or a flat rate based on the average soil properties for the entire field. Rates for each tank-mix were based on the maximum usage rate (MUR) allowed. When soil variability across a field was adequate, VRA based on algorithms were effective at five of the nine locations. Across these five locations, alg-SOM resulted in the same or better weed control at 8 weeks after treatment (WAT) compared to the flat rate and reduced herbicide use by 12% for both tank-mixes in grain sorghum. Using alg-SOMtex reduced herbicide use by 24% in grain sorghum, but had less weed control at several locations compared to the flat rate. VRA was practical at Morganville, KS in 2017. Both alg-SOM and alg-SOMtex increased the amount of herbicide applied compared to the flat rate, but alg-SOMtex resulted in greater Palmer amaranth control (92%) compared to the flat rate (71%). Separate greenhouse and field experiments were conducted in 2017 to evaluate the activity of soil-applied herbicides on controlling HPPD-inhibitor resistant Palmer amaranth populations. A dose-response greenhouse experiment of soil-applied mesotrione and isoxaflutole was performed using resistant (Stafford County) and susceptible (Riley County) Palmer amaranth populations. Reduced susceptibility was observed with resistant-to-susceptible ratios being 7.2 for mesotrione and 4.1 for isoxaflutole. Field experiments were conducted at two locations in KS with one field having HPPD-resistant (Barton County) and the other HPPD-susceptible (Reno County) Palmer amaranth populations. Treatments were three HPPD-inhibiting herbicides [mesotrione (¼X, ½X, and 1X = 210 g ha^{-1}), isoxaflutole (½X and 1X = 105 g ha^{-1}), and bicyclopyrone (1X = 50 g ha^{-1} and 2X in formulated tank-mix with bromoxynil at 700 and 1400 g ha^{-1})] in comparison to other soil-applied herbicides commonly used for Palmer amaranth control. HPPD-inhibitor treatments were applied alone and tank-mixed with atrazine (2240 g ha^{-1}). Overall, control of Palmer amaranth was reduced for HPPD-resistant compared to -susceptible populations. All treatments of mesotrione and isoxaflutole at 4 WAT resulted in 81 to 99% control in Reno County, but only 55 to 89% control in Barton County. For mesotrione and isoxaflutole treatments across both sites, Palmer amaranth control at 4 WAT was greater when 1X was applied (89%) compared to 0.5X (81%). Tank-mixing atrazine with mesotrione and isoxaflutole increased Palmer amaranth control from 82 to 88%. Soil-applied HPPD-inhibitors were most effective when applied at field usage rate in combination with atrazine for both populations. When using soil-applied HPPD-inhibitors, management recommendations should be the same regardless of Palmer amaranth population.

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Acknowledgements

I have greatly enjoyed my time at Kansas State University and owe my gratitude for all the people that have made this such a positive experience. Through teamwork and collaboration, I have learned a tremendous amount allowing me to grow as an agronomist and a researcher. It is through the countless hours of working with students, professors, and other professionals that have allowed me to be the person I am today.

At the end of the day, it is the people that matter most and will continue to positively influence me through the rest of my agricultural career. I would first like to thank my major professor, Dr. Anita Dille for providing the opportunity to continue in graduate school and creating my desire to learn about weed science. Her ability to challenge me and allow me to share my research through professional meetings has pushed me to develop connections that I will never forget. I would also like to thank Dr. Ray Asebedo for providing his precision agriculture expertise. Without the guidance on collecting and processing the data, I would have never gained the knowledge necessary to make my research happen. I would also like to thank Dr. Dallas Peterson for all of his advice and challenging my technical knowledge. Thank you to Dr. Kevin Donnelly and Dr. Colby Moorberg for allowing me teach at Kansas State University.

I also extend a special thanks to Dr. Curtis Thompson, Cathy Minihan, Dr. Mithila Jugulam, and all the other members of the weed science staff at K-State for the advice and for teaching me how to do weeds research. I am also thankful for Dr. Gary Cramer, Russell Dille, Dr. Eric Adee, Tyler Lund, Rita Stolz, and Walter Lenhart for allowing me to use their land and resources to complete my project. Thank you to Peter Bergkamp, Dakota Came, Junjun Ou, Keren Duersken, Trent Frye, Jace Bowan, Jeffery Albers, and Nate Thompson for helping with data collection and processing. Finally, a special thanks to Marshall Hay for all his guidance throughout my personal life and graduate school and for inspiring me to be a better agronomist.

Most importantly, I have to thank my family and friends for all the support. My parents, Ron and Teresa, to whom my dissertation is dedicated for all the things they have provided in my life. Without them, none of this would have been possible. From a young age, I was always taught the importance of good worth ethic and to always have confidence in my abilities. Lastly, my loving girlfriend Erin, who always had faith in me, and was always willing to help regardless of the circumstance. It is truly a blessing to have such wonderful people in my life. I am truly blessed and look forward to making many more memories with all of you.

Thank you

Chapter 1 - Literature Review

Impact of Weeds

To maximize the full potential of a crop and produce enough food to feed an exponentially growing population, producers must control pests. One of the most important pests that must be controlled are weeds. Weeds have been present since the beginning of time as God cursed the ground and promised the first man thorns and thistles (Genesis 3:18, New International Version). Weeds virtually exist in almost all fields due to their ability to persist and spread rapidly. Weeds compete against crops for light, water, and nutrients making management vital to prevent crop quality and yield loss. In Canada and the United States, it is estimated that 50% of corn and 52% soybean production would be lost to weeds if not controlled, costing approximately $43 billion annually (Soltani et al. 2016, 2017). The impact of weeds should not be overlooked and the future of sustainable agriculture across all crops relies on effective weed management systems (Mortensen et al. 2012).

Weeds must be managed to minimize the impact on crop yields. Palmer amaranth (*Amaranthus palmeri* S. Wats.), a common weed in Kansas and the most troublesome weed in the United States, can greatly reduce yields if not controlled (Van Wychen 2016). In grain sorghum, yields were reduced by 69% with dense populations of Palmer amaranth (Graham et al. 1988). In another study it was estimated that the range of grain sorghum yield loss due to weeds is between 30 and 50% but can be greater in extreme cases (Stahlman and Wicks 2000). Corn yield losses due to Palmer amaranth range from 11 to 91% when weed density was 0.5 to 8.0 plants m^{-2} of crop row (Massinga et al. 2001). Corn yield losses ranged from 11 to 74% due to competition of a related pigweed species, common waterhemp (*Amaranthus rudis* Sauer) (Steckel and Sprague 2004). In these studies the weed density was a major factor, but another critical factor was the relative emergence timing. The competitive success of a weed is highly dependent on the time of germination in addition to the density and relative growth rate of the plant (Radosevich et al. 2007). Massinga et al. (2001) determined that emergence timing had a larger impact than the weed density on corn yield when dealing with Palmer amaranth. Weeds that emerged at time of planting caused 90% yield loss at high densities compared to 48% when the weeds emerged later after the crop was established (Massinga et al. 2001). Regardless of the weed species and crop that is being impacted, weeds that emerge with the crop will have the largest impact on yield (Hall et al. 1992; Knezevic et al. 1994; Massinga et al. 2001; Steckel and Sprague 2004).

The critical period for weed control is the time during the crops development cycle where weeds must be controlled to prevent yield loss (Nieto et al. 1968). In many cases, the critical period of weed control starts with early season weed pressure, especially with highly competitive weeds, as they can be extremely detrimental to yield loss. Hall et al. (1992) found that the critical weed control period in corn starts as soon as the V3 development stage and ended at V14. In a similar study, corn yield was reduced by weeds between emergence until the weed reached a height of 15 cm (Carey and Kells 1995). Common waterhemp reduced corn yield by 50% before the V6 stage in corn and the critical weed-free period was between V4 and V10 (Steckel and Sprague 2004). In grain sorghum a similar trend was observed with yield loss beginning two weeks after planting. Yield losses were 2, 5, 16, 24, 38, and 55% when weeds were removed 2, 3, 4, 5, 6, and 8 weeks after planting (Burnside and Wicks 1967). With limited postemergence (POST) options for weed control in grain sorghum, early weed control must be achieved with a preemergence (PRE) residual herbicide. In addition to causing yield loss, lack of early-season weed control can cause future problems such as weed seed production and harvest difficulties.

Steckel and Sprague (2004) reported that common waterhemp seed production and biomass were greatest for weeds that emerged at the same time as the crop, compared to later. If the early emerging weeds were not controlled, they would have the ability to produce a large amount of seed and increase the population in future years. When Palmer amaranth emerged with corn, the early-season weeds produced between 140,000 and 514,000 seeds m^{-2} compared to the weed that emerged four weeks later that only produced between 1,800 and 91,000 seeds m^{-2} (Massinga et al. 2001). As producers try to control weeds, early season weed control practices such as using a soil-applied herbicide must be implemented.

Herbicide Weed Control Tactics

Currently, herbicides are the major pesticide input in agriculture and are an integral part of crop production. In 2016, 97% of all land area planted to corn in the U.S. was treated with herbicide and this was consistent for many other crops (USDA-NASS 2016). In 2011, 86% of land planted to grain sorghum had herbicide applied (USDA-NASS 2011). Herbicide is vital to the success of farming, but must be carefully utilized to minimize potential risks. More recently, herbicide dependence has led to and will continue to lead to the evolution and spread of herbicide-resistant weeds. Globally, there are 487 unique cases of herbicide resistance across 253 species (Heap 2018). There are 26 unique cases of herbicide resistance spanning across 6 herbicide sites of action in Kansas alone (Heap 2018).

With the increase in herbicide-resistant weed species that have extended emergence patterns, producers are being encouraged to use soil-applied herbicides with residual activity (Norsworthy et al. 2012). According to the 2017 Kansas Corn Management guide, preemergence (PRE) herbicide applications are essential to use for controlling resistant weeds before and as they emerge (Ciampitti 2017). Thompson (2014) reported that PRE herbicides are the only way to manage grasses and are the most effective control method for broadleaves in grain sorghum. Soil-applied herbicides have also been documented to control many herbicide-resistant populations of multiple species and in several cases control herbicide-resistant weeds of the same site of action. (Hausman et al. 2013, Shoup and Al-Khatib 2004, Thompson 2014). Producers have noticed the benefit of PRE herbicides and the adoption of these herbicides has increased. Kohrt and Sprague (2017) reported that 10 different soil-applied herbicides provided 89 to 98% control 72 days after planting (DAP) of a multiple herbicide-resistant population of Palmer amaranth. In another study, it was reported that soil-applied herbicides were effective at controlling herbicide-resistant weed species and reduce the risk of selecting for new herbicide-resistant weed species (Johnson et al. 2012). Atrazine, acetochlor, and s-metolachlor and they were applied to 78, 26, and 38% of all corn acres, respectively in Kansas in 2016 (USDA-NASS 2016). The percentage of acres receiving residual herbicides was much greater in grain sorghum due to limited POST herbicide options. Atrazine, dimethenamid-P, s-metolachlor, and saflufenacil were applied to 81, 20, 50, and 7% of grain sorghum acres in Kansas, respectively (USDA-NASS 2011). Regardless of the intended crop, producers will continue to be encouraged to use soil-applied herbicides in their management system to manage weed species, but this will result in increasing the environmental load of soil-applied herbicides.

Soil-Applied HPPD-Inhibitor Herbicides

More recently, 4-hydroxyphenylpyruvate dioxygenase (HPPD) inhibitors have gained popularity and are extensively used for weed control in both PRE and POST applications (Bollman et al. 2008, Mitchell et al. 2001). Mesotrione and isoxaflutole are two of the most used HPPD-inhibitors due to wide spectrum of weed control, specifically *Amaranthus* spp. and the flexibility in herbicide application timing (Bollman et al. 2008, Luscombe and Pallett 1996, Mitchell et al. 2001). Sutton et al. (2002) reported that HPPD-inhibitor herbicides are highly effective at controlling photosystem II inhibitors (PSII) and acetolactate synthase (ALS) resistant weeds. HPPD-inhibitor herbicides provided 80 to 100% control of Palmer amaranth when applied PRE in Kansas and Missouri (Johnson et al. 2012). Synergism has also been documented when mixing HPPD-inhibitor herbicides with PSII inhibitors from both PRE and POST applications for controlling herbicide-resistant weeds and specifically controlling HPPD-inhibitor resistant weeds (Armel et al. 2005, Hugie et al. 2008, Jhala et al. 2014, Thompson 2014, Walsh et al. 2012). In Stafford County, KS, Palmer amaranth was first documented and confirmed to be resistant to foliar-applied HPPD-inhibitors in 2012 (Thompson et al. 2012). This population is also resistant to ALS and PSII inhibiting herbicides. An additional HPPD-inhibitor resistant Palmer amaranth population was also documented in Nebraska (Sandell et al. 2012). Several populations of HPPD-inhibitor resistant waterhemp populations have also been documented in Illinois and Iowa (Hausman et al. 2011, McMullan and Green 2011). Foliar applications of HPPD-inhibitors were providing poor control of HPPD-inhibitor resistant species, but PRE applications were still providing adequate control at high rates (Thompson 2014). Many growers are using soil-applied HPPD-inhibitor herbicides for resistant weed management and with new HPPD-inhibitor tolerant traits in soybeans, the number of acres treated with HPPD-inhibitor herbicides will likely increase.

Soil and Herbicide Interactions

The efficacy of soil-applied herbicides is impacted by many factors including herbicide properties and formulation, herbicide rate, application technique, climate conditions, and soil properties (Leistra and Green 1990). Herbicide formulations and application techniques can be adjusted, but the soil properties and climate conditions cannot, thus creating complexity of efficacy dealing with soil-applied herbicides. Regardless, having an understanding of the interaction between specific herbicides and these factors is important to predicting herbicide effectiveness and avoiding non-target effects on crops and the environment. Duration of control is important for overall weed control effectiveness and is based on persistence of the herbicide in the soil (Buchanan and Hiltbold 1973). Herbicides that persist too long can have adverse effects on sequential crops given a specific field condition, whereas herbicides that degrade quickly are not effective for extended weed control (Curran 2016, Fink and Fletchall 1969, Peterson and Arnold 1985). For many herbicides, the relationships between specific soil properties and herbicide bioavailability are understood and have been utilized for creating herbicide labels to help producers develop their weed control strategy.

The rate of an individual soil-applied herbicide required to achieve adequate control of weed species is often related to the capacity of a specific soil to adsorb the herbicide (Peter and Weber 1985). Adsorption is the surface process in soil where a dissolved substance (herbicide) is accumulated at highly reactive solid interfaces (soil surface) and is the most important physical-chemical process for retaining substances in the soil environment (Essington 2015). Herbicide adsorption can be due to the charge unbalance between herbicide and soil binding sites, influencing the environmental fate of a herbicide, activity for plant uptake, persistence in the soil, and potential for leaching (Hartlzer 2013, Laabs and Amelung 2005, Zemolin et al. 2014). Many nonionic herbicides can also be adsorbed through Van der Waals forces, ligand exchange, covalent bonding, and other complexes (Berry and Boyd 1985, Dec and Bollag 1997, Zemolin et al. 2014). Researchers have developed analysis techniques and different coefficients to measure the amount of herbicide that is adsorbed on a particular soil (Weber et al. 2000). Adsorption is measured by soil water-herbicide partitioning coefficient (K_d) as the amount of herbicide sorbed by the soil and can be calculated by taking the difference of the total initial herbicide concentration and the herbicide concentration in the soil solution after equilibration. To account for the impact of soil organic carbon (SOC), the organic carbon partition coefficient (K_{oc}) is calculated by dividing the K_d by the fraction of organic carbon (f_{oc}) to give a more useful value to understand herbicide sorption (Weber et al. 2000). The average K_{oc} for several commonly applied herbicides are 100, 125, and 200 for atrazine, dimethenamid-P, and s-metolachlor, respectively (Shaner 2014). Measuring the soil-sorption coefficients allows for comparisons of different herbicides and gives a predictor of how each compound will behave in the soil. As herbicides become adsorbed to soil particles they become less available and are less effective for weed control, but also are less likely to leach into groundwater. Many studies have been established to understand the specific herbicide behavior across diverse soil properties proving that herbicide sorption decreases the potential for off target movement (Blumhorst et al. 1990; Weber et al. 2004; Westra et al. 2014).

Once applied to the soil, adsorption strongly influences the amount of herbicide that is active in the soil for plant uptake and weed control. Adsorption for a particular herbicide is driven by many soil factors including soil organic matter (SOM), soil texture, electrical conductivity (EC), soil pH, CEC, and soil water content (Blackshaw et al. 1994, Desutter et al. 2003, Kerr et al. 2004, Williams et al. 2002).

SOM is generally considered the most important soil property impacting herbicide adsorption. Westra et al. (2014) reported that dimethenamid-P, pyroxasulfone, and s-metolachlor adsorption were highly correlated to SOM (R^2>0.89). In another study, SOM affected saflufenacil adsorption and phytotoxicity of canola (Gannon et al. 2014). Weber et al. (2004) discovered that sorption of both weak acid and weak base herbicides were strongly related to

SOM and that the sorption of all herbicides tested were correlated with SOM. Across these three studies, herbicide bioavailability decreased with increasing SOM. Atrazine and other triazine herbicides showed the same inverse relationship between bioavailability and increasing SOM, and SOM was directly correlated with atrazine adsorption (R^2=0.94) (Rahman and Matthews 1979). S-metolachlor sorption was strongly correlated to SOM with greater amounts of SOM leading to more herbicide in solution (Gannon et al. 2013). An increase in SOM increased isoxaflutole sorption and was directly correlated (R^2=0.99) (Mitra et al. 1999). As SOM increases, higher rates of many soil-applied herbicides are required for acceptable weed control (Blackshaw et al. 1998; Blumhorst et al. 1990).

Soil texture and particle size can also play a role in herbicide adsorption. The sorption coefficient for dimethenamid-P, pyroxasulfone, and s-metolachlor all resulted in significant correlations to sand and silt percentage (Westra et al. 2015). Clay content was found to have a direct correlation with sorption coefficient for four herbicide families (Weber et al. 2004). In a similar study, atrazine sorption was directly correlated to clay content and had a large effect on herbicide sorption (Desutter et al. 2003). Adsorption of metolachlor in the Ap horizon of a silt loam soil proved to have a significant correlation to clay content, but not as highly correlated as SOM (Wood et al. 1987).

For many herbicides, the soil pH has a direct impact on herbicide adsorption. Adsorption of atrazine, a weak-base herbicide, increases in soils with low pH as the herbicide becomes cationic (McGlamery and Slife 1966). In high pH conditions, atrazine has a neutral charge, decreasing the amount of binding to soil particles. Mesotrione, a weak-acid herbicide, becomes less adsorbed as pH increases due to chemical dissociation of mesotrione to an anion with a lower potential for adsorption (Dyson et al. 2002). However, for several, common soil-applied herbicides such as s-metolachlor and dimethenamid-P, pH had no influence on adsorption (Westra et al. 2015). EC and CEC are in many cases highly correlated with other soil properties, but have an influence on herbicide adsorption. EC has been correlated with adsorption (R^2 = 0.86), and was a significant soil factor in determining adsorption of diuron (Mustafa and Gamar 1972). Weber and Peter (1982) reported herbicide adsorption was positively correlated with CEC with an $R^2 = 0.84$. The CEC proved to be an important factor in herbicide adsorption in soils with low SOM (Mustafa and Gamar 1972). Herbicide adsorption and activity is influenced by soil moisture as efficacy of many soil-applied herbicides decreases as soil becomes dry. Moyer (1987) reported decreased herbicide uptake by plants in dry conditions due to increased adsorption and decreased mobility of herbicide in the soil. Metribuzin control of downy brome was reduced when soil became moderately dry due to increased adsorption (Blackshaw et al. 1994). The influence of many soil properties on adsorption and activity of many soil-applied herbicides have been widely studied, creating an opportunity for site specific management in fields with soil variability.

Site Specific Weed Management

Integrated weed management (IWM) is a key approach for effectively controlling weeds, while minimizing dependence and other economic losses associated with the use of herbicides (Shaw 1982; Swanton et al. 1991). IWM involves many different weed control techniques including cultural, mechanical, biological, and chemical methods. In many cases, precision agriculture is not considered a management tool to be utilized in an IWM system, but impacts multiple tools. The use of precision agriculture is not a new idea and has been utilized since the early 1990's. Until more recently, precision technologies were not directly being used for weed control, but rather to increase efficiency of weed control strategies. With the introduction of new variable rate sprayer technologies (VRT), site-specific weed management (SSWM) became an IWM component focused on reducing herbicide inputs by targeting herbicide only where weeds were present.

Early SSWM research was predominately based on the fact that weeds are spatially distributed in patches and that most farmers and consultants are aware of areas of the field with persistent weed problems (Cardina et al. 1995; Dieleman and Mortensen 1999; Johnson et al. 1996). Based on this principle, it was theorized that herbicide should only be applied where weeds were predicted to cause economic loss and that reduced rates could be applied in areas of low density populations (Dieleman et al. 1996; Gerhards et al. 1997). The use of reduced herbicide rates can be effective, but one study showed that reduced applications of dicamba and imazethapyr increased the amount of seed production of surviving plants (Bussan et al. 2001). This could be even more detrimental with weeds species like Palmer amaranth that produces a greater amount of seed (Bussan et al. 2001). Registered rates of herbicides are set to provide high mortality of given weed species across a range of environments. Low rates of postemergence herbicides also allow survivors to possess minor resistance traits leading to rapid herbicide resistance evolution (Manalil et al. 2011).SSWM applications based on weeds already growing in a field or spatial patterns are very difficult to do on a large scale, due to intensive sampling required.

Another approach to SSWM is from a PRE application dealing with maximizing herbicide efficacy of soil-applied herbicides. Many soil-applied herbicide labels have various application rates based on soil properties, specifically SOM and soil texture (Anonymous 2016; 2017). As SOM increases and texture becomes finer, higher rates of the herbicide need to be applied. In fields with soil variability, the chances of off-labeled applications are likely to happen, increasing the likelihood of crop injury, poor weed control, carryover, and environmental impacts. Utilizing SSWM into the soil-applied application system will minimize undesired outcomes, but requires fine and accurate datasets of the soil properties within a field.

Soil Sensing

In order for successful implementation of precision agriculture technologies, real-time sensing systems are needed to capture useable field data. Understanding within-field variability allows producers to make better decisions on a much more detailed basis, potentially reducing input costs and maximizing yields (Lund et al. 1999). Traditional soil sampling and grid sampling techniques have been limited by cost of implementation and labor increasing the usefulness for on-the-go sensors (Bianchini and Mallarino 2002; Lauzon et al. 2005). In addition, obtaining more points of data by using a sensor has proven advantageous for spatial accuracy even if individual sampling point accuracy is lower (Sudduth et al. 1997). Efficient methods of measuring soil properties on-the-go have been developed utilizing sensors that collect dense datasets while traveling across a field. In agriculture, the main soil properties that impact management discussions include but are not limited to: soil organic matter (SOM), soil electrical conductivity (EC), pH, soil texture, cation exchange capacity (CEC), and salinity.

Soil EC has become a commonly used method to measure soil variability across a field to create management zones and assist in many agronomic practices. The soil profile EC sensor-based measurements also provide an indirect relationship with many physical and chemical soil properties. Some of these properties include: clay content, CEC, soil salinity, soil moisture, clay minerology, and SOM (Rhoades et al. 1976; Sudduth et al. 2005). Measuring EC for determining soil texture is based on the established principle that smaller soil particles such as clay conduct greater current than that of coarse sand particles (Friedman 2005, Lund et al. 1999, Williams and

Hoey 1987). Across the United States, EC measurements have been collected from many different regions and soil types with the purpose of establishing a relationship between EC and soil properties. Across 12 fields in six different states, EC had the strongest correlation with clay content and CEC ($r^2 > 0.55$) (Sudduth et al. 2005). In a similar study, shallow EC measurements were highly correlated with clay content and soil texture from depths between 0 and 25 cm ($r^2 = 0.71$) (Doolittle and Indorante 2002). Shallow EC provide useful information in determining clay content and extractable calcium content in the U.S. Southern High Plains, particularly when additional spatial data about soil types is included (Bronson et al. 2005). The correlations with many other soil properties (sand, soil moisture, organic C) were much more variable across multiple fields (Sudduth et al. 2005). By having such a strong relationship with clay content, EC values can be generalized into soil texture classes for a given field based on calibrated soil samples.

SOM is another important soil property related to crop growth and is necessary for many site-specific management practices. SOM impacts many properties in the soil and is a major component in soil structure, nutrient availability, water holding capacity, and overall soil health (Bot and Benites 2005). In addition, SOM has a positive impact on the productivity of crops grown in the Great Plains (Bauer and Black 1994). By having an accurate SOM map, growers can be aided in management strategies, including nitrogen applications, seed populations, and soil-applied herbicides (Kweon et al. 2013). Soil color is many times an evident way of estimating SOM and was able to accurately estimate the SOM content of silt loam soils in Indiana (Steinhardt and Franzmeier 1979). In most cases, darker colored soils contain more SOM compared to light colored soils. This relationship is based on the fact that the amount of SOM affects the quantity of light reflectance (Shonk et al. 1991).

While changes can be detected visually, using multispectral sensors using both visible and near-infrared (VIS-NIR) bandwidths can provide a much more accurate quantitative value of SOM. Initially, spectroscopy was highly correlated to SOM in the laboratory setting specifically using the VIS-NIR range (Hummel, J.W. Sudduth; K.A. Hollinger 2001; Stoner and Baumgardner 1981). Shonk et al. (1991) found high correlations for soils with SOM ranging 1 to 6% using red LED (660 nm). Other lab studies utilizing various band combinations to establish correlation and calibration techniques, found that wavelengths from 1640 to 2640 nm proved to be effective at estimating SOM ($R^2 = 0.89$) (Sudduth and Hummel 1993). Based on several calibration methods and data recorded in the lab, researchers have developed the potential for on-the-go sensing to predict SOM in the field (Adamchuk et al. 2004; Christy 2008; Shonk et al. 1991; Sudduth and Hummel 1993). Sudduth and Hummel (1993) reported that a mechanical sensor was more effective at predicting CEC compared to highly variable organic carbon data. An initial field test across six fields in Indiana using a single wave sensor apparatus, concluded that red light was highly effective at predicting SOM ($R^2 > 0.83$) (Shonk et al. 1991). A study in Kansas, using a sapphire window sensor mounted to the bottom of a shank, provided acceptable real-time measurements of predicted SOM ($R^2 = 0.67$). This sensor has been redefined since, increasing the accuracy of the device. In several cases, the sensor correlation was extremely accurate at predicting SOM based on lab measured calibration cores ($R^2=0.95$) (Kweon 2012). On-the-go sensors have more recently become available and have been proven to provide the ability to predict SOM.

Veris technologies have recently developed a commercially available soil optical sensor (OpticMapper™) that collects measurements in the red and near-infrared wavelengths through a window that is pressed against the soil (Lund and Maxton 2011). This optical module is mounted between two discs to cut through the soil to allow for consistent pressure and self-cleaning of the sensor. Gauge wheels surround the discs to ensure uniform depth of reflectance measurements. This multi-sensor system also includes several pairs of coulters to inject current through the soil to measure voltage change for EC data. This soil sensor has been tested across many soils, including one study on 551 ha on 15 fields in six different states. The SOM calibration results were accurate on 12 of the 15 fields with a R^2 of 0.80 or higher. For the EC data, there was a strong correlation in six of the nine fields with a R^2 of 0.86 or higher (Kweon et al. 2013). Accurate soil maps are available to many producers, increasing the potential for SSWM.

Variable-Rate Applications

Precision agriculture and more specifically variable rate applications (VRA) have been utilized for several decades. A common type of VRT system that is available, utilizes pulse width modulation (PWM) to change application volume. PMW uses solenoid values to open and close for a given time (duty cycle) to automatically adjust flow based on the sprayer controller (GopalaPillai et al. 1999). Direct injection sprayers are also available changing the chemical concentration based on the intended flow rate for the application (Qiu et al. 1998). From a herbicide perspective, VRT research has been predominately focused on the applications before the crop has emerged with the idea of only spraying areas of the fields with weeds. These on-the-go weed detection systems and patch spraying techniques reduced herbicide by approximately 30-50% (Dammer 2016; Gerhards et al. 1997; Thorp and Tian 2004). Weed-sensing spaying systems have worked best in the fallow systems before crop emergence and after crop harvest, but have sometimes missed detecting small weeds in high residue areas increasing the chance for a follow-up application (Ahrens 1994; Blackshaw et al. 1998). Tank-mixes consisting of both contact and systemic herbicides are effective to decrease the selection pressure leading to herbicide resistance, but diminish the ability for variable rate herbicide. The other area of variable rate herbicide applications is from the PRE applications timing standpoint, but follows the same concept. Currently, VRA can be implemented with many available sprayers on the market regardless of application timing.

Integrated Approaches

For VRA applications of soil-applied herbicides to be effective in the field, accurate soil sensing, proper herbicide algorithms, and advanced sprayer technology must be integrated together. The current combination of automatic tractor guidance and VRT well suits producers for site-specific preemergence applications. Weber et al. (1987) developed equations for of soil-applied herbicides to determine optimal application rate based on the SOM to ensure greater that 80% weed control. Herbicide labels also included guideline equations directed for precise applications directly related to both soil texture and SOM content (Anonymous 2004). Little research has been documented for VRA of soil-applied herbicides in regards to feasibility and weed control. However, researchers have found herbicide sorption to be spatially variable within a field due to the strong correlation with SOM and clay content (Price et al. 2009, Wood et al. 1987). Other research directed towards environmental quality proved that atrazine sorption is spatially variable and allows for the prediction of soils vulnerable to leaching (Novak et al. 1997). Relationship in the field between atrazine K_d and EC and f_{oc} and EC have been strongly correlated and can be variable within a field (Jaynes et al. 1995). Based on this information, Jaynes et al. (1995) concluded that the leaching potential of atrazine could be predicted by an EC map. In a similar study, soil EC was strongly correlated to f_{oc} which was correlated to K_d for metolachlor and metribuzin (Shaner et al. 2008). Both of these studies highlight the potential of using EC maps to predict the sorption and availability of soil-applied herbicides. By having such maps (EC and SOM), there is great potential for developing VRA maps to be more efficient with soil-applied herbicides. The implementation of VRA of soil-applied herbicide has proven to be effective on 10 ha lettuce fields. Nolte (2011) concluded that VRA of soil-applied herbicide increased the number of lettuce heads harvested by 40% all while applying 35% less herbicide compared to conventional herbicide applications. In addition, there were no differences in weed control. The potential benefits of the integration of site-specific herbicide management into large scale farms are vast, including reduced herbicide load on environment, reduced crop injury, better weed control, and lower cost (Nordmeyer 2015).

Conclusion

In Kansas alone, there were approximately 2.1 million corn hectares and 1.1 million grain sorghum hectares planted in 2017 (NASS, 2017). With significant land area having the potential to be impacted by weeds, changes in management can have substantial environment and economic effects. In addition, producers have realized the importance of sustainability and protecting soils for the future leading to the adoption of no-tillage. Adoption of no-tillage has been very rapid increasing from 45 million ha in 1999 to 111 million ha in 2009 (Derpsch et al. 2010) eliminating tillage control tactics for controlling weeds and increasing the amount of herbicide applied. As the use of soil-applied, PRE applications continue to be an effective and popular way of controlling weeds in all systems, the herbicide load on the environment will continue to increase. Soil-applied herbicide activity is greatly impacted by SOM, soil texture, and many other soil properties that can vary greatly within one field. With the advancement of new technologies, many growers understand the soil variability for each given field, but most herbicides are applied at a uniform rate. The integration of precision agriculture tools with weed control strategies will allow herbicides to be applied more efficiently at the right rate in the right place, allowing applicators to closely follow herbicide labels and be more efficient. As a result, a procedure that utilizes VRA of soil-applied herbicides based on the underlying soil properties should be developed for better SSWM.

Research Objective

The objectives of this research were to 1) Develop and implement a SSWM system to evaluate VRA applications of soil-applied herbicides based on SOM and EC for weed control in corn and grain sorghum, 2) Evaluate the efficacy of soil-applied HPPD-inhibitor herbicides for control of HPPD-inhibitor resistant Palmer amaranth in Kansas.

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Chapter 2 - Implementation of Variable-Rate Herbicide Applications Based on Soil Physical Properties

Abstract

Soil application of herbicides for preemergence (PRE) weed control is vital for corn and grain sorghum production. The amount of herbicide bound to the soil, adsorption, strongly influences the amount active in the soil for weed control and is often correlated to soil organic matter (SOM) and soil texture. These soil factors can vary within one field, making it difficult for producers to follow label recommendations and achieve adequate weed control with a uniform rate. With precision agriculture technologies, variable rate applications (VRA) can be utilized to maximize herbicide effectiveness by applying the right rate in the right place. In 2016 and 2017, herbicide algorithms were developed for two different tank-mixes to be applied at nine locations across Kansas. A Veris MSP3 system was utilized to collect and develop interpolated maps of SOM and electrical conductivity (EC). EC values were correlated with soil texture and separated into coarse, medium, and fine-textured classification groups. Three algorithms were evaluated in the field for each tank-mix based only on SOM (alg-SOM), SOM and soil texture (alg-SOMtex), or a flat rate based on the average soil properties for the entire field. Rates for each tank-mix were based on the maximum usage rate (MUR) allowed. Morganville was the only corn location with adequate soil variability to see large differences in application rates. The amount of herbicide applied on average was higher with VRA compared to the flat rate in Morganville. Although more herbicide was used, increased weed control was achieved with alg-SOMtex (92%), compared to the flat rate (71%). For all grain sorghum locations, VRA reduced the average amount of herbicide applied compared to the flat rate. Alg-SOM achieved the same amount of weed control at 8WAT as the flat rate, even with a lower rate. Alg-SOMtex reduced

the herbicide load compared to alg-SOM at four of the five grain sorghum locations, and provided the same amount of weed control at 8WAT, except at Hutch Redd in 2016. VRA of soil-applied herbicide was able to reduce herbicide load and cost for many locations, and also increase weed control when compared to a flat rate across variable fields. Using alg-SOM would require only one soil property to be collected and was able to reduce the herbicide load without decreasing weed control across all locations.

Introduction

Corn and grain sorghum are important crops grown in Kansas and across the world. In 2017, 2.10 and 1.01 million ha of total land area was planted to corn and grain sorghum, respectively (USDA-NASS 2017). Weeds need to be controlled to minimize competition with the crop and produce a high-yielding crop. According to the Weed Science Society of America, uncontrolled weeds cost growers about $43 billion annually and reduce corn yields up to 52% (Soltani et al. 2016). PRE applications of soil-applied herbicides are vital in many crops to limit early-season weed competition and potential yield loss. In grain sorghum, PRE applications are the most effective way of controlling both grass and broadleaf weeds due to limited postemergence (POST) herbicide options (Thompson 2014). Herbicide-resistant weeds species like Palmer amaranth (*Amaranthus palmeri* S. Wats) and common waterhemp (*Amaranthus rudis* Sauer) have increased the importance of PRE herbicide applications. Soil-applied herbicides that provide residual activity are critical for controlling herbicide-resistant weeds that cause early-season yield loss due to competition (Ciampitti et al. 2018, Norsworthy et al. 2012).

Many soil-applied herbicides present their own concerns from an environmental standpoint such as carryover into future crops, loss of efficacy due to degradation, or water contamination due to leaching and runoff (Helling 2005). Producers must understand the importance of the soil interaction with these herbicides to minimize environmental impacts while sustaining weed control (Helling 1971). The activity of soil-applied herbicide is affected by many soil factors including SOM, pH, texture, and soil moisture (Blackshaw et al. 1994, Kerr et al. 2004, Nordmeyer 2015). These soil properties affect the adsorption of herbicides to the soil which determines the bioavailability of the chemical in soil solution to be absorbed for control of weeds. For most herbicides, the SOM is the most critical soil property for influencing adsorption and herbicide activity (Blumhorst et al. 1990, Mitra et al. 1999, Westra et al. 2015). As SOM increases, higher rates of many soil-applied herbicides are required for acceptable weed control (Blackshaw et al. 1998; Blumhorst et al. 1990). Weber et al. (1987) developed herbicide equations to determine the effective dose based on SOM to provide greater than 80% control to account for SOM impact on herbicide bioavailability. Soil texture and particle size also play a role in herbicide adsorption. The sorption coefficients for dimethenamid-P, pyroxasulfone, and s-metolachlor were correlated to percent sand and silt in the soil (Westra et al. 2015). Clay content was found to have a direct correlation with sorption coefficient for two herbicide families, organophosphorus and amide (Weber et al. 2004). SOM and clay content have been reported to be related to sorption of many herbicides in the soil (Peter and Weber 1985, Pusino 1992, Singh et al. 2001). Researchers have found that the adsorption of many different herbicides including atrazine, alachlor, isoxaflutole, and metolachlor, were correlated to SOM, pH, and clay content and that adsorption was spatially variable for a given field (Ghidey et al. 1997, Novak et al. 1997, Price et al. 2009, Wood et al. 1987). To account for herbicide activity based on soil, many soil-applied herbicide labels provide a specific rate based on general soil properties, creating a challenge of managing soil-applied herbicides in fields with great amount of variability. Variable-rate applications (VRA) of soil-applied herbicides has resulted in reduction of herbicide use and increased weed control when the right rate is applied based on label and effective dose needed for weed control. However, these studies of VRA consisted of only one active ingredients chosen to control a single weed species (Metcalfe et al. 2017, Qiu et al. 1998, Williams and Mortensen 2000).

To quantify the variability of herbicide adsorption across a field requires an intensive sampling plan to effectively determine soil properties. A multi-sensor platform, Veris MSP3 (Veris Technologies, Salina, KS), has been developed and allows producers to map electrical conductivity (EC) and SOM to document soil variability within a field with one efficient pass across the field (Lund et al. 1999). This on-the-go implement utilizes coulter electrodes that inject a current directly in the soil and measures the change in voltage between two coulters, and is taken across a field. Electrical conductivity can be further correlated with soil texture to map the soil texture in a given field (Lund et al. 1999). An approximate measure of SOM is based on a spectrometer that emits red and near-infrared wavelengths from a window that is pressed against the soil surface to measure reflectance. Reflectance has been widely used as a way to approximate SOM with high accuracy of correlations ($R^2 > 0.80$) with standard soil tests (Kweon 2012). By generating EC and SOM maps for individual fields, we can estimate potential for herbicides to leach or to be adsorbed across fields that are variable (Jaynes et al., 1995). Shaner et al. (2008) found significant correlations between Kd (adsorption coefficient) of metribuzin and metolachlor with fraction of organic carbon (f_{oc}) that was significantly correlated with EC as determined by a Veris sensor. It is clear that adsorption of herbicides is directly correlated to soil properties. These soil properties can be quickly measured in producer fields, creating the possibility for site specific weed management (SSWM) of soil-applied herbicides.

Precision agriculture (PA) is not a new concept and is utilized in many different ways to assist producers and to increase the possibility of VRA of soil-applied herbicides. In Kansas, approximately 86% of farmers are using at least one PA tool on their farm, with 25% of farms using VRA technology (Miller et al. 2017). In order to make accurate soil-applied herbicide prescriptions, the underlying soil variability must be understood. Spatially-dense EC and SOM maps can be developed and aid in the development of effective prescription maps for soil-applied herbicide applications. Precision agriculture technology is available for VRA of soil-applied herbicides, but a procedure needs to be developed for optimizing herbicide rate to minimize cost, increase herbicide efficacy, and decrease herbicide load. Research has shown the major impacts of soil on the efficacy and activity of soil-applied herbicides, thus emphasizing the need to take this VRA idea to the field. The objectives of this study were to 1) develop and evaluate a procedure for effective VRA of soil-applied herbicide tank-mixes based on Veris MSP3 soil data and 2) compare VRA algorithms based only on SOM and algorithms based on SOM and soil texture to a traditional flat rate in corn and grain sorghum fields across Kansas with two different soil-applied herbicide tank-mixes.

Materials and Methods

Soil Data Collection

Nine different field experiments were established in the spring of 2016 or 2017 across Kansas to develop a procedure for VRA of soil-applied herbicides based on underlying soil properties. Before planting, a Veris MSP3 soil mapper was pulled across the field on 10 m swaths to determine SOM and EC. EC data were collected at a depth of 0 to 30 cm and SOM data were collected to a depth of 5 cm. Multiple calibration samples from each location were collected to a depth of 7.6 cm on the same day as Veris mapping and samples were processed in the Kansas State University Soil Testing lab for SOM, particle size analysis, pH, and cation exchange capacity to calibrate and correlate the Veris data. The raw soil analysis were submitted to Veris® FieldFusion™ for cleaning and calibration as a producer would do. Correlations between EC values from the Veris and soil texture information from the calibration samples were examined and EC ranges were established for each field to determine soil texture. The soil textures were divided into three groups (coarse, medium, and fine) to be used in herbicide algorithms for each individual plot. Coarse soil texture included sand, loamy sand, and sandy loam, while medium soil texture included loam, silt loam, and silt, and fine soil texture included sandy clay loam, silty clay loam, clay loam, sandy clay, silty clay, and clay. The plot size at each location varied based on extent of soil variability and amount of land area available for the project.

Herbicide Applications

Two separate tank-mixes were evaluated in corn: 1) saflufenacil, dimethenamid-P, and atrazine and 2) bicyclopyrone, mesotrione, s-metolachlor, and atrazine. Two tank-mixes were also evaluated in grain sorghum: 1) saflufenacil, dimethenamid-P, and atrazine and 2) mesotrione, s-metolachlor, and atrazine. For each tank-mix there were three algorithms: 1) rate based on SOM (alg-SOM), 2) rated based on SOM and texutre (alg-SOMtex), and a flat rate (flat) to simulate a traditional recommended herbicide application. In addition to the six herbicide treatments, a non-treated check was included for a total of seven treatments. A randomized complete block design with nine replications was established at each location for a total of 63 plots. All herbicide treatments were applied with a four or six nozzle boom equipped with TeeJet (TeeJet Technologies, Springfield, IL) Air Induction Extended Range or Turbo TeeJet Air Induction 11002 nozzles. In 2016 a sprayer filled with bulk mixture of each tank-mix was attached to a JD4052r tractor with a calibrated hydrostatic transmission. For each plot, VRA was simulated by adjusting the speed to apply the specific rate. In 2017, the spray boom was attached to a JD5310 sprayer tractor and calibrated to deliver 140 L ha^{-1} at 255 kPa. Herbicide was precisely measured into individual 2 L bottles depending on rate needed for each plot.

Herbicide Algorithms

For each of the two tank-mixes, four separate second-order polynomial models with one quantitative predictor (SOM) were developed and based on the model:

$$Y = \left(\frac{(ax^2+bx+c)}{d}\right) \qquad [2.1]$$

where Y refers to the percentage of maximum use rate (MUR) of the tank-mix to apply, a, b, and c are numerical coefficients to fit the model, d is the maximum total application rate of each tank-mix, and x is percentage of SOM. Rate of individual tank-mix partners are determined by the equation:

$$\mathrm{Rate} = (\mathrm{Y} * \mathrm{MUR}) \qquad [2.2]$$

where Y is the percentage of MUR derived from the algorithm and MUR is the maximum use rate for each tank-mix active ingredient. For VRA based on alg-SOM, a single model accounted only for the SOM to determine application rate. VRA treatments based on both SOM and the soil texture, determined by the EC, utilized the specific algorithm developed for each of the soil texture classes (coarse, medium, and fine). All model parameters and MUR of each tank-mix active ingredient are summarized in Table 2.1and Table 2.2. The algorithms were developed based on herbicide labels for each individual tank-mix partner with MUR being recommended for a fine-textured soil with ≥ 3% SOM. SOM was used as the quantitative variable due to being the dominant soil property influencing herbicide adsorption and binding across many different herbicides (Westra et al. 2015; Gannon et al. 2014; Weber et al. 2000). Increasing SOM within a plot increased the herbicide rate to be applied. The higher the EC value, the finer the soil texture and a higher rate of herbicide would be applied. By using separate algorithms for both SOM and for the combination of SOM and texture, allowed for comparison to determine the more suitable soil property or properties for making VRA of soil-applied herbicides.

Data Interpolation and Processing

Calibrated data were imported into ArcMap10.5.1 (Environmental Systems Research Institute Inc., Redlands, CA) to finalize maps and create prescription maps for herbicide treatments. Interpolated maps of both SOM and EC were created using the kriging tool in the spatial analyst toolbox. A spherical semivariogram model was used within the kriging tool to provide an accurate spatial correlation. Based on the soil data, a randomized complete block design was setup with nine replications using the fishnet tool from the sampling data management toolbox in ArcMap10.5.1. Blocks were separated across the entire field area to capture needed soil variability for rate differentiation. GPS coordinates from all fishnet corners were recorded in the software and established in the field using a handheld Bad Elf GNSS Surveyor (Bad Elf, Tariffville, CT) to create a georeferenced plot layout in the field. To determine the ranges of EC values for each texture class, the georeferenced calibration samples and EC maps were overlaid and examined to match EC to texture. Ranges of EC were then used to determine the soil texture within each plot. The fishnet tool in the data management toolbox allowed for blocks to be positioned in the field with cell length and cell width being manipulated to match plot size. Plot size varied for each location to match soil variability allotted for each research field. Herbicide rates were then calculated using the raster calculator in the spatial analyst toolbox. Conditional statements were used to input all herbicide algorithms and calculate the amount of herbicide to be applied across the field. The mean function in the zonal statistic tool in the spatial analyst toolbox was used t calculate the herbicide rate to be applied in each plot designated by the fishnet. To convert the calculated rate to a more practical herbicide rate, the integer tool in the spatial analyst toolbox was used to convert each raster cell value to an integer. The treatments were randomized across all blocks and a treatment map was created. The herbicide rate was selected using the integer calculated based on the particular algorithm for the different treatments and the underlying soil properties.

Location Descriptions and Data Collection

A total of nine fields were used in this study including two corn and two grain sorghum fields in 2016 and two corn and three grain sorghum fields in 2017 across Kansas. Corn locations were in Northeast Kansas (Rossville, Topeka, and Manhattan) and North Central Kansas (Morganville). Grain sorghum sites were in Northeast Kansas (Manhattan), South Central Kansas (Hutchinson (Hutch)), and central Kansas (Salina). Location, timing of all agronomic operations, and data collection dates are summarized in Table 2.3. Field locations were in dryland or irrigated environments on both research and producer lands. Corn or grain sorghum were planted in 0.38 or 0.76 m rows at each location. Weeds that emerged before planting were controlled to ensure all plots were weed free when applying PRE. For locations in no-tillage production, single or multiple chemical burndown applications were made before planting. Locations that were in conventional tillage production were tilled, or tilled with a combination of herbicide before PRE was applied. Fertilizer was applied based on predicted yield goal for each location. Visual assessment of weed control was performed two, four, six, and eight weeks after treatment (WAT) on a scale of 0 (no control) to 100% (complete control). Crop injury was visually assessed 2 and 4 WAT on a scale of 0 (no stunting) to 100% (plant death), but minimal injury was observed across all locations, except for Manhattan in 2016. Individual weed species were harvested from a 0.25 m^2 quadrat within plots with high weed densities and were harvested from the entire plot when weed density was low. Biomass samples were bagged, dried for two weeks, and weighed. Weed density values were converted to plants m^{-2} and biomass was converted to g m^{-2}. In 2016, grain was hand harvested from 2 m of the middle two rows from a representative area within each plot when a plot combine harvester was not used. In 2017, grain was harvested from the middle two rows of the entire plot for all hand harvested locations. Grain moisture was adjusted to 15.5% for corn and 13.5% for grain sorghum and yield was converted to kg ha^{-1}.

Statistical Analysis

All data were analyzed using the GLIMMIX procedure in SAS University Edition (SAS Institute Inc., 100 SAS Campus Drive, Cary, NC) with means separated using Tukey's HSD test ($\alpha = 0.05$). Interactions of main effects of rate (three levels) and tank-mix (two levels) were not significant across all response variables, therefore rate and tank-mix were the only fixed effects considered. Significance of fixed effects across all response variables and locations are summarized in Table 2.8 and Table 2.9. Comparison of models using Akaike Information Criteria (AIC) proved that using X,Y centroid coordinates from each plot as a random effect, generated the smallest AIC by dealing with the underlying spatial covariance. AIC is commonly used for comparing covariance structures within models and the model with lowest AIC should be used (Bozdoganm 1987). Therefore a spherical covariance structure was utilized in the spatial model. Model comparison also revealed that replication and block should not be included as random effects in the statistical model because the residual from the coordinates accounted for the field variability. To better meet assumptions of variance, percent weed control values were logit transformed for all observation dates. Weed density and biomass data were subjected to square-root transformations. Back transformed data were used to present means across all data. Pearson correlation coefficients were calculated between SOM, EC, herbicide rate applied, Palmer amaranth control, Palmer amaranth biomass, and yield using PROC CORR with significance at $P \leq 0.05$ in SAS.

Results and Discussion

Tank-Mix Algorithms

Herbicide algorithms were developed to determine percentage of rate to apply based on the MUR for each tank-mix component. To account for SOM being the most dominant factor impacting herbicide adsorption and activity, both algorithms determined rate based on SOM. Many current herbicide labels recommend the MUR to be applied when soil has greater than 3% SOM, therefore rate based on both herbicide algorithms was 100% of the MUR for all soils with ≥ 3.0% SOM (Anonymous 2016a, 2017). For alg-SOMtex, soil EC data from the Veris were correlated to soil texture based on the calibration soil samples. Soil textures were divided into three broad texture classes, similar to those on many herbicide labels, to determine rate (Anonymous 2014, 2016b). Previous research on VRA of soil-applied herbicides, used several different methods of creating algorithms to determine rate based on labelled rate or effective dose for given SOM and soil texture (Khakural et al. 1994, Metcalfe et al. 2017, Qiu et al. 1998, Williams and Mortensen 2000). Changing rate based on only the label or effective dose for a given soil was shown to be effective when using a single active ingredient, but was limited in usefulness when tank-mixing multiple herbicides to control multiple weed species. Tank-mixing herbicides is vital for herbicide resistance management as using 2.5 sites of action were 83 times less likely to produce herbicide-resistant weed seed compared to using 1.5 sites of action (Evans et al. 2016, Norsworthy et al. 2012). General regression developed for alg-SOM and alg-SOMtex utilized both the labelled rates of each tank-mix components and facilitated change in herbicide effective dose based on SOM. To account for soil texture having a small impact on herbicide adsorption, three separate algorithms were developed for alg-SOMtex based on the texture class. Recommended rates of formulated tank-mixes available in many cases do not apply the MUR used in the algorithms. Producers wanting to use these algorithms on formulated tank-mixes would need to adjust accordingly based on the tank-mix components and the MUR labelled for their environment. As each tank-mix active ingredient responds differently in the soil, creating algorithms for tank-mixes was challenging and needs further research. For each location, a flat rate of each tank-mix was applied to simulate traditional application. For tank-mix 1 (saflufenacil, dimethenamid-P and atrazine), the flat rate was based on the labelled rate of saflufenacil for the average soil properties within each location. The flat rate of tank-mix 2 (bicyclopyrone, mesotrione, s-metolachlor, and atrazine) was determined by the labelled rate of mesotrione for the average soil properties within each location. Saflufenacil and mesotrione were used to determine tank-mix rate to apply as they were most apt to cause crop injury. The flat rate of tank-mix 1 applied in grain sorghum for all locations was 100% of the MUR as label indicated a single rate of saflufenacil to be applied regardless of soil properties (Anonymous 2016b). Using high rates for the flat rate in grain sorghum had a big impact on overall rate and cost of flat rate herbicide applications compared to VRA and may not be realistic rates for the grain sorghum locations in this study.

VRA in Corn

VRA of soil-applied herbicides was evaluated at two locations in corn in 2016 and two locations in 2017. Low variability of < 1.0% SOM and only small changes in soil texture were observed in Rossville, Manhattan, and Topeka, therefore VRA would not be practical (Table

2.4). Small differences in SOM and soil texture limited the variation in herbicide rate applied based on algorithms compared to the flat rate. In Morganville, greater soil variability was observed, with SOM ranging from 0.1 to 3.3% with an average of 2.1%. The EC varied from 0.8 to 76.0 mS m^{-1} and consisted of sand, loamy sand, sandy loam, sandy clay loam, and clay loam soil textures based on particle size analysis of Veris calibration samples (Table 2.6). Based on correlation between soil texture and EC, soil EC values less than 8 mS m^{-1} were considered coarse-textured, 8 to 20 mS m^{-1} were considered medium-textured, and all values greater than 20 mS m^{-1} were considered fine-textured soils (Table 2.7). Across all corn locations, adequate precipitation (> 2.5 cm) was received within one WAT for PRE activation (Table 2.10). Precipitation totals within one WAT were 3.2, 13.4, 3.3, and 2.5 cm in Rossville, Manhattan, Topeka, and Morganville, respectively. In Manhattan in 2016, heavy rainfall (13.4 cm) during one day caused severe soil erosion, decreasing the seed depth and in severely eroded areas exposing the seed to the soil surface and causing herbicide injury. Seasonal rainfall most likely did not impact overall weed control across corn locations. Weed species and weed densities were variable across the four corn locations in 2016 and 2017. In Rossville in 2016, populations of Palmer amaranth and ivyleaf morningglory (*Ipomoea hederacea* Jacq.) emerged throughout the growing season with average densities of 5 and 9 plants m^{-2}, respectively. In Morganville in 2017, Palmer amaranth populations in non-treated plots ranged from 2 to 6 plants m^{-2}. No weeds emerged in Manhattan in 2016 and in Topeka in 2017, therefore weed data were not collected. Corn injury was minimal at all locations except for Manhattan in 2016. At 2 WAT, corn injury was severe (52 to 86%), but there were no differences between algorithms (Table 2.14). By 4 WAT, corn injury decreased to less than 25%, and algorithm had no impact. All algorithms resulted in the same corn yield for each location (Table 2.13 and Table 2.16).

Significance of fixed effects revealed no interaction between algorithm and tank-mix across all response variables for corn locations; therefore fixed effects were analyzed separately (Table 2.8). In Rossville in 2016, all algorithms provided the same amount of Palmer amaranth control at 4 and 8 WAT with all applications resulting in greater than 97 and 83%, respectively (Table 2.13). Average Palmer amaranth density (1.4 plants m^{-2}) and biomass (21.6 g m^{-2}) were also the same for all algorithms. Algorithms provided greater than 95% ivyleaf morningglory control at 4 WAT. By 8 WAT, overall ivyleaf morningglory control was reduced (≤ 60%), but all algorithms provided the same level of control. Variable and poor ivyleaf morningglory control at later observation times has been reported with PRE applications of soil-applied herbicides (Bhullar et al. 2012, Bollman et al. 2006, Johnson et al. 2012). Ivyleaf morningglory density was the same for all algorithms, with an average of 1.6 plants m^{-2} (Table 2.13). Ivyleaf morningglory biomass was greater for alg-SOM (13.4 g m^{-2}) compared to the flat rate (1.5 g m^{-2}). Alg-SOMtex had the same biomass (8.2 g m^{-2}) compared to alg-SOM and was not different than the flat rate. No differences in Palmer amaranth and ivyleaf morningglory control and density based on algorithm in Rossville was most likely due to small variations in herbicide rate applied due to lack of soil variability. For tank-mix 1, the average rates applied were 70, 65, and 67% of the MUR for alg-SOM, alg-SOMtex, and the flat rate, respectively (Table 2.11). The rates for tank-mix 2 were 71 and 61% of the maximum for alg-SOM and alg-SOMtex, respectively and 64% for the flat rate. Although the same level of weed control was achieved for both algorithms compared to the flat rate, VRA at this Rossville location would not be practical due to little soil variability.

In Morganville in 2017, all algorithms provide effective control (≥ 97%) of Palmer amaranth at 4 WAT (Table 2.16). Alg-SOMtex provided greater Palmer amaranth control (92%)

at 8WAT compared to the flat rate (71%). Alg-SOM provided the same amount of Palmer amaranth control (87%) compared to alg-SOMtex (92%), but did not result in increased weed control compared to the flat rate (71%). Remaining Palmer amaranth density (1.2 plants m^{-2}) and biomass (8.6 g m^{-2}) were the same for all algorithms at 8 WAT. The differences in weed control between flat rate and alg-SOM was most likely due to the differences in average herbicide rate applied (Table 2.11). The flat rate was 67 and 64% of MUR for tank-mix 1 and 2, respectively, and this accounted for the fact that a large part of the field consisted of coarse-texture soil and low SOM levels. The average rate applied for tank-mix 1 with alg-SOM (81% of the MUR) and alg-SOMtex (76% of the MUR) were both greater than the flat rate applied. For tank-mix 2, average rates of 85 and 76% of the MUR were applied with alg-SOM and alg-SOMtex, respectively. Although greater herbicide was applied on average with VRA algorithms, large variations of herbicide rates were applied with alg-SOM, ranging from 50 to 100% of the MUR, and alg-SOMtex ranging from 39 to 100%, accounting for soil variability. The increased amount of herbicide applied with VRA based on alg-SOMtex resulted in a greater level of Palmer amaranth control at 8 WAT compared to the flat rate.

Reduction of weed control with flat rate applications was most likely in areas of the field with fine-textured soils with > 2.5% SOM where greater amounts of adsorption of herbicides in both tank-mixes decreased available herbicide for weed control. Adsorption of many soil-applied herbicides increases as SOM increases, requiring more herbicide to be applied to achieve effective weed control in these areas of the field, explaining weed control reduction when using the lower, flat rate (Bauer and Black 1994, Blumhorst et al. 1990, Nordmeyer 2015, Shaner et al. 2006, Weber et al. 1987, Westra et al. 2015). VRA using alg-SOM and alg-SOMtex accounted for the increased adsorption in the areas by using more herbicide compared to the flat rate.

Lower rates of herbicide applied with alg-SOM and alg-SOMtex compared to the flat rate likely resulted in the same weed control in areas of low SOM areas and coarse-textured soil as herbicide dose required for effective weed control is lower due to less herbicide adsorption. Zhang et al. (2009) reported that higher weed control was maintained in coarse-textured soils compared to fine-textured soils, suggesting lower rates of herbicide could be used in coarse-textured soils compared to fine-textured soils. Many tank-mixes that include atrazine are not labelled in coarse-textured soils and VRA algorithms developed in this study would allow to more closely follow herbicide labels with decreased rates in these areas compared to the flat rate. VRA based on alg-SOM and alg-SOMtex provided the same or better weed control compared to the flat rate and should be implemented in fields with high amounts of soil variability, similar to Morganville, to maximize weed control in areas of high SOM and fine-textured soil, and minimize environmental impacts in areas with low SOM and coarse-textured soil.

In Rossville, tank-mix 1 (saflufenacil, dimethenamid-P, and atrazine) and tank-mix 2 (bicyclopyrone, mesotrione, s-metolachlor, and atrazine) resulted in the same amount of Palmer amaranth control at 4 (≥ 98%) and 8 WAT (89%), density (1.4 plants m^{-2}), biomass (21.5 g m^{-2}), and corn yield (10,180 kg ha^{-1}) (Table 2.13). In Morganville in 2017, both tank-mixes provided the same amount of Palmer amaranth control at 4 WAT (> 90%), but tank-mix 2 resulted in a greater level of weed control (93%) compared to tank-mix 1 (73%) at 8 WAT (Table 2.16). Reduction in weed control most likely decreased the amount of corn yield for tank-mix 1 (8,450 kg ha^{-1}) compared to tank-mix 2 (10,110 kg ha^{-1}). In Manhattan, the corn injury level was greater for tank-mix 1 (74%) compared to tank-mix 2 (34%) (Table 2.14). The early season injury impacted the final corn yield, with tank-mix 1 averaging 8,820 kg ha^{-1} and tank-mix 2 averaging

10,020 kg ha^{-1}. PPO-inhibitor herbicide injury has been documented in other research, but differ from these results as plots with corn injury did result in yield reduction (Soltani et al. 2009).

VRA in Grain Sorghum

VRA of soil-applied herbicides were evaluated in grain sorghum at two locations in 2016 (Salina and Hutch Redd) and at three locations in 2017 (Hutch pivot, Hutch Redd, and Manhattan). Four out of the five locations (Salina, Hutch Redd in 2016, Hutch Redd in 2017, and Hutch pivot) had > 1.5% variation in SOM with all locations consisting of multiple soil texture classes, providing adequate locations for implementing and evaluating VRA (Table 2.4). The Hutch pivot had the most variability with SOM ranging from 0.4 to 3.0% and consisted of both coarse- and medium-textured soils (Table 2.5). In Manhattan, the SOM was >3.0% for most of the field, therefore the MUR of each tank-mix should be applied and VRA would not be practical. In 2016, Salina received limited precipitation in the early part of the growing season with only 1.1 cm of rainfall by one WAT and no rainfall during the second WAT (Table 2.10). The herbicide was likely not activated during the time of first weed emergence flushes. Hutch Redd in 2016 received a rainfall event of 8.0 cm within one WAT, activating the herbicide. The heavy rainfall also resulted in several areas of the field being flooded for several days reducing grain sorghum stand. Plots with reduced grain sorghum stands were not included in the data analysis. In 2017, all grain sorghum sites received low amounts of rainfall throughout the first WAT. Both Hutch locations received 0.7 cm and Manhattan received no rainfall. Through three WAT, the Hutch pivot, Hutch Redd, and Manhattan locations received 1.7, 1.7, 0.7 cm of rainfall, most likely impacting the amount of herbicide in soil solution (Table 2.10). At the Hutch pivot, sprinkler irrigation was utilized to deliver an additional 2.0 cm of water across all plots.

Low amounts of rainfall in 2017 may have influenced weed control for PRE applications, but erratic precipitation is not uncommon for environments where grain sorghum is planted.

All grain sorghum locations had populations of weeds to assess herbicide efficacy, except for Manhattan in 2017. At Hutch Redd in 2016, populations of Palmer amaranth and large crabgrass (*Digitaria sanguinalis (L.)* Scop.*)* at densities of 23 and 10 plants m^{-2} respectively were observed in the nontreated plots. At Hutch Redd in 2017, populations of Palmer amaranth and large crabgrass were present at densities of 8 and 22 plants m^{-2}, respectively. Reduction in Palmer amaranth density in 2017 compared to 2016 was most likely due to limited rainfall to promote weed germination, combined with increased large crabgrass pressure due to the earlier planting date. At the Salina location in 2016 and Hutch Pivot location in 2017, Palmer amaranth was the only weed species that emerged. An average of 10 plants m^{-2} was observed in Salina, and 13 plants m^{-2} at the Hutch pivot at 8 WAT.

In Salina in 2016, all algorithms provided the same amount of Palmer amaranth control at 4 (≥ 97%) and 8 WAT (≥ 92%) (Table 2.15). At Hutch Redd in 2016, alg-SOM resulted in the same level of Palmer amaranth control (82%) compared to the flat rate (87%) at 4 WAT. Alg-SOMtex provided the same amount of Palmer amaranth control (78%) as alg-SOM, but resulted in lower weed control compared to the flat rate. At 8WAT, overall Palmer amaranth control was greatly reduced (≤ 30%), but alg-SOM provided the same amount of control compared to the flat rate. Alg-SOMtex resulted in less Palmer amaranth control (8%) compared to the flat rate (30%). All algorithms provided the same level of large crabgrass control at 4 WAT (≥ 87%). By 8 WAT, alg-SOM resulted in the same level of large crabgrass control (72%) compared to the flat rate (80%), while alg-SOMtex provided less large crabgrass control (59%) compared to the flat rate. Similar results were observed at the Hutch pivot with alg-SOM and the flat rate resulting in the same level of Palmer amaranth control of ≥ 85% (Table 2.17). Alg-SOMtex resulted in 84% control of Palmer amaranth which was not different compared to alg-SOM, but provided less control compared to the flat rate. By 8 WAT, all algorithms resulted in ≥ 80% Palmer amaranth control. Although there were no differences in weed control at 8 WAT, Palmer amaranth densities were highest for both alg-SOM and alg-SOMtex with 1.2 plants m^{-2} compared to the flat rate with 0.4 plants m^{-2} by 8 WAT. Palmer amaranth biomass was the same for all algorithms regardless of differences in density. At Hutch Redd in 2017, greater Palmer amaranth and large crabgrass control was observed at 4 and 8 WAT compared to 2016. Increased weed control with PRE applications was most likely due to earlier planting date and lack of early season Palmer amaranth competition. All algorithms provided > 88% control of Palmer amaranth at 4 WAT and > 89% control at 8 WAT. Similarly, density and biomass were the same for all algorithms with an average of 0.6 plants m^{-2} and 3.5 g m^{-2}, respectively. Large crabgrass control at 4WAT, was greatest with the flat rate (93%) compared to alg-SOM (80%) and alg-SOMtex (83%). However, by 8 WAT all algorithms resulted in ≥ 81% large crabgrass control. For all grain sorghum sites, alg-SOM resulted in the same level of weed control compared to the flat rate. By 8 WAT, alg-SOMtex resulted in the same level of weed control at all sites except for Hutch Redd in 2016.

Although weed control was the same, VRA decreased the amount of herbicide applied at all locations that had soil variability suited for VRA (Table 2.12). Across these four locations (Salina, Hutch Redd in 2016 and 2017, and Hutch Pivot), the rate of tank-mix 1 was reduced by 19% on average when alg-SOM was used compared to the flat rate. For tank-mix 2, herbicide was reduced by 10% compared to the flat rate. Alg-SOMtex reduced herbicide rate more than alg-SOM at all sites except for Salina in 2016. Reduction in herbicide rate applied for tank-mix 1 and 2 compared to the flat rate were 30 and 18%, respectively. At the Hutch pivot in 2017, where the greatest soil variability was observed, herbicide reduction was greatest across both tank-mixes for alg-SOM (24%) and alg-SOMtex (34%). In a similar study, isoxaflutole rate was reduced by up to 47% compared to a flat rate when site-specific applications were utilized, with rate being determined by effective dose based on soil organic carbon (OC) and soil texture (Williams and Mortensen 2000). Across all grain sorghum locations, grain sorghum yield was the same for all algorithms. Compared to the corn locations, greater weed populations and adequate soil variability allowed VRA of soil-applied herbicides to be evaluated for weed control. Locations of Salina, Hutch Redd in 2016 and 2017, and Hutch Pivot had high SOM and soil texture variability, and proved VRA can be effective for decreasing amount of herbicide while still obtaining the same level of weed control compared to traditional flat rate.

At Hutch Redd in 2016, tank-mix 2 (mesotrione, S-metolachlor, and atrazine) resulted in greater Palmer amaranth control at 4 WAT (87%) compared to tank-mix 1 (saflufenacil, dimethenamid-P, and atrazine) (77%) (Table 2.15). Similarly at 8 WAT, tank-mix 2 provided a greater level of weed control with 31% compared to 10% with tank-mix 1. In 2017 at Hutch Redd, similar results were observed with tank-mix 2 providing 94% control of Palmer amaranth compared to 88% control with tank-mix 1 at 4 WAT (Table 2.17). Palmer amaranth densities were also lower for tank-mix 2 (9.9 plants m^{-2}) compared to tank-mix 1 (15.4 plants m^{-2}) Tank-mix 2 also provided a greater level of large crabgrass control (90%) compared to tank-mix 1 (81%) at 4 WAT. Similarity, large crabgrass biomass was greater for tank-mix 1 compared to tank-mix 2 with 12.3 and 3.4 g m^{-2}, respectively.

Economic Comparison

Comparison of costs between algorithms was analyzed based on tank-mix price provided by average retail prices in Kansas. Cost for soil mapping and other requirements needed for VRA were not included in cost comparison. Average, minimum, and maximum herbicide costs were determined based on application rates across plots for each treatment at all locations (Table 2.18 and Table 2.19). Herbicide cost was greater for VRA compared to flat rate treatments at all corn locations, except for Manhattan in 2016. In Morganville, herbicide cost was increased compared to the flat rate for both tank-mixes by an average of \$24.80 ha^{-1} for alg-SOM and \$14.80 ha^{-1} for alg-SOMtex (Table 2.18). The increased cost was critical to improve Palmer amaranth control with alg-SOMtex compared to the flat rate. Although herbicide cost on average for VRA was higher than the flat rate, VRA decreased cost by an average of \$26.60 ha^{-1} based on the minimum rate applied for both tank-mixes in areas of the field where less herbicide was needed for weed control. Across all grain sorghum locations, the average cost ha^{-1} decreased when using VRA of tank-mix 1 compared to the flat rate (Table 2.19). For Salina in 2016, Hutch Redd in 2016 and 2017, and Hutch pivot in 2017, the average reduction in cost was \$20.40 and \$31.50 ha^{-1} for alg-SOM and alg-SOMtex, respectively. At the Hutch pivot in 2017, where soil variability was the greatest, VRA reduced the cost by up to \$69.90 ha^{-1} with alg-SOMtex compared to the flat rate. Reduction in cost was similar for tank-mix 2, except for Manhattan in 2017 where cost was greater on average for VRA compared to the flat rate. Across the other four locations, alg-SOM and alg-SOMtex reduced the average herbicide cost compared to the flat rate by \$10.80 and \$19.40 ha^{-1}, respectively. At the Hutch pivot, herbicide cost compared to the flat rate cost was reduced by \$25.80 ha^{-1} on average for both algorithms and reduced herbicide by up to \$56.50 ha^{-1}. By using VRA, cost was reduced in many cases due to reduction in herbicide rate applied. For most locations, reduction in cost did not have an impact on weed control or corn or grain sorghum yield harvested and similar reductions in herbicide cost would be expected on producer fields with variability.

VRA Algorithm Comparison

Based on SOM and soil texture data, collected and mapped using Veris MSP3, VRA was practical at six of the nine locations tested in the study. When comparing both VRA algorithms, alg-SOMtex decreased the herbicide load in many locations compared to alg-SOM, but often resulted in reduced weed control. Alg-SOMtex would require more data to be collected and would be impractical when EC and soil texture were not strongly correlated based on calibration samples. Using EC to predict soil texture to make herbicide recommendations could potentially be a limitation as EC is influenced by other factors such as soil salinity, CEC, soil moisture, bulk density, and SOM in addition to soil texture (Corwin and Lesch 2003, McNeill 1992, Rhoades et al. 1999). Additionally, in all locations where weeds were present, SOM was positively correlated with EC indicating that only one soil property would be necessary (Table 2.20). Across all grain sorghum and corn locations, alg-SOM resulted in the same or better weed control at 4 and 8 WAT compared to the flat rate, with the exception of large crabgrass at Hutch Redd in 2017. In cases of high soil variation like at the Hutch pivot in 2017, alg-SOM reduced the herbicide used by 24% on average for both tank-mixes compared to the flat rate and resulted in the same level of Palmer amaranth control. Similar results were observed at the Hutch Redd site in 2017, with alg-SOM reducing herbicide applied by 19 and 13% for tank-mix 1 and 2, respectively. Reduced herbicide load with alg-SOM would greatly reduce the cost for producers and reduce the chance of environmental impact compared to the flat rate. In Morganville in 2017, application rates on average were higher for alg-SOM (81 % of MUR) compared to the flat rate (67% of MUR), but alg-SOM provided greater control of Palmer amaranth compared to the flat rate. In locations with adequate variability for VRA, alg-SOM increased weed control in corn and decreased herbicide load and cost in grain sorghum compared to the flat rate, highlighting the need for site-specific weed management of soil-applied herbicides. SOM was the main influencer of soil-applied herbicide efficacy, and alg-SOM would provide the most practical algorithm to determine rates for VRA of soil-applied tank-mixes for producers.

Practical Implications and Conclusion

Traditionally, producers use a flat rate of soil-applied herbicide across an entire field based on many different factors, including herbicide cost, weed infestation, and average soil properties. As the soil impacts the efficacy of soil-applied herbicides, producers must understand the variability within a field. In fields with varying soil properties like SOM and soil texture, the Veris MSP3 provided an easy and effective way to map SOM and determine soil texture based on EC to make VRA of soil-applied herbicides. Algorithms developed in this study, provided an easy way to adjust herbicide rate based on soil properties and more closely follow herbicide labels. VRA based on algorithms proved to increase weed control, decrease the herbicide load on the environment, and decrease cost across several locations used in this experiment. Alg-SOMtex reduced the amount of herbicide applied on average compared to alg-SOM, but many times weed control was reduced when compared to a flat rate. Alg-SOM resulted in the same or better weed control than alg-SOMtex and provided a more balanced approach between herbicide rates and weed control. With potential regulations around many soil-applied herbicides, VRA may provide a solution and reduce the risk of environmental problems while maintaining high levels of early-season weed control. Producers that want to utilize VRA could create SOM maps using Veris MSP3 and use alg-SOM to effectively apply tank-mixes of soil-applied herbicides.

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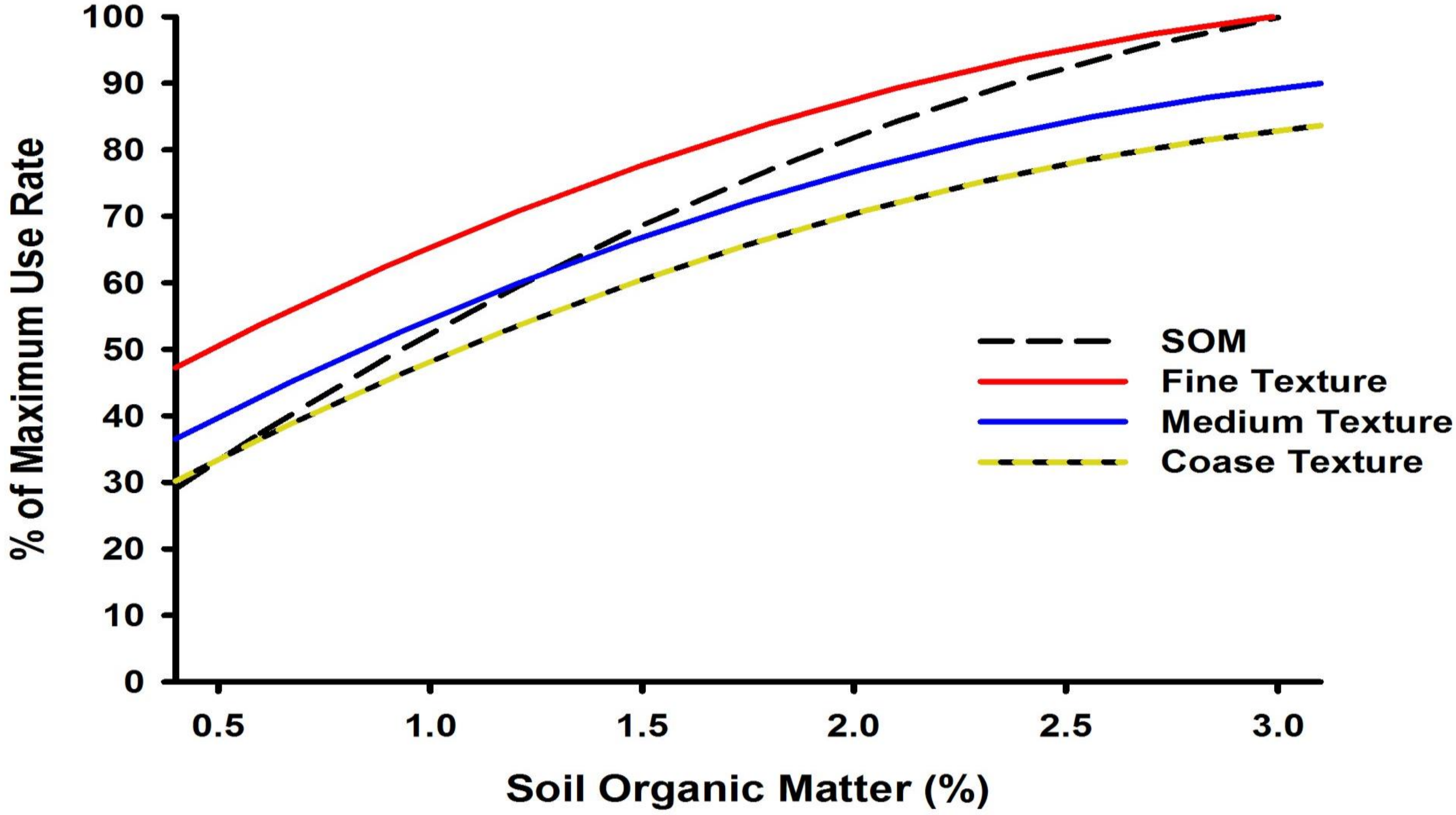

Figure 2.1. Regression of herbicide algorithms to determine percentage of maximum use rate (Y) of tank-mix 1 (saflufenacil, dimethenamid-P, and atrazine) based on percentage of soil organic matter (x) in corn. Regression determined by equation 2.1 with model parameters in Table 2.1.

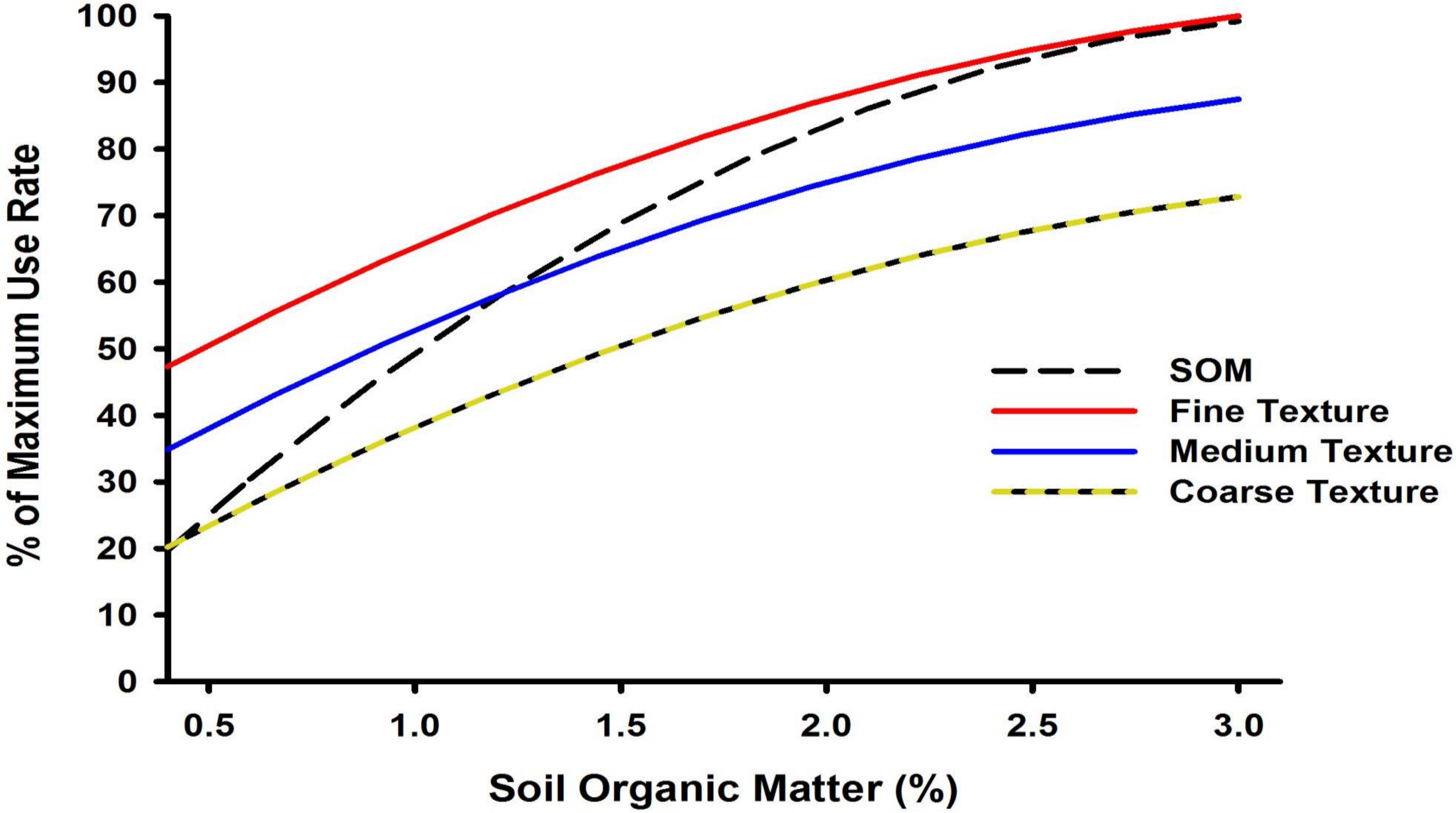

Figure 2.2. Regression of herbicide algorithms to determine percentage of maximum use rate (Y) of tank-mix 2 (bicyclopyrone, mesotrione, S-metolachlor, and atrazine) based on percentage of soil organic matter (x) in corn. Regression determined by equation 2.1 with all model parameters in Table 2.1.

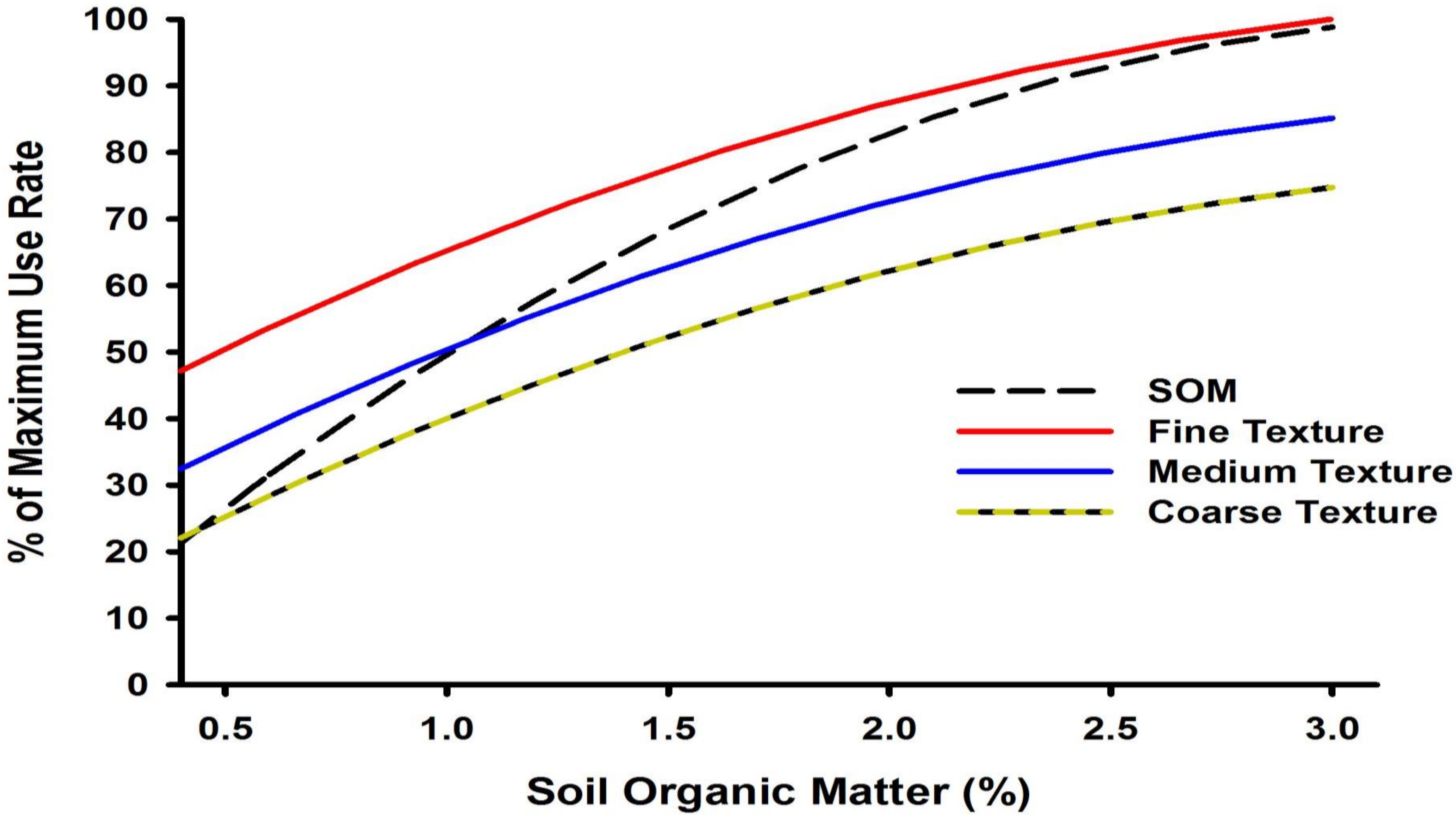

Figure 2.3. Regression of herbicide algorithms to determine percentage of maximum use rate (Y) of tank-mix 1 (saflufenacil, dimethenamid-P, and atrazine) based on percentage of soil organic matter (x) for grain sorghum. Regression determined by equation 2.1 with model parameters in Table 2.2.

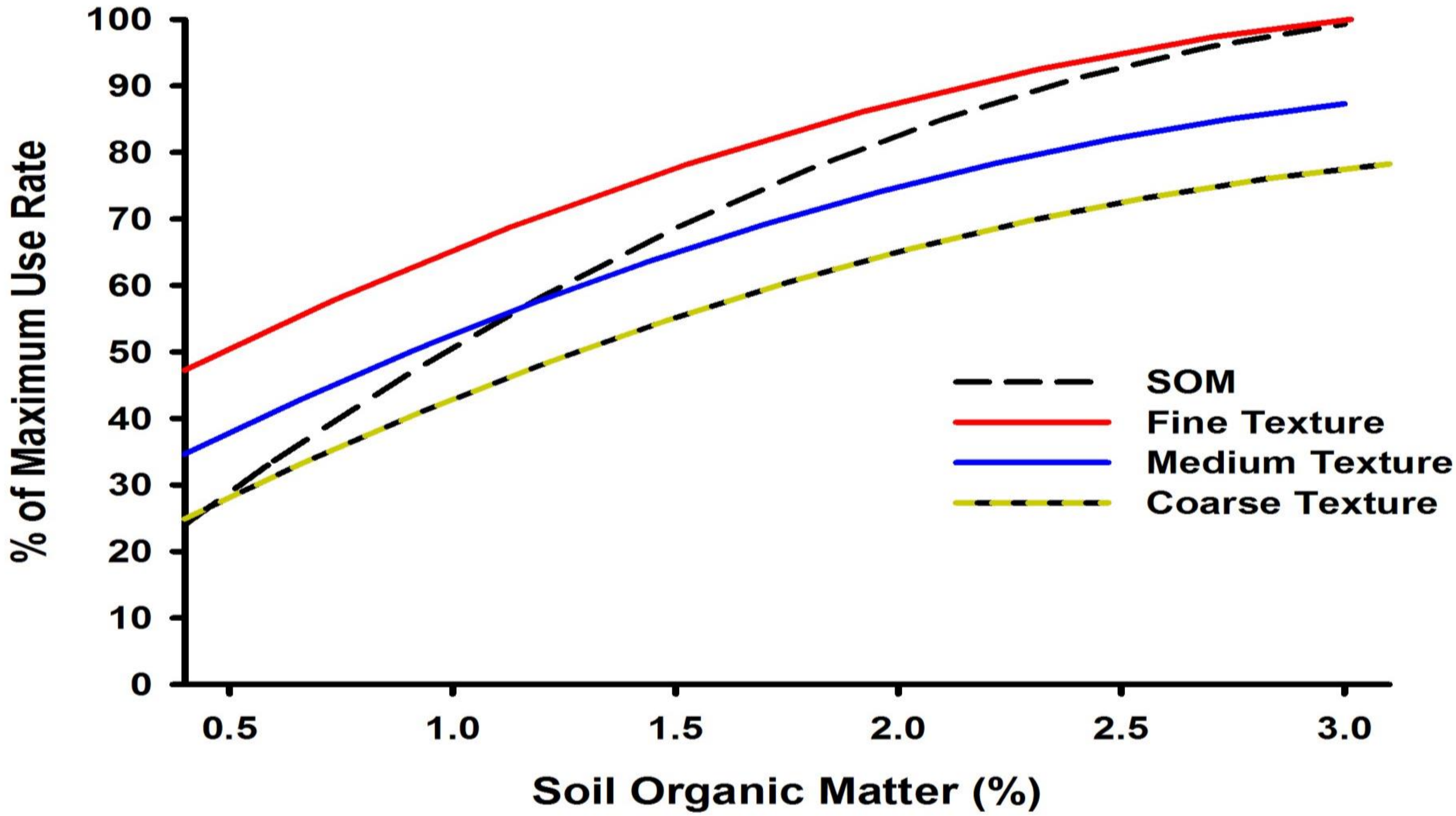

Figure 2.4. Regression of herbicide algorithms to determine percentage of maximum use rate (Y) of tank-mix 2 (mesotrione, S-metolachlor, and atrazine) based on percentage of soil organic matter (x) for grain sorghum. Regression determined by equation 2.1 with model parameters in Table 2.2.

Table 2.1. Second-order polynomial model parameters for corn algorithms to determine percentage of maximum use rate (MUR) to apply based on only soil organic matter (SOM) or SOM and soil texture class (coarse, medium, fine) for both tank-mixes.[a]

		Model Parameters				Tank-Mix MUR			
Tank-Mix	Algorithm	a	b	c	d	saflufenacil	dimethenamid-P	atrazine	
1	alg-SOM	-5.13	41.53	10.01	88.58	90	1100	2240	
	alg-SOMtex (Coarse)	-4.30	32.57	14.37	88.58	90	1100	2240	
	alg-SOMtex (Medium)	-4.30	32.57	20.00	88.58	90	1100	2240	
	alg-SOMtex (Fine)	-4.30	32.57	29.59	88.58	90	1100	2240	
						bicyclopyrone	mesotrione	atrazine	s-metolachlor
2	alg-SOM	-13.54	90.01	-5.28	144.87	50	270	2240	2260
	alg-SOMtex (Coarse)	-7.04	58.28	9.08	144.87	50	270	2240	2260
	alg-SOMtex (Medium)	-7.04	58.28	30.28	144.87	50	270	2240	2260
	alg-SOMtex (Fine)	-7.04	58.28	48.39	144.87	50	270	2240	2260

[a]Model: $Y=(ax^2+bx+c)/d$; where Y is percentage of tank-mix MUR, x is SOM.
Application Rate = Y * MUR of each tank-mix component

Table 2.2. Second-order polynomial model parameters for grain sorghum algorithms to determine percentage of maximum use rate (MUR) to apply based on only soil organic matter (SOM) or SOM and soil texture class (coarse, medium, fine) for both tank-mixes. Rate to apply[a]

		Model Parameters						
		Numerical Coefficients				Tank-Mix MUR		
Tank-Mix	Algorithm	a	b	c	d	saflufenacil	dimethenamid-P	atrazine
1	alg-SOM	-7.56	51.59	-0.74	86.97	50	1100	2240
	alg-SOMtex (Coarse)	-4.22	31.98	7.07	86.97	50	1100	2240
	alg-SOMtex (Medium)	-4.22	31.98	16.08	86.97	50	1100	2240
	alg-SOMtex (Fine)	-4.22	31.98	29.05	86.97	50	1100	2240
						mesotrione	s-metolachlor	atrazine
2	alg-SOM	-7.56	54.18	3.34	98.55	224	1880	2240
	alg-SOMtex (Coarse)	-4.79	36.24	10.79	98.55	224	1880	2240
	alg-SOMtex (Medium)	-4.79	36.24	20.37	98.55	224	1880	2240
	alg-SOMtex (Fine)	-4.79	36.24	32.92	98.55	224	1880	2240

[a]Model: $Y=(ax^2+bx+c)/d$; where Y is percentage of tank-mix MUR, x is SOM.
Application Rate = Y * MUR of each tank-mix component

Table 2.3. Coordinates, agronomic operations, and timing of operation and data collection for locations in 2016 and 2017 in Kansas.

	2016				2017				
Agronomic Operation[a]	Rossville	Manhattan	Salina	Hutch Redd	Topeka	Morganville	Hutch Pivot	Hutch Redd	Manhattan
Location (lat, long)	39.1181, -95.9237	39.1264, -96.6482	38.7987, -97.4331	37.9563, -98.1154	39.0770, -95.7696	39.4531, -97.2081	37.9440, -98.1085	37.9563, -98.1164	39.1266, -96.6351
Moisture	Irrigated	Dryland	Dryland	Dryland	Irrigated	Irrigated	Irrigated	Dryland	Dryland
Crop	Corn	Corn	Sorghum	Sorghum	Corn	Corn	Sorghum	Sorghum	Sorghum
Hybrid	GH-12J11	GH-12J11	P85Y40	P84G62	PR7493	P1257AM	SP-7715	SP-7715	SP-7715
Row spacing (cm)	76	76	38	76	76	38	76	76	76
Seeding rate (seeds ha^{-1})	79,200	79,200	123,800	119,000	79,200	79,200	119,000	119,000	119,000
Dates									
Veris mapping	Mar 25	Apr 12	Apr 19	Mar 17	Apr 13	Apr 11	May 18	May 18	Nov 17
Tillage	Apr 20	Apr 1	No-till	Apr 10	Apr 18	No-till	No-till	Apr 5	No-till
Burndown	May 10	-	Jun 11	Jun 10	-	Apr 15	May 26	May 27	Jun 1
Planting	May 4	May 19	Jun 9	Jun 14	Apr 25	May 9	May 25	May 25	Jun 7
PRE application	May 10	May 22	June 11	Jun 15	Apr 25	May 9	May 27	May 27	Jun 7
Weed biomass harvest	Sept 1	-	Sept 8	Sept 8	-	June 19	Jul 7	Jul 24	-
Grain harvest	Sept 21	Sept 25	Oct 13	Oct 13	Sept 21	Oct 12	Oct 25	Oct 25	Oct 26
Harvest method	Combine	Hand	Hand	Hand	Combine	Hand	Hand	Hand	Combine

[a]Abbreviations: PRE, preemergence; lat, latitude; long, longitude.
(-) No agronomic operation or data collection.

Table 2.4. Summary of soil organic matter (SOM) and electrical conductivity (EC) data collected by the Veris MSP3 at nine locations across Kansas in 2016 and 2017.[a]

			SOM						EC					
Year	Location	*n*	Mean	SD	CV	Min	Med	Max	Mean	SD	CV	Min	Med	Max
2016	Rossville	2173	1.6	0.1	6.3	1.3	1.6	1.8	7.7	1.6	20.8	3.8	7.7	12.1
	Manhattan	3397	2.4	0.1	4.2	2.0	2.4	2.6	42.5	0.6	1.4	15.9	43.4	74.0
	Salina	6414	2.1	0.4	19.0	1.0	2.2	3.9	42.3	11.2	26.5	12.1	50.3	133.2
	Hutch Redd	2571	2.0	0.4	20.0	0.9	1.9	2.8	24.1	9.6	39.9	5.6	22.7	46.9
2017	Topeka	2600	1.7	0.1	5.9	1.3	1.7	2.2	29.2	14.1	48.3	6.6	24.4	70.1
	Morganville	1632	2.1	0.8	38.1	0.1	2.1	3.3	15.4	12.6	81.9	0.8	11.5	76.0
	Hutch Pivot	2105	1.9	0.6	31.6	0.4	2.1	3.0	46.4	19.4	41.8	10.3	48.5	88.8
	Hutch Redd	1685	2.1	0.3	14.3	1.0	2.1	2.6	41.9	23.5	38.3	14.2	41.8	81.1
	Manhattan	1955	3.2	0.1	3.1	2.8	3.2	3.5	60.7	10.9	18.0	26.6	61.2	82.7

[a]Abbreviations: *n*, number of samples; SD, standard deviation; CV, coefficient of variation, Min, minimum; Med, median; Max, Maximum.

Table 2.5. Soil testing lab information for Veris calibration soil samples collected from depth to 7.6 cm across all locations in 2016.[a]

Crop	Location	Sample	Latitude	Longitude	SOM[b]	Soil Texture[c] Sand	Silt	Clay	Class[d]	pH
					%					
Corn	Rossville	1	39.1181366	-95.9236884	1.6	76	18	6	sandy loam	6.7
		2	39.1185016	-95.9238118	1.6	70	24	6	sandy loam	8.0
		3	39.1184083	-95.9231751	1.9	58	32	10	sandy loam	7.5
		4	39.1183033	-95.9252984	1.7	66	26	8	sandy loam	7.4
		5	39.1185383	-95.9227668	1.5	50	42	8	loam	7.2
		6	39.1184666	-95.9248833	1.3	68	26	6	sandy loam	7.0
	Manhattan	1	39.1263910	-96.6481934	2.5	26	50	24	silt loam	6.0
		2	39.1267233	-96.6487834	2.3	20	48	32	silty clay loam	5.9
		3	39.1258350	-96.6488833	2.3	16	48	36	silty clay loam	6.2
		4	39.1250650	-96.6486633	2.1	10	52	38	silty clay loam	6.1
		5	39.1254233	-96.6475117	2.6	14	48	38	silty clay loam	6.4
Grain sorghum	Hutch Redd	1	37.9567384	-98.1152650	2.3	44	34	22	loam	5.6
		2	37.9565118	-98.1150333	2.8	46	28	26	loam	5.6
		3	37.9561001	-98.1153933	2.1	54	28	18	sandy loam	5.4
		4	37.9561168	-98.1158133	2.3	48	30	22	loam	5.6
		5	37.9564218	-98.1162750	1.4	66	20	14	sandy loam	5.8
		6	37.9566668	-98.1166750	1.4	66	20	14	sandy loam	5.3
		7	37.9567218	-98.1161583	2.0	56	24	20	sandy loam	5.7
		8	37.9560250	-98.1150600	1.3	66	22	12	sandy loam	5.1
		9	37.9561401	-98.1164333	2.1	46	28	26	loam	5.8
		10	37.9565168	-98.1154733	1.9	52	30	18	loam	5.3

[a]Abbreviations: SOM, soil organic matter.
[b] Loss-on-ignition (Ball 1964)
[c] Particle size analysis by Hydrometer Method (Bouyoucos 1962)
[d] Based on Soil Texture Calculator (USDA-NRCS 2008)

Table 2.6. Soil testing lab information for Veris calibration soil samples collected from a depth to 7.6 cm at locations in 2017.[a]

Crop	Location	Sample	Latitude	Longitude	SOM[b]	Soil Texture[c] Sand	Silt	Clay	Class[d]	pH
						%				
Corn	Topeka	1	39.0771633	-95.7707816	2.0	34	42	24	loam	6.1
		2	39.0773800	-95.7695950	1.6	52	34	14	loam	7.4
		3	39.0770033	-95.7698784	1.4	58	32	10	sandy loam	6.7
		4	39.0763733	-95.7692784	1.9	50	40	10	loam	6.7
		5	39.0765733	-95.7706550	1.7	54	34	12	sandy loam	7.9
	Morganville	1	39.4534227	-97.2070973	2.4	50	24	26	sandy clay loam	6.9
		2	39.4537900	-97.2081156	1.5	70	20	10	sandy loam	6.7
		3	39.4530857	-97.2084858	0.6	90	4	6	sand	7.1
		4	39.4524440	-97.2089635	1.1	80	14	6	loamy sand	7.1
		5	39.4523711	-97.2077534	3.6	28	44	28	clay loam	7.0
Grain sorghum	Hutch Pivot	1	37.9440800	-98.1075866	1.1	88	6	6	loamy sand	7.3
		2	37.9439300	-98.1087066	3.0	48	32	20	loam	7.3
		3	37.9441866	-98.1087133	2.0	70	18	12	sandy loam	7.5
		4	37.9443749	-98.1086733	1.4	76	14	10	sandy loam	7.6
	Hutch Redd	1	37.9565899	-98.1157750	1.2	74	16	10	sandy loam	6.2
		2	37.9560218	-98.1157833	2.3	50	30	20	loam	5.2
		3	37.9561734	-98.1165416	2.4	46	30	24	loam	5.4
		4	37.9566850	-98.1164650	1.6	68	20	12	sandy loam	5.4
	Manhattan	1	39.1256783	-96.6347685	2.9	14	56	30	silty clay loam	6.7
		2	39.1265216	-96.6348449	3.3	20	54	26	silt loam	6.8
		3	39.1269850	-96.6354900	3.1	18	40	42	silty clay	5.9
		4	39.1261583	-96.6357434	3.6	18	52	30	silty clay loam	5.6
		5	39.1258916	-96.6351467	3.3	18	54	28	silty clay loam	6.0

[a]Abbreviations: SOM, soil organic matter.
[b] Loss-on-ignition (Ball 1964)
[c] Particle size analysis by Hydrometer Method (Bouyoucos 1962)
[d] Based on Soil Texture Calculator (USDA-NRCS 2008)

Table 2.7. Values of electrical conductivity (EC) that were used to classify field areas as coarse-, medium-, and fine-textured classes.

Year	Location	EC Range		
		Coarse Texture	Medium Texture	Fine Texture
		mS m^{-1}		
2016	Rossville	<7.5	≥ 7.5	-
	Manhattan	-	< 25	≥ 25
	Salina	< 31	31 - 40	> 40
	Hutch Redd	≤ 19	> 19	-
2017	Topeka	< 25	≥ 25	-
	Morganville	< 8	8 - 20	> 20
	Hutch Pivot	≤ 40	> 40	-
	Hutch Redd	≤ 40	> 40	-
	Manhattan	-	< 50	≥ 50

(-) Soil texture class not at location.

Table 2.8. P-values for analysis of fixed effects and interactions of weed control at 4 and 8 weeks after treatment (WAT), weed density and biomass at all corn locations in 2016 and 2017.

			Palmer amaranth				Ivyleaf morningglory				
			Control				Control				
Year	Location	Fixed Effect	4WAT	8WAT	Density	Biomass	4WAT	8WAT	Density	Biomass	Yield
2016	Rossville	Algorithm	0.907	0.405	0.101	0.485	0.310	0.260	0.084	**0.012**[a]	0.618
		Tank-mix	0.516	0.136	0.070	0.263	**0.002**	0.952	**0.046**	0.108	0.616
		Interaction[b]	0.940	0.291	0.182	0.607	0.618	0.980	0.650	0.563	0.956
	Manhattan	Algorithm	-	-	-	-	-	-	-	-	0.631
		Tank-mix	-	-	-	-	-	-	-	-	**0.007**
		Interaction	-	-	-	-	-	-	-	-	0.686
2017	Topeka	Algorithm	-	-	-	-	-	-	-	-	0.713
		Tank-mix	-	-	-	-	-	-	-	-	0.873
		Interaction	-	-	-	-	-	-	-	-	0.829
	Morganville	Algorithm	0.369	**0.028**	0.342	0.0624	-	-	-	-	0.378
		Tank-mix	0.543	**0.003**	0.154	0.381	-	-	-	-	**<.0001**
		Interaction	0.937	0.582	0.132	0.867	-	-	-	-	0.556

[a]Numbers in bold are significant where P-value ≤ 0.05.
[b]Interaction of Algorithm and Tank-mix.
(-) data not collected.

Table 2.9. P-values for analysis of fixed effects and interactions of weed control at 4 and 8 weeks after treatment (WAT), weed density and biomass at all grain sorghum locations in 2016 and 2017.

			Palmer amaranth				Large crabgrass				
			Control				Control				
Year	Location	Fixed Effect	4WAT	8WAT	Density	Biomass	4WAT	8WAT	Density	Biomass	Yield
2016	Hutch Redd	Algorithm	**0.006**[a]	**0.003**	0.650	0.276	0.576	**0.004**	0.812	0.694	0.489
		Tank-mix	**<0.0001**	**0.0003**	**0.037**	0.059	**0.006**	**<0.0001**	0.170	0.163	0.331
		Interaction[b]	.058	0.270	0.847	0.605	0.876	0.634	0.863	0.683	0.512
	Salina	Algorithm	0.274	0.824	0.612	0.651	-	-	-	-	0.094
		Tank-mix	0.093	0.091	0.406	0.195	-	-	-	-	**0.025**
		Interaction	0.510	0.798	0.601	0.820	-	-	-	-	0.298
2017	Hutch Redd	Algorithm	0.337	0.501	0.788	0.368	**0.008**	0.280	0.055	0.181	0.354
		Tank-mix	**0.049**	0.161	0.483	0.422	**0.021**	0.218	0.110	**0.009**	0.169
		Interaction	0.308	0.289	0.422	0.877	0.714	0.784	0.420	0.415	0.311
	Hutch Pivot	Algorithm	**0.024**	0.060	**0.007**	0.0624	-	-	-	-	0.126
		Tank-mix	0.139	0.324	0.570	0.381	-	-	-	-	0.954
		Interaction	0.250	0.666	0.764	0.867	-	-	-	-	0.740
	Manhattan	Algorithm	-	-	-	-	-	-	-	-	0.393
		Tank-mix	-	-	-	-	-	-	-	-	0.487
		Interaction	-	-	-	-	-	-	-	-	0.981

[a]Numbers in bold are significant, P-value ≤ 0.05.
[b]Interaction of Algorithm by Tank-mix.
(-) data not collected.

Table 2.10. Weekly rainfall totals recorded across all locations.

			Rainfall								
			Weeks after PRE[a]								
Year	Location	Application date	1	2	3	4	5	6	7	8	Total
			cm								
2016	Rossville	May 10	3.2	0.8	16.7	0.6	2.0*	6.3*	2.0*	5.2	36.8
	Manhattan	May 22	13.4	2.1	1.2	1.9	12.2	2.4	0.3	0.8	34.3
	Salina	Jun 11	1.1	0.0	1.8	2.7	1.0	0.0	4.7	1.8	13.1
	Hutch Redd	Jun 15	8.0	2.8	5.6	1.1	2.1	1.3	2.7	4.2	27.8
2017	Topeka	Apr 25	3.3	0.6	0.1	10.4	2.1	3.4	2.1*	6.5	28.5
	Morganville	May 9	2.5	8.1	2.0	2.5	2.2*	3.4*	6.9	3.1*	30.7
	Hutch Pivot	May 27	0.7	2.2*	0.8	0.7	1.8	2.3*	0.7	2.0*	11.2
	Hutch Redd	May 27	0.7	0.2	0.8	0.7	1.8	0.3	0.7	0.0	5.2
	Manhattan	Jun 7	0.0	0.3	0.4	6.3	0.0	0.0	1.0	2.4	10.4

[a]Abbreviations: PRE, preemergence.
*2.0 cm of supplemental water provided by irrigation.

Table 2.11. Comparison of percentages of maximum use rates applied for algorithms of tank-mix 1(saflufenacil, dimethenamid-P, and atrazine) and tank-mix 2 (bicyclopyrone, mesotrione, s-metolachlor, and atrazine) at corn locations in 2016 and 2017.[a]

			Tank-mix 1				Tank-mix 2			
Year	Site	Algorithm	Mean	CV	Min	Max	Mean	CV	Min	Max
			%				%			
2016	Rossville	alg-SOM	70	4.0	64	73	71	5.0	66	74
		alg-SOMtex	65	2.6	63	69	60	13.0	53	68
		Flat	67	0.0	67	67	64	0.0	64	64
	Manhattan	alg-SOM	89	2.5	87	92	91	1.9	89	93
		alg-SOMtex	90	3.6	85	94	89	4.4	84	94
		Flat	97	0.0	97	97	74	0.0	74	74
2017	Topeka	alg-SOM	68	7.3	60	73	71	6.3	61	77
		alg-SOMtex	70	6.8	65	79	52	7.8	46	58
		Flat	67	0.0	67	67	64	0.0	64	64
	Morganville	alg-SOM	81	26.1	46	100	85	19.4	54	99
		alg-SOMtex	76	28.9	43	100	76	33.2	34	100
		Flat	67	0.0	67	67	64	0.0	64	64

[a]Abbreviations: CV, coefficient of variation, Min, minimum; Max, maximum.

Table 2.12. Comparison of percentages of maximum use rates applied for algorithms of tank-mix 1 (saflufenacil, dimethenamid-P, and atrazine) and tank-mix 2 (mesotrione, s-metolachlor, and atrazine) at grain sorghum locations in 2016 and 2017.[a]

			Tank-mix 1				Tank-mix 2			
Year	Site	Algorithm	Mean	CV	Min	Max	Mean	CV	Min	Max
			%				%			
2016	Salina	alg-SOM	82	5.9	75	86	82	4.8	74	87
		alg-SOMtex	86	5.4	78	90	78	10.8	67	92
		Flat	100	0.00	100	100	84	0.0	84	84
	Hutch Redd	alg-SOM	85	6.5	75	91	83	8.3	70	93
		alg-SOMtex	68	13.3	52	52	71	8.9	56	82
		Flat	100	0.0	100	100	84	0.0	84	84
2017	Hutch Pivot	alg-SOM	75	26.9	43	95	71	26.2	46	90
		alg-SOMtex	60	29.8	34	79	66	27.7	43	85
		Flat	100	0.0	100	100	94	0.0	94	94
	Hutch Redd	alg-SOM	81	15.4	52	91	81	15.8	60	91
		alg-SOMtex	67	18.8	44	78	71	16.9	50	80
		Flat	100	0.0	100	100	94	0.0	94	94
	Manhattan	alg-SOM	99	0.61	99	100	100	0.3	99	100
		alg-SOMtex	97	5.3	86	100	97	4.8	89	100
		Flat	100	0.0	100	100	94	0.0	94	94

[a]Abbreviations: CV, coefficient of variation, Min, minimum; Max, maximum.

Table 2.13. Summary and comparison of fixed effects of algorithm and tank-mix on Palmer amaranth and ivyleaf morningglory control 4 and 8 weeks after treatment (WAT), weed density and biomass, and corn yield for each location in 2016.

			Palmer amaranth				Ivyleaf morningglory				
Location	Fixed Effect	Level	4WAT	8WAT	Density	Biomass	4WAT	8WAT	Density	Biomass	Yield
					plants m^{-2}	g m^{-2}			plants m^{-2}	g m^{-2}	kg ha^{-1}
Rossville	Algorithm	alg-SOM	98	83	2.0	29.8	98	49	2.1	13.4 a[a]	9970
		alg-SOMtex	97	93	0.8	12.4	96	47	1.9	8.2 ab	10270
		Flat	98	93	1.5	22.5	98	60	0.7	1.5 b	10300
	Tank-mix	1	97	85	1.8	28.3	99 a	52	2.1 a	9.7	10960
		2	98	93	1.0	14.7	95 b	52	1.0 b	4.2	11100
Manhattan	Algorithm	alg-SOM	-	-	-	-	-	-	-	-	9170
		alg-SOMtex	-	-	-	-	-	-	-	-	9690
		Flat	-	-	-	-	-	-	-	-	9390
	Tank-mix	1	-	-	-	-	-	-	-	-	8820 b
		2	-	-	-	-	-	-	-	-	10020 a

[a]Means followed by the same letter within a column for each fixed effect are not statistically different according to Tukey-Kramer's HSD where $\alpha \leq 0.05$. Values reported are back-transformed.
(-) data not collected.

Table 2.14. Significance and summary of Manhattan crop injury ratings 2 and 4 weeks after treatment (WAT) in 2016.

		2WAT	4WAT
Fixed Effect	Level	Crop Injury	Crop Injury
		%	%
Algorithm	alg-SOM	56	24
	alg-SOMtex	55	20
	Flat	52	24
P-value		0.432	0.203
Tank-mix	1	74 a[a]	40 a
	2	34 b	6 b
P-value		<0.0001	<0.0001

[a]Means followed by the same letter within a column for each fixed effect are not statistically different according to Tukey-Kramer's HSD where $\alpha \leq 0.05$.

Table 2.15. Summary and comparison of fixed effects of algorithm and tank-mix on Palmer amaranth and large crabgrass control 4 and 8 weeks after treatment (WAT), density, biomass, and yield across grain sorghum locations in 2016.

			Palmer amaranth				Large crabgrass				
Location	Fixed Effect	Level	4WAT	8WAT	Density	Biomass	4WAT	8WAT	Density	Biomass	Yield
			—— % ——		plants m^{-2}	g m^{-2}	—— % ——		plants m^{-2}	g m^{-2}	kg ha^{-1}
Hutch Redd	Algorithm	alg-SOM	82 ab[a]	21 a	13.3	83.4	89	72 ab	1.3	7.4	4720
		alg-SOMtex	78 b	8 b	13.4	94.5	84	59 b	1.9	14.5	4470
		Flat	87 a	30 a	10.9	65.2	89	80 a	1.4	10.6	4600
	Tank-mix	1	77 b	10 b	15.4 a	95.8	80	55 b	2.2	15.9	4680
		2	87 a	31 a	9.9 b	66.7	92	83 a	1.0	6.4	4510
Salina	Algorithm	alg-SOM	98	92	2.0	39.9	-	-	-	-	9180
		alg-SOMtex	99	93	1.6	32.4	-	-	-	-	9710
		Flat	99	94	1.0	20.8	-	-	-	-	9990
	Tank-mix	1	98	90	1.2	20.2	-	-	-	-	9980 a
		2	99	95	1.9	42.9	-	-	-	-	9310 b

[a]Means followed by the same letter within a column for each fixed effect are not statistically different according to Tukey-Kramer's HSD test on transformed data where $\alpha \leq 0.05$. Values reported are back-transformed.
(-) data not collected.

Table 2.16. Summary and comparison of fixed effects of algorithm and tank-mix on Palmer amaranth and control 4 and 8 weeks after treatment (WAT), density, biomass, and yield across corn locations in 2017.

			Palmer amaranth				
Location	Fixed Effect	Level	4WAT	8WAT	Density	Biomass	Yield
			—— % ——		plants m^{-2}	g m^{-2}	kg ha^{-1}
Morganville	Algorithm	alg-SOM	99	87 ab[a]	1.3	11.5	8990
		alg-SOMtex	99	92 a	0.8	10.6	9540
		Flat	98	71 b	1.5	3.6	9310
	Tank-mix	1	98	73 b	1.5	6.8	8450 b
		2	99	93 a	0.9	9.6	10110 a
Topeka	Algorithm	alg-SOM	-	-	-	-	12300
		alg-SOMtex	-	-	-	-	11450
		Flat	-	-	-	-	11250
	Tank-mix	1	-	-	-	-	11930
		2	-	-	-	-	12080

[a]Means followed by the same letter within a column for each fixed effect are not statistically different according to Tukey-Kramer's HSD test on transformed data where $\alpha \leq 0.05$. Values reported are back-transformed.
(-) data not collected.

Table 2.17. Summary and comparison of fixed effects of algorithm and tank-mix on Palmer amaranth and large crabgrass control 4 and 8 weeks after treatment (WAT), density, biomass, and yield across grain sorghum locations in 2017.

			Palmer amaranth				Large crabgrass				
Location	Fixed Effect	Level	4WAT	8WAT	Density	Biomass	4WAT	8WAT	Density	Biomass	Yield
			—— % ——		plants m^{-2}	g m^{-2}	—— % ——		plants m^{-2}	g m^{-2}	kg ha^{-1}
Hutch Redd	Algorithm	alg-SOM	90	90	0.6	4.6	80 b[a]	81	7.4 a	11.5	2840
		alg-SOMtex	89	93	0.7	4.2	83 b	84	5.0 ab	7.1	2980
		Flat	94	94	0.4	1.8	93 a	90	1.6 b	4.0	3140
	Tank-mix	1	88 b	90	0.7	1.1	81 b	82	6.1	12.3 a	2630
		2	94 a	94	0.5	2.7	90 a	88	2.8	3.4 b	2870
Hutch Pivot	Algorithm	alg-SOM	88 ab	84	1.2 a	11.5	-	-	-	-	4650
		alg-SOMtex	84 b	80	1.2 a	10.6	-	-	-	-	4700
		Flat	95 a	93	0.4 b	3.6	-	-	-	-	5080
	Tank-mix	1	93	89	0.8	6.8	-	-	-	-	4820
		2	87	84	1.0	9.6	-	-	-	-	4810
Manhattan	Algorithm	alg-SOM	-	-	-	-	-	-	-	-	8270
		alg-SOMtex	-	-	-	-	-	-	-	-	8170
		Flat	-	-	-	-	-	-	-	-	7820
	Tank-mix	1	-	-	-	-	-	-	-	-	8100
		2	-	-	-	-	-	-	-	-	7900

[a]Means followed by the same letter within a column for each fixed effect are not statistically different according to Tukey-Kramer's HSD test on transformed data where $\alpha \leq 0.05$. Values reported are back-transformed.
(-) data not collected.

Table 2.18. Cost comparison of both algorithms based rates and flat rate treatments across both tank-mixes based on mean, minimum (min) and maximum (max) rates applied to corn plots at all locations.

			Tank-mix 1			Tank-mix 2		
Year	Site	Algorithm	Mean	Min	Max	Mean	Min	Max
				$ ha^{-1}			$ ha^{-1}	
2016	Rossville	alg-SOM	94.0[a]	82.1	101.1	106.4	90.9	115.4
		alg-SOMtex	90.7	73.3	96.0	99.7	67.9	105.7
		Flat	88.1	88.1	88.1	94.8	94.8	94.8
	Manhattan	alg-SOM	118.9	107.6	123.6	135.7	123.3	140.3
		alg-SOMtex	123.1	100.8	126.4	138.8	111.1	142.5
		Flat	127.5	127.5	127.5	109.6	109.6	109.6
2017	Topeka	alg-SOM	97.6	82.1	113.6	111.1	90.9	130.1
		alg-SOMtex	93.4	73.4	105.1	102.8	67.9	116.0
		Flat	88.1	88.1	88.1	94.8	94.8	94.8
	Morganville	alg-SOM	106.4	60.5	131.4	125.9	80.0	146.7
		alg-SOMtex	99.9	56.5	131.4	112.6	50.4	148.1
		Flat	88.1	88.1	88.1	94.8	94.8	94.8

[a]Herbicide costs were based on average retail prices in Kansas in 2018.

Table 2.19. Cost comparison of both algorithms and flat rate treatments across both tank-mixes based on mean, minimum (min) and maximum (max) rates applied to grain sorghum plots at locations.

			Tank-mix 1			Tank-mix 2		
Year	Site	Algorithm	Mean	Min	Max	Mean	Min	Max
				$ ha^{-1}			$ ha^{-1}	
2016	Salina	alg-SOM	86.9[a]	79.4	91.1	90.9	82.0	96.4
		alg-SOMtex	91.1	82.6	95.3	86.5	74.3	102.0
		Flat	105.9	105.9	105.9	93.1	93.1	93.1
	Hutch Redd	alg-SOM	90.0	79.4	96.4	92.0	77.6	103.1
		alg-SOMtex	72.0	55.1	83.7	78.7	62.1	90.9
		Flat	105.9	105.9	105.9	93.1	93.1	93.1
2017	Hutch Pivot	alg-SOM	79.4	45.5	100.6	78.7	51.0	99.8
		alg-SOMtex	63.6	36.0	83.7	73.2	47.7	94.2
		Flat	105.9	105.9	105.9	104.2	104.2	104.2
	Hutch Redd	alg-SOM	85.8	55.1	96.4	89.8	66.5	100.9
		alg-SOMtex	71.0	46.6	82.6	76.7	55.4	88.7
		Flat	105.9	105.9	105.9	104.2	104.2	104.2
	Manhattan	alg-SOM	104.9	104.9	105.9	110.8	107.7	110.8
		alg-SOMtex	102.7	91.1	105.9	107.5	98.6	110.8
		Flat	105.9	105.9	105.9	104.2	104.2	104.2

[a]Herbicide costs were based on average retail prices in Kansas in 2018.

Table 2.20. Pearson correlation coefficients between soil organic matter (SOM) and electrical conductivity (EC), Rate, Palmer amaranth control at 8 weeks after treatment (WAT) and biomass, and yield at locations where weed control efficacy was evaluated.[a]

						Palmer amaranth		
Crop	Year	Location	*n*	SOM*EC	SOM*Rate	SOM*8WAT	SOM*Biomass	SOM*Yield
Corn	2016	Rossville	54	**0.276**[b]	0.140	**-0.300**	**0.349**	**0.321**
	2017	Morganville	54	**0.960**	**0.718**	**0.811**	**-0.726**	**0.872**
Grain Sorghum	2016	Salina	54	**0.997**	**0.346**	**0.472**	**0.002**	**0.001**
		Hutch Redd	42	**0.666**	**0.417**	-0.114	0.138	0.087
	2017	Hutch Pivot	54	**0.955**	**0.647**	-0.136	0.051	**0.332**
		Hutch Redd	54	**0.777**	**0.616**	**0.287**	**-0.581**	**0.314**

[a]Abbreviations: *n*, number of plots.
[b]Numbers in bold are significant, P-value ≤ 0.05.

Chapter 3 - Efficacy of Soil-Applied HPPD-Inhibitor Herbicides on Kansas HPPD-Resistant Palmer Amaranth (*Amaranthus palmeri)*

Abstract

Palmer amaranth is a troublesome weed with widespread herbicide resistance that makes it difficult to control for growers. A population of Palmer amaranth was identified in Stafford County, KS (SF(R)), as resistant to POST applications of both mesotrione, a 4-hydroxyphenylpyruvate dioxygenase (HPPD) inhibitor herbicide, and to atrazine, a photosystem II (PSII) inhibiting herbicide. Anecdotal evidence from the field has indicated that PRE applications of mesotrione provided modest control of HPPD resistant populations. Greenhouse studies were conducted to evaluate the PRE efficacy of two HPPD-inhibiting herbicides (mesotrione and isoxaflutole) on SF(R) population and an additional susceptible population from Riley County, KS (RL(S)). Reduced susceptibility and greater seedling survival were observed in the SF(R) population for both herbicides at recommended field use rates. Resistant-to-sensitive (R/S) ratios using the LD_{50} was 7.2 for mesotrione and 4.1 for isoxaflutole. Field experiments were conducted in 2017 at a producer's field in Barton County, KS with a reported HPPD-inhibitor and atrazine-resistant population and in Reno County, KS with a confirmed HPPD-inhibitor susceptible and atrazine-resistant population. The experiment was a randomized complete block design with 18 treatments applied PRE into a non-crop scenario in Reno County and in grain sorghum in Barton County. Three HPPD-inhibiting herbicides: mesotrione, isoxaflutole, and bicyclopyrone plus bromoxynil, were applied at multiple rates with and without 2,240 g ha^{-1} of atrazine. Palmer amaranth control was visually evaluated 4 weeks after treatment. At both sites, mesotrione (89%) provided better control than isoxaflutole (81%) on average

across both rates. Bicyclopyrone was the least effective HPPD-inhibiting herbicide across both rates providing 55 and 65% control of susceptible and resistant populations, respectively. Mesotrione and isoxaflutole applied at 1X performed better (89% control) compared to ½X (81% control). For all herbicides, the higher rate provided better control than lower rates. The addition of atrazine increased weed control from 82 to 88% when added to all HPPD-inhibiting herbicides. For mesotrione treatments across both sites, Palmer amaranth control was reduced to less than 90% when rates lower than 1X were applied. When comparing populations, weed control efficacy with mesotrione was reduced from 92 to 79% in the resistant population compared to the susceptible populations. Overall reduction of weed control on the resistant population demonstrated reduced sensitivity to soil applied HPPD-inhibiting herbicides compared to the susceptible population, but the same trends were observed. HPPD-inhibiting herbicides should be used at maximum labelled use rates and tank-mixed with atrazine for best residual control of all Palmer amaranth populations as part of an integrated weed management plan.

Introduction

Palmer amaranth (*Amaranthus palmeri* S. Wats.) is a dioecious, C4, summer annual plant species that is native to southwestern United States and northwestern Mexico (Sauer 1957). A single female plant can produce up to 600,000 seeds when in a non-competitive environment greatly augmenting the soil seedbank (Keeley et al. 1987). Once emerged, high photosynthetic rates allow for rapid growth, and provide a competitive advantage over crops at high temperatures and in water limiting situations (Ehleringer 1983, Horak and Loughin 2000, Ward et al. 2013). Palmer amaranth is a successful invader of disturbed agricultural lands and is a concern across many states (Jhala et al. 2014, Sauer 1957). These characteristics contribute to

Palmer amaranth persisting as one of the most economically important weeds with the potential of causing yield loss up to 79 and 91% in soybeans and corn, respectively (Bensch et al. 2003, Massinga et al. 2001). With the innate ability to survive in a wide range of agricultural environments, Palmer amaranth will continue to coexist with crops in modern-day fields (Steckel 2007).

Producers rely on use of herbicides to face the challenges of managing Palmer amaranth. Unfortunately, the evolution of herbicide-resistant Palmer amaranth populations to various products has limited the effective options for chemical control across KS (Peterson 1999). Before 2009, Palmer amaranth evolved resistance to multiple herbicide sites of action including acetolactate synthase (ALS) inhibitors, microtubule inhibitors, photosystem II (PSII) inhibitors, and 5-enolpyruvylshikimate-3-phosphate synthase (EPSPS) inhibitors with several of cases of multiple resistance (Heap 2018). Integrated weed management (IWM) that includes a soil-applied herbicide or preemergence (PRE) herbicide with residual activity is critical for controlling herbicide-resistant Palmer amaranth (Ciampitti et al. 2018, Norsworthy et al. 2012). Kohrt and Sprague (2017) reported that 10 soil-applied herbicides provided 89 to 98% control of a multiple herbicide-resistant population of Palmer amaranth 72 days after planting. In several other studies, it was reported that PRE soil-applied herbicides resulted in $\geq 95\%$ control of glyphosate-resistant Palmer amaranth control at 4 WAT (Meyer et al. 2015). More recently, 4-hydroxyphenylpyruvate dioxygenase (HPPD)-inhibitors have gained popularity and are extensively used for weed control both as foliar- and soil-applied herbicide applications (Bollman et al. 2008, Mitchell et al. 2001). Mesotrione and isoxaflutole are two of the most utilized HPPD-inhibitors due to a wide-spectrum of weed control, specifically *Amaranthus* spp, and the flexibility in timing of application (Bollman et al. 2008, Luscombe and Pallett 1996, Mitchell et al. 2001). Sutton et al. (2002) reported that HPPD-inhibitors were highly effective on controlling PSII- and ALS-resistant weeds. HPPD-inhibitors resulted in 80 to 100% control of Palmer amaranth when applied PRE in KS and Missouri (Johnson et al. 2012). Synergism has also been documented when mixing HPPD-inhibitors with PSII-inhibitors at both PRE and postemergence (POST) application timings for controlling herbicide-resistant weeds and furthermore controlling HPPD-inhibitor resistant weeds (Armel et al. 2005, Hugie et al. 2008, Jhala et al. 2014, Thompson 2014, Walsh et al. 2012).

Palmer amaranth was first documented and later confirmed to be resistant to foliar-applied HPPD-inhibitors in Stafford County, KS in 2012 (Thompson et al. 2012). This population was initially found resistant to Huskie® (Bayer CropScience LP), a mixture of pyrasulfotole (HPPD-inhibitor) and bromoxynil (PS II-inhibitor). This population was later found resistant to several other HPPD-inhibitors including mesotrione, tembotrione, and topramezone (Lally et al. 2010, Thompson et al. 2012). Unlike many cases of herbicide resistance, this field had no history of applications of HPPD-inhibitors, but did have a long history of PSII- and ALS-inhibitor herbicides. Rapid detoxification and increased HPPD gene expression were the mechanisms conferring resistance in this Palmer amaranth population (Nakka et al. 2017). Another HPPD-inhibitor resistant Palmer amaranth population was also documented in Nebraska (Sandell et al. 2012). Several populations of HPPD-inhibitor resistant waterhemp (*Amaranthus tuberculatus* Sauer) have also been documented in Illinois and in Iowa (Hausman et al. 2011, McMullan and Green 2011). In areas of HPPD-resistant Palmer amaranth, resistance to POST applications at labeled rates were well documented and confirmed (Jhala et al. 2014, Nakka et al. 2017, Thompson et al. 2012) Foliar applications of HPPD-inhibitors were not providing control of HPPD-inhibitor resistant species, but PRE applications were still providing adequate control at high rates (Thompson 2014). Many growers are using soil-applied HPPD-inhibitors due to limited options in regards to weed resistance management. The number of growers using HPPD-inhibitor will likely increase with new HPPD-inhibitor tolerant traits being added to soybeans. The response of HPPD-inhibitors applied to the soil for controlling HPPD-inhibitor resistant waterhemp has been documented (Hausman et al. 2013), but has not been evaluated in Palmer amaranth. Understanding the efficacy of soil-applied herbicides on HPPD-inhibitor resistant Palmer amaranth is crucial to developing effective weed management recommendations for HPPD-resistant populations. The objectives of this study were to (1) assess the dose-response of soil-applied mesotrione and isoxaflutole on HPPD-inhibitor resistant Palmer amaranth compared to a known susceptible population in the greenhouse and (2) evaluate the activity of soil-applied herbicides on controlling HPPD-inhibitor resistant Palmer amaranth populations under field conditions.

Materials and Methods

Dose-Response under Greenhouse Conditions

A HPPD-inhibitor resistant Palmer amaranth population from Stafford County, KS and a susceptible population from Riley County, KS, denoted as SF(R) and RL(S), respectively, were used in this study. HPPD-inhibitor resistant Palmer amaranth seed was initially collected from Stafford County in 2011 and a homogenous population of SF(R) was produced by crossing male and female plants that survived a mesotrione application at field use rate (105 g ha^{-1}) in the greenhouse (Nakka et al. 2017, Thompson et al. 2012). Seed was collected from surviving female inflorescences and used for this study. The RL(S) population was harvested from the Department of Agronomy Ashland Bottoms Research Farm near Manhattan, KS in the fall of 2009 and was confirmed to be susceptible to the field use rate of mesotrione in the greenhouse.

Plastic plots (8.25 cm by 8.25 cm by 9.0 cm) were filled to the top with silty clay loam field soil (pH 6.5; 2.8% organic matter) that was evenly wetted until soil was easily formed into a ball. Soil wetting procedures were based on preliminary data, where maximum seed germination was achieved when soil was not completely saturated (data not shown). To avoid uneven seed distribution, 16 seeds from each population were sown on the soil surface in a 4 by 4 grid with 1 cm spacing from all pot sides. Seeding population was determined by initial germination tests and calculated to represent a dense population in the field. To cover seed, the same field soil was passed through a 2 mm soil sieve over the top of each pot and tamped to ensure seed to soil contact. Pots were then surface watered using a 0.5 liter per minute (LPM) mister nozzle to ensure uniform moisture distribution and adequate water for seed germination.

Immediately after planting and watering, mesotrione (Callisto, Syngenta Crop Protection LLC, Greensboro, NC) and isoxaflutole (Balance Pro, Bayer Crop Science, Triangle Park, NC) treatments were applied to the corresponding pots. For the susceptible population, both mesotrione and isoxaflutole rates ranged from 1.6 to 210 g ha^{-1}. For the resistant population, mesotrione rates ranged from 13 to 1680 g ha^{-1} and isoxaflutole ranged from 3.3 to 840 g ha^{-1}. Herbicide treatments were applied using compressed air, bench-type, research sprayer (DeVries Manufacturing, 86956 State Highway 251, Hollandale, MN) equipped with a Teejet 80015LP flat-fan nozzle, calibrated to deliver 140 L ha^{-1} at 255 kPa in a single pass at 6.37 km h^{-1}. After all herbicide applications, mefenoxam (Ridomil Gold SL, Syngenta Crop Protection LLC) at a rate of 560 g ha^{-1} was applied using bench sprayer to prevent damping off and other pathogens that cause seedling mortality. Approximately 0.8 cm of water was applied to each pot after herbicide application using a 0.5 LPM mister nozzle to simulate rainfall to leach herbicide into soil solution. Pots were then moved back into the greenhouse and arranged in a randomized complete block design with six replications for each treatment, with two runs separated temporally. To ensure moisture was not a factor, pots were lightly watered on the surface three times a day using a 0.5 LPM mister nozzle until moist to touch. Watering procedures were carefully monitored to provide enough water to keep seeds germinating, but not too much water to leach the herbicide down from the surface. More frequent watering events using less water each pass was determined to be the most effective irrigation technique (data not shown). Greenhouse conditions were maintained at 32/22 C day/night and 16/8 photoperiod, supplemented with 250 µmol m^{-1} s^{-1} using 400-W sodium lighting.

At 21 days after treatment (DAT), the surviving seedlings in each pot were counted and harvested. Initial analysis using the MIXED procedure in JMP PRO 12 (SAS Institute, 100 SAS Campus Drive, Cary, NC) resulted in no significant differences between runs, so data were combined. Combined count data were analyzed using the dose-response curve package, drc (Knezevic et al. 2007, Seefeldt et al. 1995) in R 3.1.2 software (R Foundation for Statistical Computing, Vienna, Austria) using the four parameter log-logistic model shown below:

$$y = c + \frac{d-c}{1+\exp\{b[\log(x)-\log(LD_{50})]\}} \qquad [3.1]$$

where y is the number of surviving seedlings (plants/pot), b is the slope of the curve, c is the lower limit, d is the upper limit, and LD_{50} is the dose required for 50% reduction in seedling count. The LD_{90} was calculated and is the dose required for 90% reduction in seedling count. Estimates of the LD_{50} and LD_{90} values for each herbicide were calculated from the seedling survival data and used to determine the difference in the level of resistance between SF(R) and RL(S) populations by calculating the R:S ratio.

Efficacy under Field Conditions

Field experiments were conducted in 2017 at two KS locations, with one field having HPPD-resistant and the other one HPPD-susceptible Palmer amaranth populations. Both populations were resistant to atrazine (PSII inhibitors). Information about both of the sites is summarized in Table 3.1. The HPPD-resistant population site was located in Barton County (38.316019, -98.812979) approximately 15 km away from the first documented HPPD-resistant Palmer amaranth population in KS (Thompson et al. 2012). Previous screening proved this population was resistant to POST applications of mesotrione (105 g ha^{-1}) (data not shown). The soil at this site was an Attica loamy fine sand (Coarse-loamy, mixed, superactive, mesic Udic Haplustalfs) with 0.8% organic matter and a pH of 6.6. A preplant burndown was applied before PRE applications to remove all emerged weeds and grain sorghum was planted three days later. PRE herbicides were applied the day after planting on May 29, 2017. The HPPD-susceptible site was located in Reno County at the Department of Agronomy South Central Kansas Experiment Field (37.929270ºN, 98.023207ºW). The soil at this site was an Ost loam (Fine-loamy, mixed superactive, mesic Udic Argiustolls) with 2.5% organic matter and a pH of 6.3. Tillage was conducted before PRE applications to control emerged weeds and the field was maintained as a non-crop site for entire study. PRE herbicides were applied two days after tillage on May 27, 2017. Soil properties, herbicide application dates, and weekly precipitation totals for both sites are presented in Table 3.1.

A total of 18 herbicide treatments and a non-treated control were evaluated for Palmer amaranth control at each site (Table 3.2). A randomized complete block design with four replications was used and plots were 3 m by 9 m. Herbicide treatments consisted of three different HPPD-inhibiting herbicides (mesotrione, isoxaflutole, and bicyclopyrone) at different rates along with other commonly used herbicides for Palmer amaranth control (Table 3.2). Mesotrione treatments were ¼X, ½X, and 1X (210 g ha^{-1}), while isoxaflutole treatments were ½X and 1X (105 g ha^{-1}) of the recommended field use rates. Bicyclopyrone treatments were 1X (50 g ha^{-1}) and 2X rates in formulated combination with bromoxynil (700 and 1400 g ha^{-1}) at the recommended use rate for corn. Each of the HPPD-inhibitor-only treatments were also tank-mixed with atrazine (2,240 g ha^{-1}). Four other soil-applied herbicide treatments included atrazine, linuron, s-metolachlor, and a combination of mesotrione + linuron for Palmer amaranth control comparison for a total of 18 herbicide treatments (Table 3.2). Treatments were applied using a CO_2 backpack sprayer calibrated to deliver 187 L ha^{-1} at 255 kpa with a four nozzle boom with TTI11002 nozzles spaced 51 cm apart (TeeJet Technologies, Wheaton, IL). Palmer amaranth control ratings were taken 15 and 30 DAT using a scale from 0 (no control) to 100% (complete control) and were based on stand reduction compared to the non-treated control. Palmer amaranth height, density, and aboveground biomass data were collected 30 DAT from the center 0.76 m of each entire plot. Density data were converted to plants m^{-2} and biomass data were converted to mg m^{-2}. To improve normality, density and biomass data were subjected to the square-root and log transformations, respectively, and results were back-transformed for discussion.

All field data were analyzed using the MIXED procedure in JMP Pro 12 and means were separated using Fisher's Protected LSD test ($\alpha = 0.05$). When all 18 treatments were included, interactions of the main effects (site and treatment) were significant. Therefore, treatment and site were considered fixed effects and replication was considered a random effect. To understand the specific interactions of the HPPD-inhibitor herbicide treatments, two separate analyses of extracted data subsets were examined: 1) ½X and 1X treatments of mesotrione and isoxaflutole with and without atrazine, and 2) ¼X, ½X, and 1X treatments of mesotrione with and without atrazine. Initial analysis of both extracted data subsets revealed site was not significant, therefore data were pooled across both sites. Replications were nested within site and considered as a random effect. In the analyses of fixed effects of the first extracted data subset, a 2 by 2 by 2 factorial design was utilized to compare fixed effects of herbicide, rate, with or without atrazine as a tank-mix partner, and all interactions. In analysis of the second extraction subset, a 3 by 2 factorial was utilized with rate (3 levels) and with or without atrazine as the fixed effects.

Results and Discussion

Dose-Response under Greenhouse Conditions

The majority of Palmer amaranth uniformly emerged between 3 and 4 days after planting in the greenhouse. HPPD-inhibitor injury was observed on all emerged seedlings and included bleached cotyledons and stunted growth. Bleaching symptomology of SF(R) persisted for a shorter time (data not shown) likely due to its ability to metabolize mesotrione 2.5 times faster compared to susceptible populations (Nakka et al. 2017). Based on count data at 21 DAT, the lethal dose of mesotrione required to reduce survival by 50% (LD_{50}) was 61.5 g ha^{-1} for SF(R) compared to only 9.2 g ha^{-1} for RL(S) populations (Table 3.3). For isoxaflutole, LD_{50} was 21.7 g ha^{-1} for SF(R) and only 5.3 g ha^{-1} for RL(S) populations. Similar LD_{50} values of 63.3 g mesotrione ha^{-1} were reported on a HPPD-inhibitor population of waterhemp when herbicide was applied to the soil (Hausman et al. 2013). A greater lethal dose of 150 g mesotrione ha^{-1} was required to reduce Palmer amaranth biomass by 50% when applied POST compared to PRE application (Nakka et al. 2017). To achieve 90% reduction in seedling survival, 303 g mesotrione ha^{-1} were required for SF(R) compared to only 27.7 g mesotrione ha^{-1} for RL(S) populations (Table 3.3). Rates of isoxaflutole required for 90% reduction were less at 149.9 g ha^{-}

^{1} for SF(R), and only16.6 g ha^{-1} for RL(S). Rates of both herbicides to control 90% of SF(R) were greater than the field use rate. By 21 DAT, complete mortality of the RL(S) population was observed with 53 g mesotrione ha^{-1} and 26 g isoxaflutole ha^{-1} (FFigure 3.1 and Figure 3.2). For SF(R), survivors were seen in several individual replications at rates as high as 420 g mesotrione ha^{-1} and 210 g isoxaflutole ha^{-1}. Although field rates of both HPPD-inhibitors applied PRE reduced the seedling survival of SF(R), there were still survivors and a decreased level of weed control than expected in the field.

The R/S ratio calculated based on LD_{50}, demonstrated that SF(R) was more resistant to mesotrione compared to isoxaflutole (Table 3.3). SF(R) population was 7.2 times more resistant to mesotrione and 4.1 times more resistant to isoxaflutole compared to the susceptible populations. In a similar study, HPPD-inhibitor resistant waterhemp populations were 12.7 and 8.8 times more resistant to soil-applied mesotrione compared to a susceptible population (Hausman et al. 2013). The greater level of resistance was most likely due to the LD_{50} being lower in the susceptible population of waterhemp (5.0 g ha^{-1}) compared to susceptible population of Palmer amaranth (8.5 g ha^{-1}). The R/S ratio for POST applications of mesotrione on the same resistant and susceptible KS populations was much greater as SF(R) was 17.8 times more resistant than RL(S) (Nakka et al. 2017).

Overall, field-labeled rates of both mesotrione and isoxaflutole were not effective for controlling the resistant population of Palmer amaranth in KS, opposed to being highly effective with 100% control of susceptible plants. By utilizing a controlled greenhouse study, the efficacy of soil-applied mesotrione and isoxaflutole were characterized and proved to be less effective on controlling HPPD-inhibitor resistant populations compared to susceptible populations. Soil-applied herbicides have resulted in reduced efficacy on controlling resistant populations in many different studies (Falk et al. 2006, Hausman et al. 2013, Umphres et al. 2018, Wuerffel et al. 2015). SF(R) was more resistant to mesotrione than isoxaflutole and higher rates of mesotrione were required to get effective control under ideal greenhouse conditions (Table 3.3). Both herbicides were able to control the resistant population, but required greater than field use rates.

Efficacy under Field Conditions.

All Treatment Comparison

Mesotrione applied at ½X and 1X rates were effective at controlling the susceptible Palmer amaranth population, resulting in greater than 90% control, while the ¼X only provided 83% control at 4 WAT (Table 3.4). All mesotrione rates decreased the susceptible Palmer amaranth density and biomass equally, compared to the non-treated check. Palmer amaranth density was ≤ 30 plants m^{-2} for all mesotrione rates, compared to 294 plants m^{-2} and biomass was ≤ 280 mg m^{-2} for all mesotrione rates, compared to 11,230 mg m^{-2} for the non-treated check. Mesotrione applied at ½X and 1X resulted in 76 and 86% control, respectively, of the HPPD-resistant Palmer amaranth population, while the ¼X rate only provided 58% control. Bollman et al. (2006) reported decreased weed control efficacy when using ¼X rate of mesotrione compared to 1X rate. Mesotrione applications at 1X resulted in greater weed control of HPPD-inhibitor resistant Palmer amaranth (86%) in this study, compared to a HPPD-inhibitor resistant waterhemp in a similar field study (53 to 65%) (Hausman et al. 2013). Palmer amaranth density was greater with applications of ¼X rate of mesotrione (6 plants m^{-2}), compared to 1X rate (1 plant m^{-2}), but both rates decreased density compared to the non-treated check (15 plants m^{-2}) (Table 3.4). Mesotrione applied at 1X was the only rate of mesotrione that decreased Palmer amaranth biomass (440 mg m^{-2}) compared to the non-treated check (17,770 mg m^{-2}). Greater amounts of rainfall immediately after emergence at the resistant site in Barton County resulted in greater biomass harvested in each treatment compared to the susceptible site in Reno County (Table 3.1). Palmer amaranth control was reduced with applications of mesotrione when comparing susceptible and resistant populations, but reduced level of weed control was only observed when the ¼X rate was applied (Table 3.4). Mesotrione + atrazine treatments provided the greatest amount of weed control across both populations, regardless of the mesotrione rate, resulting in ≥ 90% control of the susceptible population and ≥ 80% control of the resistant population. Palmer amaranth density was ≤ 9 plants m^{-2} for all mesotrione rates + atrazine for the susceptible populations, and ≤ 2 plants m^{-2} for the resistant population. This is due to the synergism between HPPD-inhibitor herbicides and PS II-inhibitors (Abendroth et al. 2006, Armel et al. 2005, Hugie et al. 2008, Jhala et al. 2014). Mesotrione tank-mixed with atrazine resulted in 91% control compared to 66% control with mesotrione alone when applied POST on a similar HPPD-inhibitor resistant Palmer amaranth population in Nebraska (Jhala et al. 2014). Mesotrione + linuron also provided the same level of weed control as mesotrione + atrazine on the susceptible (94%) and resistant populations (66%). Mesotrione + linuron treatments resulted in Palmer amaranth densities of 6 and 4 plants m^{-2} for the susceptible and resistant populations, respectively.

Isoxaflutole applied at ½X and 1X rates resulted in 81% and 89% weed control of the susceptible population, respectively, but only the 1X rate of isoxaflutole provided the same amount of control as 1X of mesotrione (94%) (Table 3.4). Isoxaflutole and mesotrione applications at the 1X rate resulted in the same Palmer amaranth control, density and biomass at each individual site. In a similar study, isoxaflutole applied at 1X rate, provided greater than 87% control of Palmer amaranth by 8 WAT across multiple sites (Johnson et al. 2012). Susceptible Palmer amaranth density was greater for the ½X rate of isoxaflutole (55 plants m^{-2}) compared to the 1X rate (14 plants m^{-2}) (Table 3.4). In comparison to the resistant Palmer amaranth population, isoxaflutole applied at 1X resulted in 83% control, but control was reduced to 55% when using the ½X rate. Similarly, Palmer amaranth density was lower for isoxaflutole applied at 1X rate (2 plants m^{-2}) compared to ½X rate (7 plants m^{-2}) for the resistant population. Applications of ½X of isoxaflutole on the resistant population also resulted in greater amount Palmer amaranth biomass (7,450 mg m^{-2}) compared to 1X (1,260 mg m^{-2}). All isoxaflutole + atrazine treatments provided the same amount of weed control as all mesotrione + atrazine treatments across both sites (Table 3.4). For the susceptible population, both rates of isoxaflutole + atrazine resulted in ≥ 91% control and ≥ 71% control of the resistant populations. In another study, isoxaflutole + atrazine provided greater than 98% control of Palmer amaranth across multiple locations when applied PRE (Johnson et al. 2012).

Several other commonly applied PRE herbicides were evaluated in the field experiment. Palmer amaranth control was less than 66% for treatments of atrazine, linuron, and bicyclopyrone + bromoxynil across both sites (Table 3.4). Atrazine only provided 43 and 63% control of the HPPD-inhibitor resistant and susceptible populations as they were both resistant to PSII-inhibitors. Kohrt and Sprague (2017) reported similar poor levels of control with atrazine on a different multiple-resistant Palmer amaranth population. Linuron provided ≤ 44% control across both sites (Table 3.4). S-metolachlor provided 89% control of the susceptible population, but was not effective by only providing 64 % control of the resistant population. In a similar study, S-metolachlor or atrazine resulted in less than adequate control of HPPD-inhibitor resistant waterhemp (Hausman et al. 2013). All treatments of bicyclopyrone + bromoxynil resulted in ≤ 66% control of Palmer amaranth and were the least effective compared to the other HPPD-inhibitors applied at field rates across both resistant and susceptible populations. Tank-mixing bicyclopyrone + bromoxynil with atrazine increased the level of weed control for the susceptible population resulting in 76 and 85% control at 1X and 2X rates, respectively. For the resistant population, tank-mixing atrazine with bicyclopyrone + bromoxynil had little impact on weed control with both treatments providing ≤ 54% control regardless of the rate. For the resistant Palmer amaranth population, treatments of linuron, bicyclopyrone + bromoxynil with or without atrazine, ¼X and ½X of mesotrione, and ½X of isoxaflutole did not reduce the amount of Palmer amaranth biomass (≥ 5,700 mg m^{-2}) compared to the non-treated control (17,770 mg m^{-2}). Bicyclopyrone + bromoxynil should not be applied alone to control Palmer amaranth regardless of the population.

Palmer amaranth density in non-treated plots averaged 294 and 15 plants m^{-2} in Reno and Barton County, respectively (Table 3.4). For the susceptible populations, all herbicides reduced Palmer amaranth density by ≥ 154 plants m^{-2} compared to the non-treated control. Palmer amaranth density was 118 plants m^{-2} for linuron treatments, 63 plants m^{-2} for atrazine, and 12 plants m^{-2} for s-metolachlor. The Palmer amaranth density was highest for bicyclopyrone + bromoxynil at 1X (140 plants m^{-2}) and 2X (87 plants m^{-2}) compared to all other herbicide treatments. Application of 1X of mesotrione and isoxaflutole resulted in the same Palmer amaranth density, but higher densities were observed with ½X of isoxaflutole. For the resistant population, all treatments excluding bicyclopyrone at 2X and both bicyclopyrone + atrazine treatments, reduced the Palmer amaranth density at 4 WAT. The ½X rate of isoxaflutole resulted in a higher density of Palmer amaranth with 7 plants m^{-2} compared to the 1X field use rate with 2 plants m^{-2}. All mesotrione + atrazine and isoxaflutole + atrazine treatments resulted in the same Palmer amaranth density, regardless of population.

Comparison of Mesotrione and Isoxaflutole with or without Atrazine

Analysis of fixed effects of herbicide, rate, and addition of atrazine for visual control and density revealed no interactions, but all main effects were significant (Table 3.5). Mesotrione provided greater levels of weed control when compared to isoxaflutole for visual control and across sites (Table 3.6). Visual control of Palmer amaranth at 4 WAT was greater for mesotrione with 89% control compared to 81% control for isoxaflutole. Palmer amaranth density was lower with mesotrione treatments compared to isoxaflutole, with 2.4 and 5.6 plants m^{-2}, respectively. Greater Palmer amaranth control with mesotrione compared to isoxaflutole was consistent with other reports (Kohrt and Sprague 2017), although these two herbicides provided the same amount of HPPD-inhibitor resistant waterhemp control when applied PRE at field use rates (Hausman et al. 2013). Across both herbicides, increasing the rate from ½X to1X rate provided greater weed control of 81 and 89% control, respectively and Palmer amaranth density decreased from 5.7 plants m^{-2} to 2.4 plants m^{-2} (Table 3.6). Adding atrazine to HPPD-inhibitor herbicides increased weed control from 82 to 88% and decreased Palmer amaranth density from 6.4 to 2.1 plants m^{-2}. The greatest amount of weed control was achieved when mixing atrazine and 1X rates of mesotrione or isoxaflutole. Several studies have reported synergistic effect of mixing HPPD-inhibitor and PSII-inhibitor herbicides on controlling both HPPD-inhibitor susceptible and resistant populations (Abendroth et al. 2006, Hugie et al. 2008, Jhala et al. 2014, Kohrt and Sprague 2017).

For the Palmer amaranth biomass data, an interaction between fixed effects of rate and addition of atrazine was observed (Table 3.5). Palmer amaranth biomass was the same for ½X of mesotrione or isoxaflutole + atrazine (260 mg m^{-2}), 1X of mesotrione or isoxaflutole (240 mg m^{-2}), and 1X mesotrione or isoxaflutole + atrazine (200 mg m^{-2}) (Table 3.7). Treatments of mesotrione at ½X without atrazine resulted in the greatest amount of Palmer amaranth biomass of 1210 mg m^{-2}. Mesotrione resulted in greater weed control compared to isoxaflutole across both sites, but regardless of HPPD-inhibitor used, the highest field use rate should be applied. Atrazine should be tank-mixed with mesotrione and isoxaflutole to increase weed control of both HPPD-inhibitor susceptible and resistant populations.

Comparison of Mesotrione with or without Atrazine

Visual control of Palmer amaranth was affected by the interaction of mesotrione rate and addition of atrazine, while no interaction was observed for density and biomass and only the main effects were significant (Table 3.8). The greatest Palmer amaranth control was observed with 1X of mesotrione tank-mixed with atrazine, ½X tank-mixed with atrazine, and 1X of mesotrione, all resulting in ≥ 90% control (Table 3.9). Vyn et al. (2006) reported similar control of waterhemp with mesotrione applied at 1X. Applying ½X of mesotrione resulted in inadequate control of 83%. Mesotrione at ¼X in combination with atrazine resulted in 86% control, but mesotrione alone resulted in the least control of only 70% (Table 3.9).

The lowest amount of Palmer amaranth density was observed with applications of 1X of mesotrione compared to the ½X and ¼X rate with 1.5, 3.8, and 6.8 plants m^{-2}, respectively (Table 3.10). Mesotrione applied at ½X and 1X resulted in the less Palmer amaranth biomass with 160 and 240 mg m^{-2}, respectively, compared to ¼X with 710 mg m^{-2}. Soil-applied mesotrione applications of less than 1X resulted in poor weed control of similar pigweed species on a sandy loam soil with low organic matter in Virginia (Armel et al. 2003). Atrazine, tank-mixed with mesotrione, decreased the density of Palmer amaranth from 6.4 to 1.8 plants m^{-2} compared to when mesotrione was applied alone. Palmer amaranth biomass decreased from 620 to 190 mg m^{-2} when atrazine and mesotrione where tank mixed compared to mesotrione alone

(Table 3.10). Armel et al. (2005) observed similar reductions in weed biomass when tank-mixing mesotrione and atrazine compared to mesotrione alone. Mesotrione should be applied at 1X in combination with atrazine to maximize both HPPD susceptible and resistant populations of Palmer amaranth.

Conclusion

Results from the dose-response experiment confirmed that SF(R) was less susceptible to soil-applied HPPD-inhibitor herbicides compared to RL(S) at rates much lower than recommended in the field. Additionally, experiments in the field demonstrated similar reduced efficacy of soil-applied HPPD-inhibitor herbicides in controlling HPPD-inhibitor resistant Palmer amaranth in Barton County. However, overall trends of increasing control using higher HPPD-inhibitor herbicide rates and tank-mixing HPPD-inhibitors with atrazine were consistent across both susceptible and resistant populations. Overall weed control was reduced in on the resistant population, but management recommendations should not differ regardless of the Palmer amaranth population when using soil-applied HPPD-inhibitor herbicides. The greatest levels of Palmer amaranth control, reduction in density, and reduction in biomass were achieved with 1X rates of mesotrione or isoxaflutole, in combination with atrazine. No PRE treatment provided complete Palmer amaranth control by 4 WAT, thus an integrated management approach including multiple sites of action, tillage, crop rotation, and POST herbicides should be utilized (Kohrt and Sprague 2017, Norsworthy et al. 2012, Ward et al. 2013). HPPD-inhibitor herbicides are still an effective herbicide site of action when combined with atrazine for controlling HPPD-resistant Palmer amaranth populations when applied to the soil at recommended use rates.

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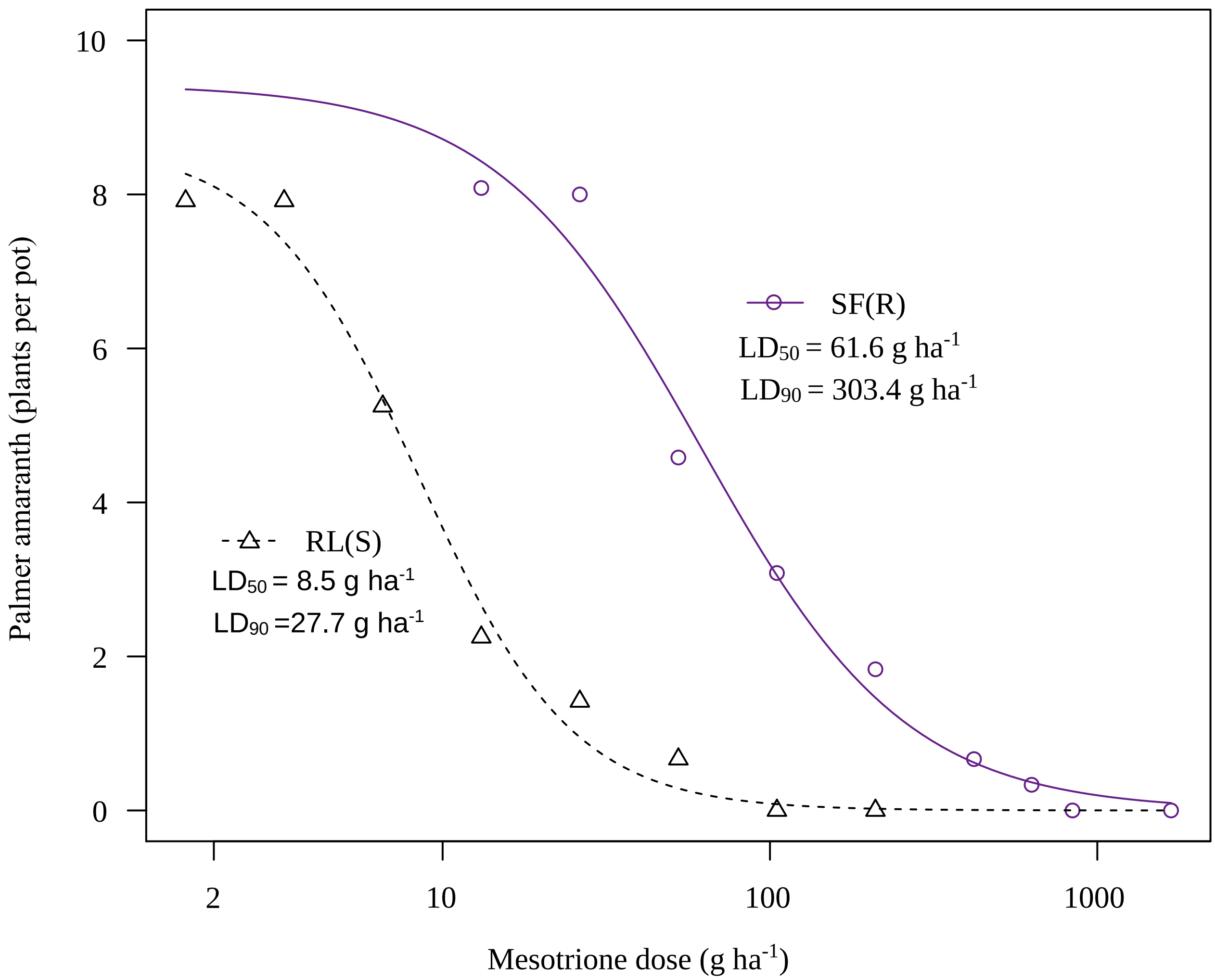

Figure 3.1. Non-linear dose response analysis of seedling emergence of susceptible (RL(S)) and resistant (SF(R)) Palmer amaranth populations in response to soil-applied mesotrione. (Non-linear regression model: $Y = C + (D-C) / (1 + \exp[b(\log(x) - \log(LD_{50}))])$)

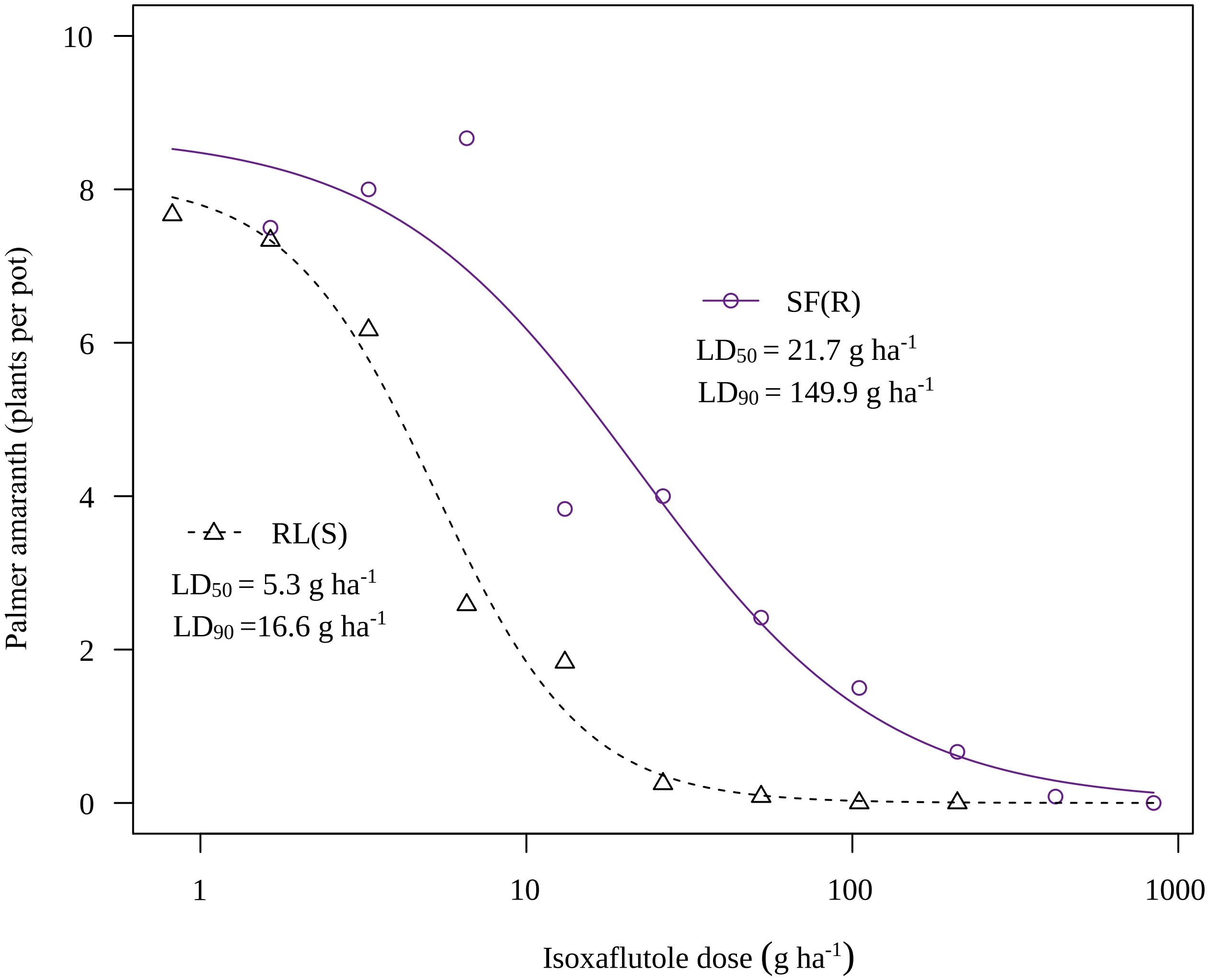

Figure 3.2. Non-linear dose response analysis of seedling emergence of susceptible (RL(S)) and resistant (SF(R)) Palmer amaranth populations in response to soil-applied isoxaflutole. (Non-linear regression model: $Y = C + (D-C) / (1 + \exp[b(\log(x) - \log(LD_{50}))])$)

Table 3.1. Soil characteristics, preemergence (PRE) herbicide application dates, and weekly rainfall totals for field experiments in 2017.[a]

						Rainfall			
						Weeks after PRE application			
Location	Population	Soil Type	Soil pH	Organic Matter	Date of PRE	1	2	3	4
				%		mm			
Barton County	Resistant	Attica[a] loamy fine sand	6.6	0.8	May 29	9	5	22	13
Reno County	Susceptible	Ost[b] loam	6.3	2.5	May 27	3	1	19	6

[a]Coarse-loamy, mixed, superactive, mesic Udic Haplustalfs
[b]Fine-loamy, mixed superactive, mesic Udic Argiustolls

Table 3.2. Herbicide active ingredients and trade names, application rates, and manufacturer information for Palmer amaranth control in field experiments. Herbicides were applied preemergence (PRE).

Active Ingredient	Trade Name	Rates	Manufacturer[a]
		g ai ha^{-1}	
Mesotrione	Callisto	53, 105, 210 (1X)	Syngenta Crop Protection LLC
Isoxaflutole	Balance Flexx	53, 105 (1X)	Bayer CropScience LP
Bicyclopyrone +bromoxynil	Talinor	50 +700 (1X), 100 + 1400	Syngenta Crop Protection LLC
Atrazine	AAtrex	2240	Syngenta Crop Protection LLC
S-metolachlor	Dual II Magnum	2140	Syngenta Crop Protection LLC
Linuron	Lorox	700	NovaSource INC.

[a] Manufacturer information: Syngenta Crop Protection, LLC, Greensboro, NC, www.syngenta.com; Bayer CropScience, Research Triangle Park, NC, www.cropscience.bayer.com; NovaSource INC., Phoenix, AZ, www.novasource.com

Table 3.3. Response summary of susceptible (RL(S)) and resistant (SF(R)) Palmer amaranth population emergence to mesotrione and isoxaflutole treatments 4 weeks after treatment (WAT).[a]

	Mesotrione		Isoxaflutole	
Population	LD_{50}	LD_{90}	LD_{50}	LD_{90}
	g ai ha^{-1}			
RL(S)	8.5 (0.7)	27.7 (3.4)	5.3 (0.5)	16.6 (2.5)
SF(R)	61.6 (7.4)	303.4 (33.4)	21.7 (3.6)	149.9 (26.1)
R/S	7.2*	10.9*	4.1*	9.0*

[a]Abbreviations: LD_{50}, rate causing 50% reduction in seedling survival; LD_{90}, rate causing 90% reduction in seedling survival; R/S, resistance index [ratio of LD_{50} or LD_{90} of susceptible (RL(S)) and resistant (SF(R)) populations].
[b]Values in parenthesis are ± 1 standard error.
*R and S values are significantly different at P<0.001.

Table 3.4. Mean Palmer amaranth control, density and biomass at 4 weeks after treatment for the HPPD-inhibitor susceptible (Reno County) and resistant (Barton County) field sites in 2017.

		Control		Density		Biomass	
Herbicide	Rate	Susceptible	Resistant	Susceptible	Resistant	Susceptible	Resistant
	g ai ha^{-1}	%		plants m^{-2}		mg m^{-2}	
Mesotrione	53	83 c-e[a]	58 c-e	30 d-f	6 c-e	280 e-h	5800 a-c
Mesotrione	105	90 a-d	76 a-d	24 e-g	4 c-g	160 e-h	5700 a-c
Mesotrione	210	94 ab	86 ab	9 f-i	1 g	90 g-i	440 e
Isoxaflutole	53	81 cd	55 de	55 c-e	7 b-d	330 d-g	7450 ab
Isoxaflutole	105	89 a-c	83 ab	14 f-h	2 e-g	60 hi	1260 de
Bicyclopyrone + bromoxynil	50 + 240	33 g	64 b-e	140 b	6 c-e	3800 ab	7480 ab
Bicyclopyrone + bromoxynil	100 + 240	66 ef	55 de	87 bc	9 a-c	1400 b-d	6780 a-c
Atrazine	2240	63 f	43 e	63 cd	5 c-f	910 b-e	4180 b-d
S-metolachlor	2140	89 a-c	64 b-e	12 f-i	6 b-d	130 f-i	3520 b-d
Linuron	700	44 g	43 e	118 b	8 b-e	1800 bc	6640 a-c
Mesotrione + atrazine	53 + 2240	90 a-c	81 ab	9 f-i	2 e-g	90 g-i	1850 b-d
Mesotrione + atrazine	105 + 2240	97 a	84 ab	2 hi	2 e-g	10 j	1770 c-e
Mesotrione + atrazine	210 + 2240	99 a	89 a	1 i	1 fg	10 j	1140 de
Isoxaflutole + atrazine	53 + 2240	91 a-c	71 a-d	9 f-i	4 c-g	80 g-i	3440 b-d
Isoxaflutole + atrazine	105 + 2240	96 ab	79 a-c	5 g-i	3 d-g	30 i-j	3020 b-d
Bicyclopyrone + bromoxynil + atrazine	50 + 700 + 2240	76 de	43 e	50 c-e	13 ab	510 c-f	7710 ab
Bicyclopyrone + bromoxynil + atrazine	100 + 1400 + 2240	85 b-d	54 de	15 f-h	9 a-c	110 g-i	7430 a-c
Mesotrione + linuron	105 + 700	94 ab	66 a-d	6 g-i	4 c-g	90 g-i	1950 b-d
Nontreated	-	-	-	294 a	15 a	11230 a	17770 a

[a]Means followed by the same letter within a column are not statistically different according to Fisher's protected LSD (α = 0.05).

Table 3.5. P values as a result of the analyses of variance combined across sites of fixed effects and interactions for mesotrione and isoxaflutole treatments with or without atrazine for Palmer amaranth control, density, and biomass. Bold P-values indicate were $P \leq 0.05$.

Fixed Effect	Control	Density	Biomass
		P-Value	
Herbicide	**.0003**	**.0035**	**.0143**
Rate	**.0004**	**.0025**	**.0034**
Herbicide by Rate	.1393	.9577	.6160
Atrazine[a]	**.0078**	**.0002**	**.0086**
Herbicide by Atrazine[a]	.6779	.5230	.2376
Rate by Atrazine	.0909	.1077	**.0369**
Herbicide by Rate by Atrazine[a]	.3922	.5321	.8052

[a]With or without tank-mix of atrazine

Table 3.6. Palmer amaranth control, density, and biomass at 4 weeks after treatment, of data subset including mesotrione and isoxaflutole treatments combined across sites.

Fixed Effect	Level	Control	Density	Biomass
		%	plants m^{-2}	mg m^{-2}
Herbicide	Mesotrione	89 a[a]	2.4 b	240 b
	Isoxaflutole	81 b	5.6 a	520 a
Rate	1/2X	81 b	5.7 a	570
	1X	89 a	2.4 b	220
Atrazine[b]	With	88 a	2.1 b	230
	Without	82 b	6.4 a	540

[a]Means followed by the same letter within a column for each fixed effect are not statistically different according to Fisher’s protected LSD ($\alpha = 0.05$).
[b]With or without tank-mixing atrazine

Table 3.7. Palmer amaranth biomass of extracted subset of treatments with mesotrione and isoxaflutole treatments with rate by atrazine interaction combined across sites.

Rate	Biomass	
	No Atrazine	Atrazine
	—— mg m^{-2} ——	
1/2X	1210 a[a]	260 b
1X	240 b	200 b

[a]Means followed by the same letter within entire table are not statistically different according to Fisher's protected LSD ($\alpha = 0.05$).

Table 3.8. Combined site analysis of significance of fixed effects and interactions for mesotrione treatments with or without atrazine across Palmer amaranth control, density and biomass.

Fixed Effect	Control	Density	Biomass
		P-Value	
Rate	**<0.0001**	**0.0002**	**0.0024**
Atrazine[a]	**<0.0001**	**<0.0001**	**0.0007**
Rate by Atrazine[a]	**0.0264**	0.6717	0.1859

[a]With or without tank-mix of atrazine

Table 3.9. Palmer amaranth control at 4 weeks after treatment of the subset of mesotrione treatments rates and addition of atrazine interaction combined across sites.

Rate	Control	
	No Atrazine	Atrazine
g mesotrione ha^{-1}	——— % ———	
53	70 d[a]	86 bc
105	83 c	90 ab
210	90 ab	94 a

[a]Means followed by the same letter within entire table are not statistically different according to Fisher's protected LSD ($\alpha = 0.05$).

Table 3.10. Palmer amaranth density and biomass across mesotrione rates (averaged across addition of atrazine) and across tank-mix with atrazine (averaged across mesotrione rates) when combined across field experiments in 2017.

Fixed Effect	Level	Density	Biomass
		plants m^{-2}	mg m^{-2}
Rate	1/4X	6.8 a[b]	710 a
	1/2X	3.8 a	350 ab
	1X	1.5 b	160 b
Atrazine[a]	With	1.8 b	190 b
	Without	6.4 a	620 a

[a]With or without tank-mixing atrazine

[b]Means followed by the same letter within a column for each fixed effect are not statistically different according to Fisher's protected LSD ($\alpha = 0.05$).

Appendix A - Site Maps

Interpolated SOM, EC, and texture class maps, plot layout, and locations of soil calibration samples across all nine sites.

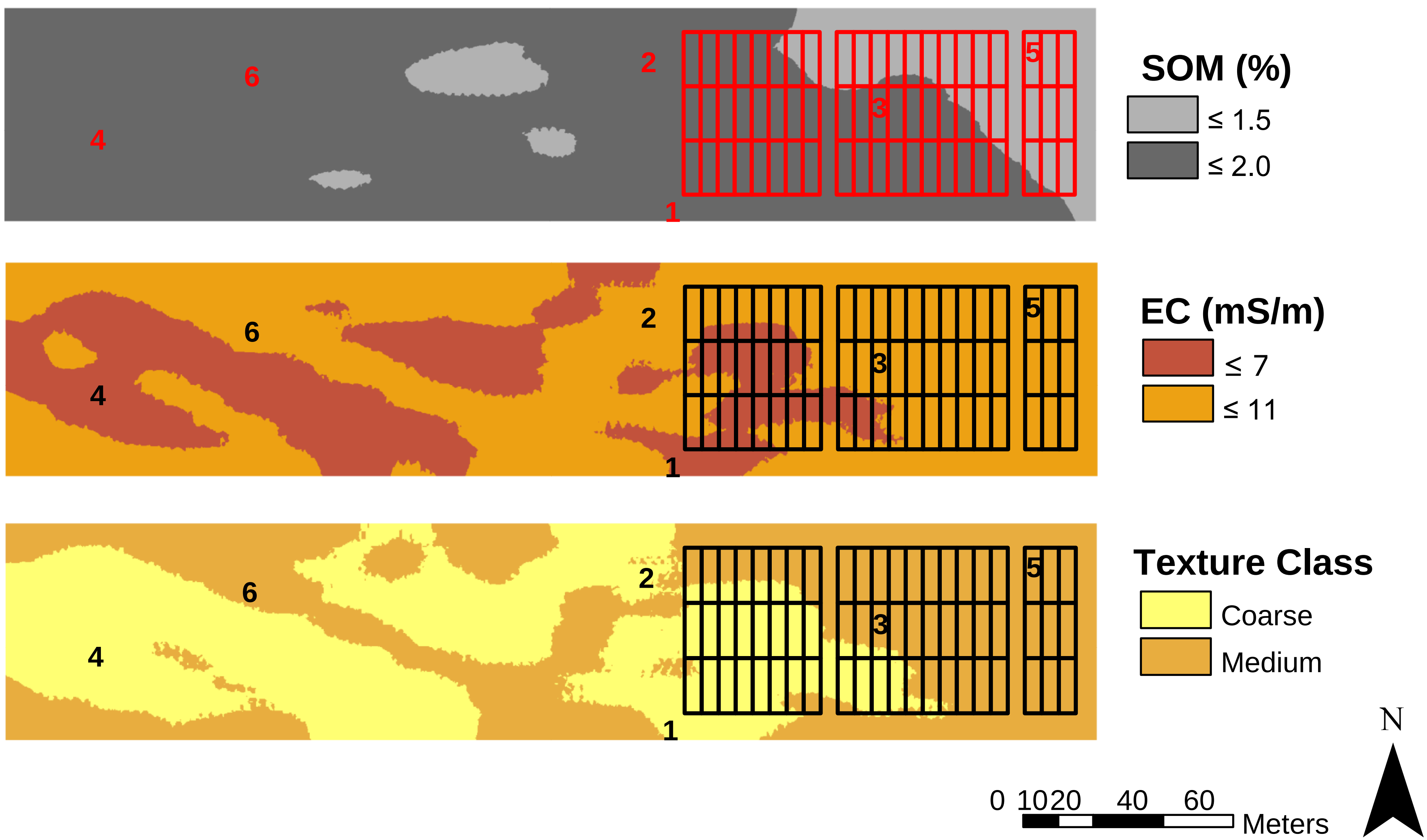

Figure A.1. Rossville SOM (top), EC (middle), and texture class (bottom) interpolated maps based on Veris data in 2016. Boxes indicate individual plots and numbers represent location of soil calibration samples.

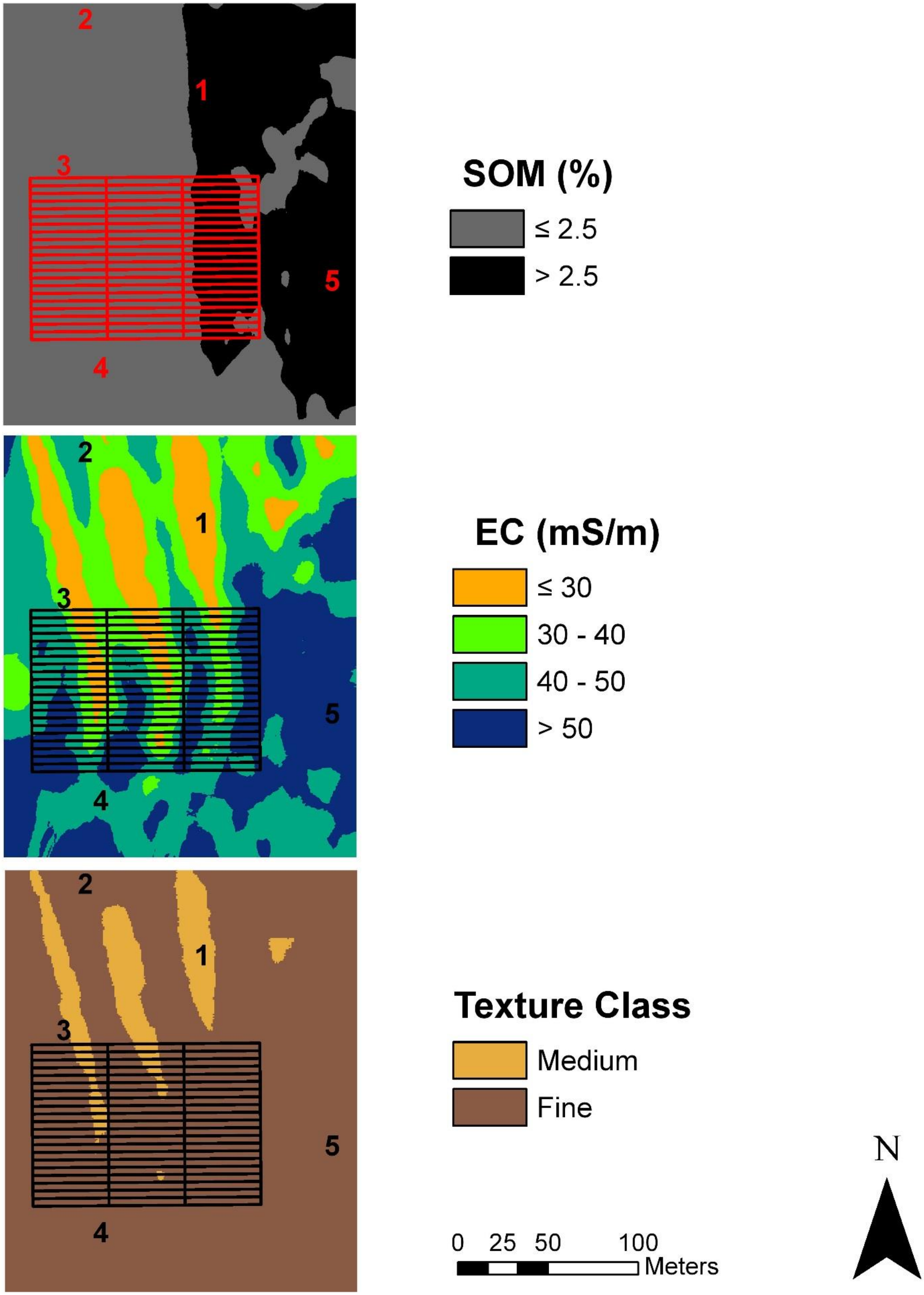

Figure A.2. Manhattan SOM (top), EC (middle), and texture class (bottom) interpolated maps based on Veris data in 2016. Boxes indicate individual plots and numbers represent location of soil calibration samples.

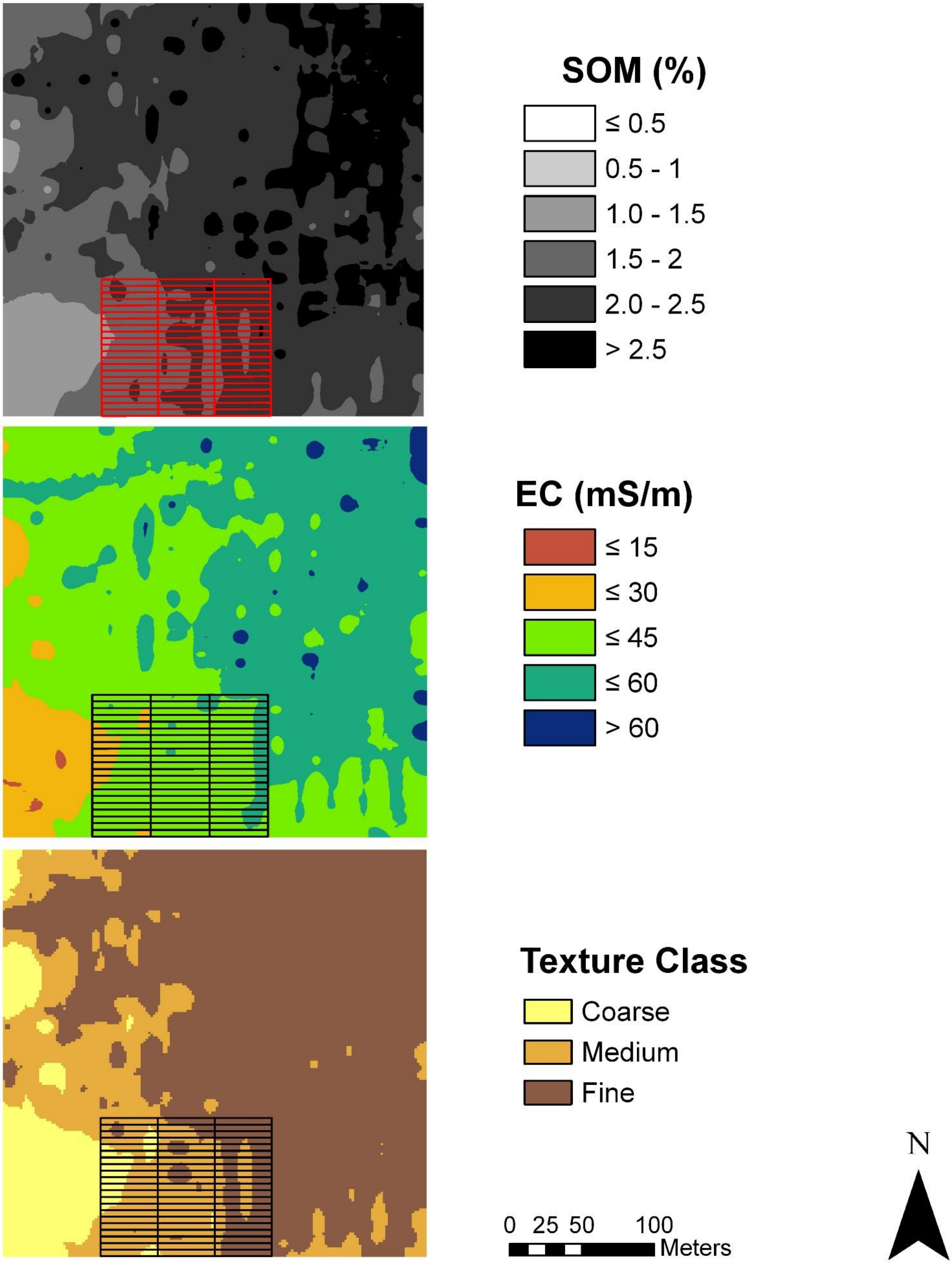

Figure A.3. Salina SOM (top), EC (middle), and texture class (bottom) interpolated maps based on Veris data in 2016. Boxes indicate individual plots and numbers represent location of soil calibration samples.

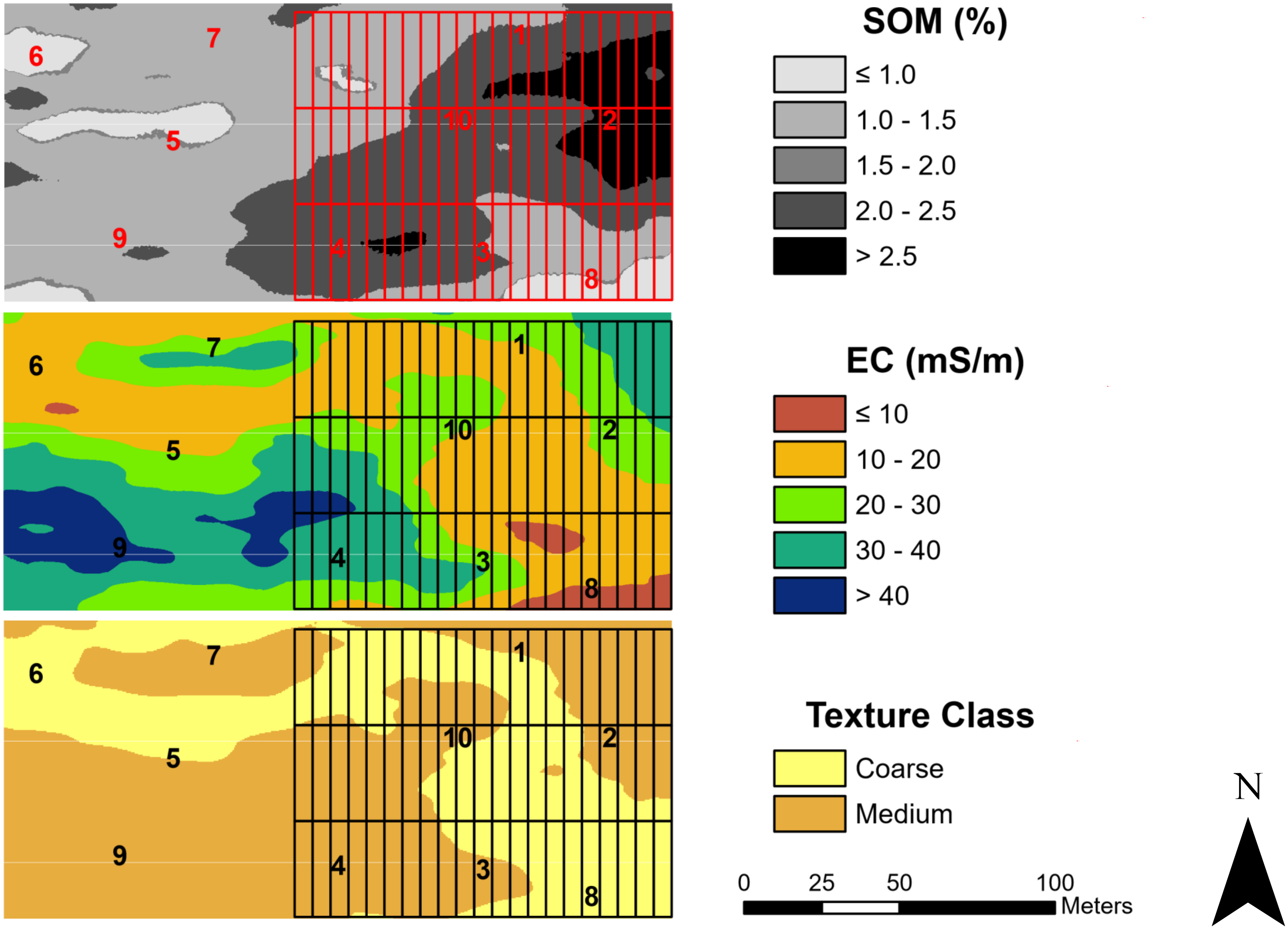

Figure A.4. Hutchinson North Redd SOM (top), EC (middle), and texture class (bottom) interpolated maps based on Veris data in 2016. Boxes indicate individual plots and numbers represent location of soil calibration samples.

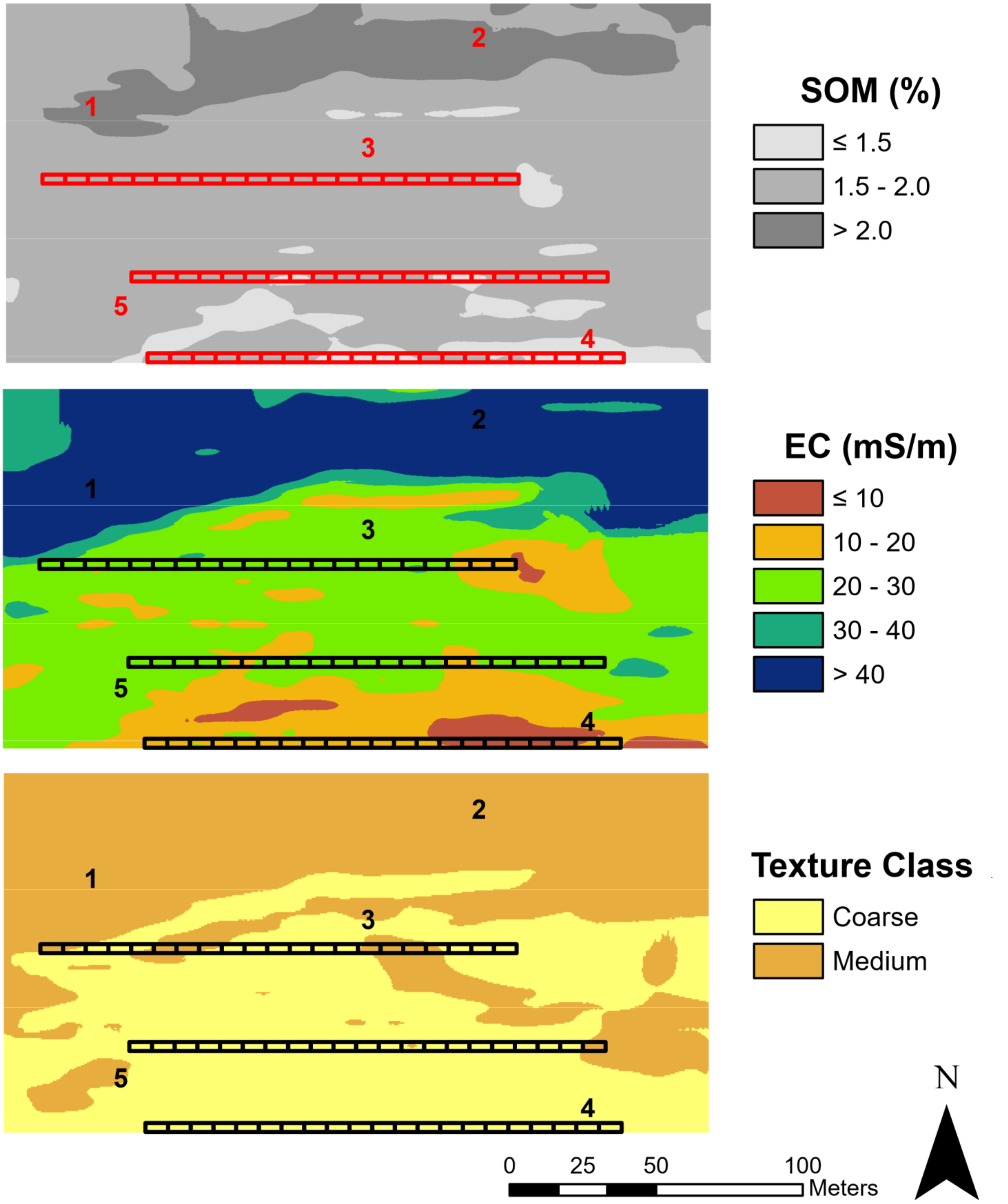

Figure A.5. Topeka SOM (top), EC (middle), and texture class (bottom) interpolated maps based on Veris data in 2017. Boxes indicate individual plots and numbers represent location of soil calibration samples.

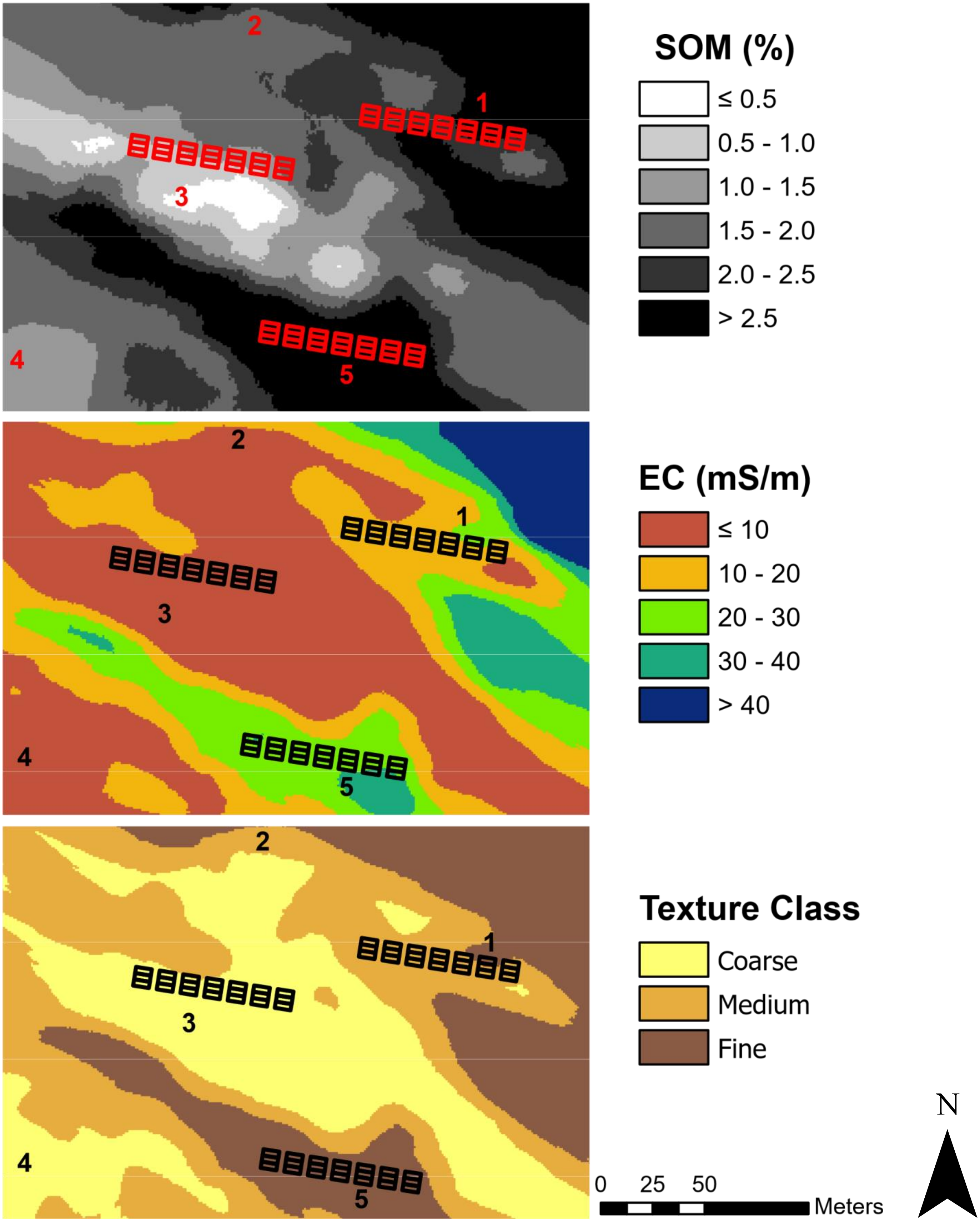

Figure A.6. Morganville SOM (top), EC (middle), and texture class (bottom) interpolated maps based on Veris data in 2017. Boxes indicate individual plots and numbers represent location of soil calibration samples.

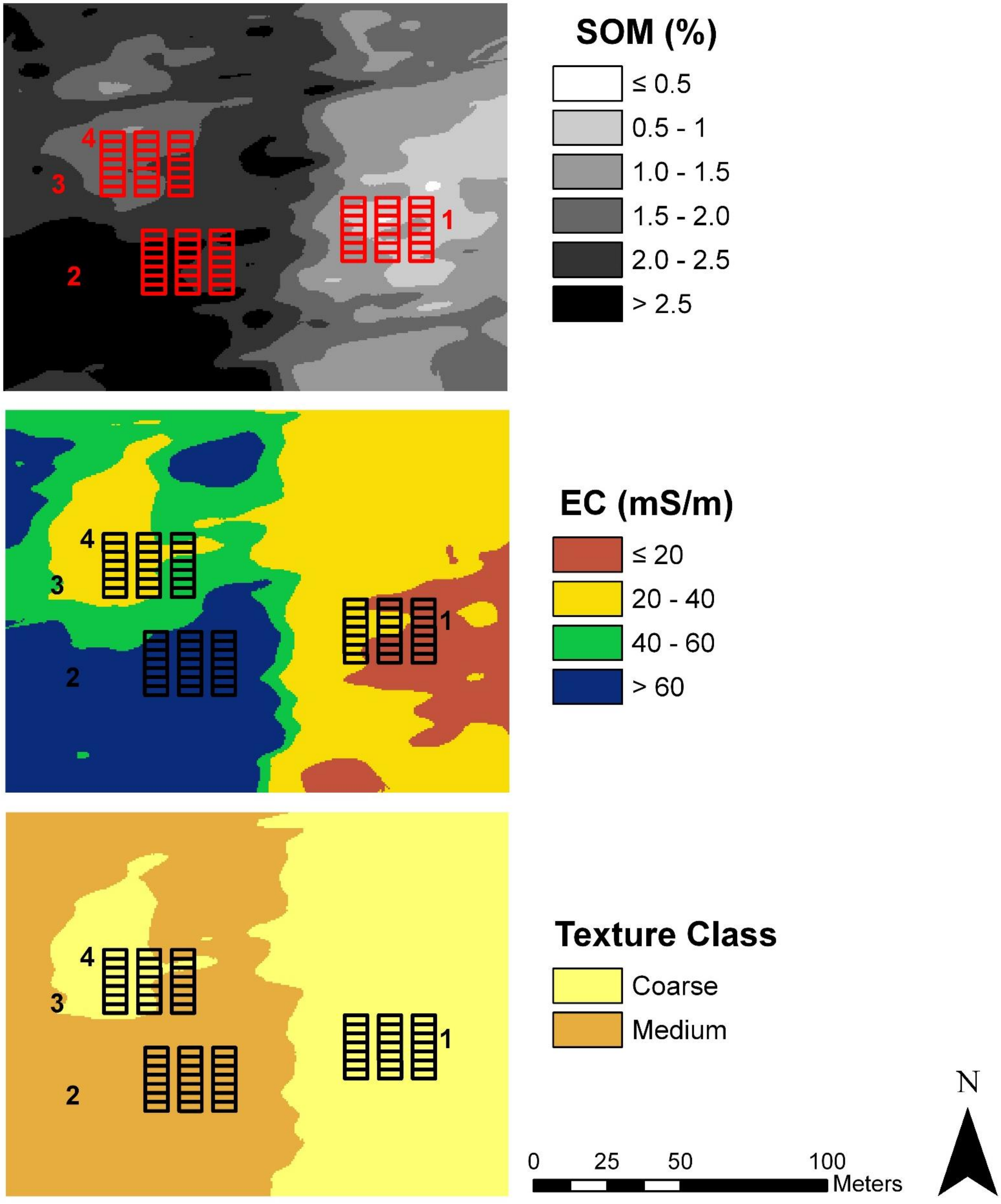

Figure A.7. Hutch Pivot SOM (top), EC (middle), and texture class (bottom) interpolated maps based on Veris data in 2017. Boxes indicate individual plots and numbers represent location of soil calibration samples.

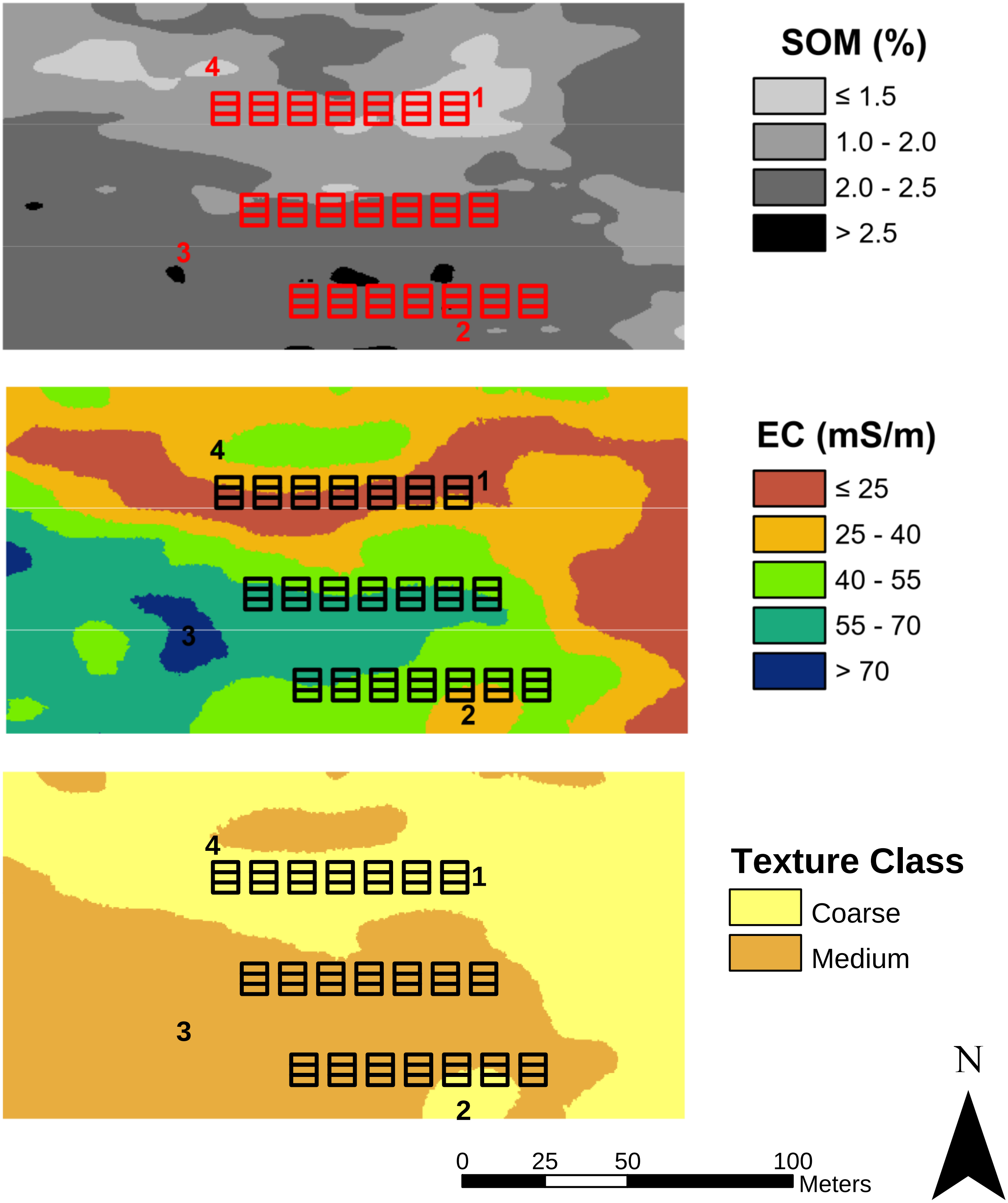

Figure A.8. Hutch Redd SOM (top), EC (middle), and texture class (bottom) interpolated maps based on Veris data in 2017. Boxes indicate individual plots and numbers represent location of soil calibration samples.

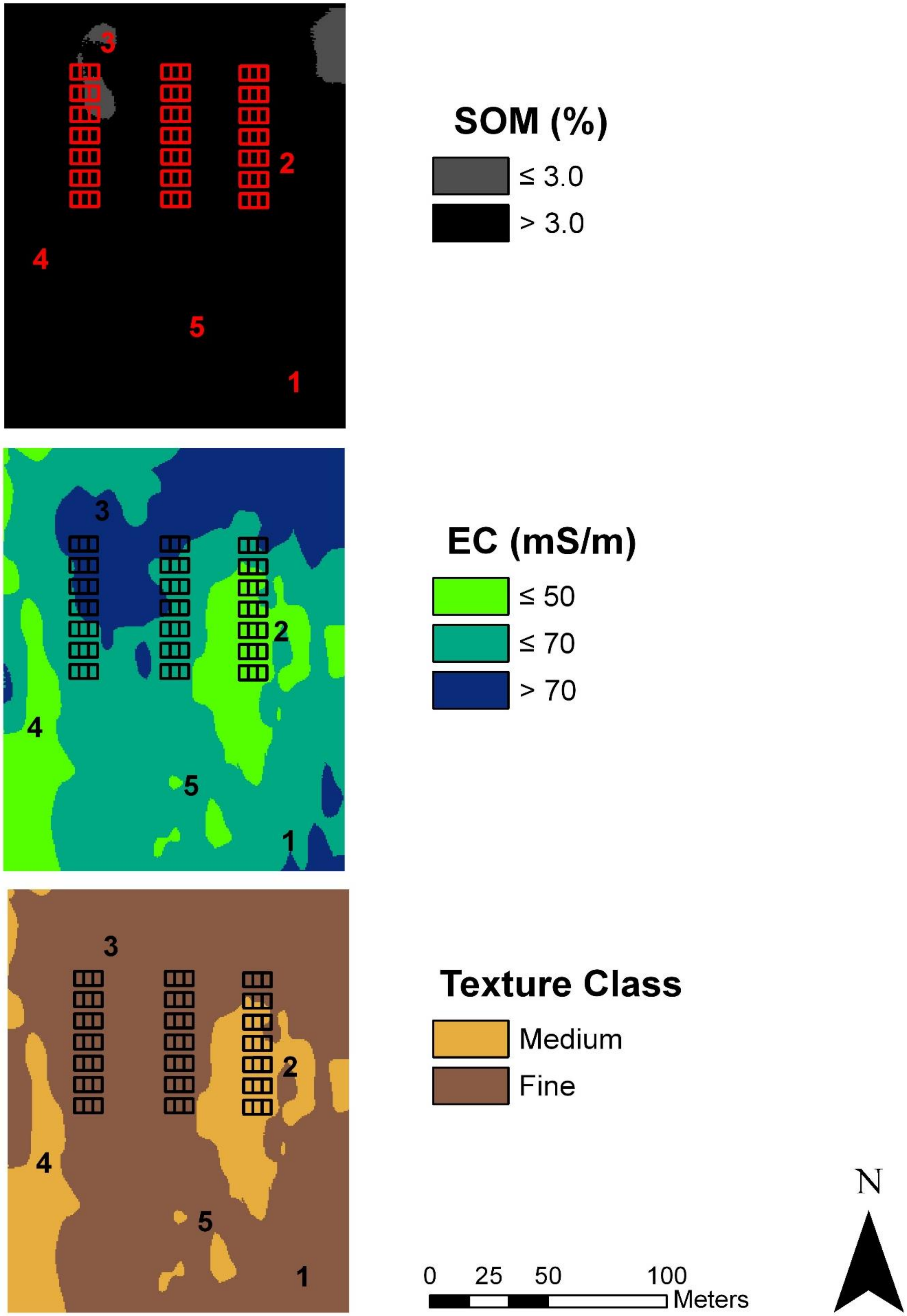

Figure A.9. Manhattan SOM (top), EC (middle), and texture class (bottom) interpolated maps based on Veris data in 2017. Boxes indicate individual plots and numbers represent location of soil calibration samples.

Appendix B - Individual Location Descriptions

2016 – Rossville

At the Kansas River Valley Experiment Field two km southeast of Rossville (39°07'06.2"N and 95°55'24.2"W), a field cultivator was used to control emerged weeds two weeks before planting. Corn was planted under irrigation in 0.76-m rows on May 4. Plot size was 4.6 m wide by 30.5 m long and PRE applications were made on May 10. Grain was harvested with plot combine from the center four rows of each plot, weighed, and yield was determined at 15.5% moisture.

2016 – Manhattan

This site was at the Kansas State University, Ashland Bottoms Research Farm eight km southwest of Manhattan (39°07'31.7"N and 96°38'55.7"W). The field was conventionally tilled and field cultivated to control emerged weeds one week before planting. On May 19, corn was planted in 0.76-m rows with plots established at 4.6 m wide by 45.7 m long. PRE treatments were applied May 22 and there were no weeds emerged at the time of application. Throughout the season there were no weeds to access herbicide efficacy. Corn ears were hand harvested at maturity and later shelled to determine grain yield for each plot. Yield was calculated at a moisture of 15.5%.

2016 – Salina

On a producer's no-tillage farm southeast of Salina (38°47'54.9"N and 97°25'59.2"W), grain sorghum was drilled in 0.38-m rows on June 9. To control emerged Palmer amaranth, a burndown was applied immediately before PRE treatments on June 11. Plots were 4.6 m wide by 45.7 m long. At maturity, grain heads were clipped from 4 m of row in representative area of individual plots and placed in a dryer at 140º C for one week. Grain was weighed and tested for moisture content and yield was determined at 13.5% moisture.

2016- Hutch Redd

At the KSU South Central Kansas Experiment Redd Foundation field (37°57'22.7"N and 98°06'55.1"W) early field cultivation was used to control winter annual weeds two months before planting. Grain sorghum was planted in 0.76-m rows on June 14 and a PRE applications were applied the following day immediately after herbicide burndown was applied to control emerged weeds. Grain heads were clipped from 4 m of row in representative area within the center two rows of each individual plot and placed in a dryer at 140º C for one week. Grain was weighed and tested for moisture and yield was determined at 13.5% moisture.

2017 – Topeka

At the Kansas River Valley irrigated Experiment Field 10 km west of Topeka (39°04'37.7"N and 95°46'12.4"W), field cultivation was used to provide control of emerged weeds two weeks before planting. Corn was later planted in 0.76-m rows on April 25 and plot size was 3.05 m wide by 6.1 m long. PRE herbicide treatments were applied immediately after planting on April 25. Throughout the season there were no weeds to access herbicide efficacy. Grain was harvested with plot combine from the center four rows of each plot, weighed, and yield was determined at 15.5% moisture.

2017 – Morganville

A producer’s no-tillage field south of Morganville (39°27'15.3"N and 97°12'23.6"W) received a burndown one month before planting to control winter annual weeds that were emerged. On May 9, corn was planted in 0.38-m rows and PRE treatments were applied the same day. Plot size was 3.05 m wide by 6.1 m long with 3.05 m alleyways in between each plot. Corn ears were hand harvested from the center two rows for length of entire plot and placed in burlap sacks to be shelled. Shelled grain was weighed and tested for moisture and yield was calculated at 15.5% moisture.

2017 – Hutch Pivot

Two separate burndowns were applied at the irrigated KSU South Central Kansas Experiment Pivot (37°56'39.4"N and 98°06'28.8"W) two weeks before and the day of planting to control all weeds that had emerged prior to planting. Grain sorghum was planted in 0.76-m rows on May 25 and plot size was 3.05 m wide by 6.1 m long with 3.05m alleyways in between each plot. PRE treatments were applied May 27. Grain sorghum heads were hand harvested from the center two rows for length of entire plot and shelled. Shelled grain was weighed and tested for moisture and yield was calculated at 13.5% moisture.

2017 – Hutch North Redd

In 2017, the site at the KSU South Central Kansas Experiment Redd Foundation field (37°57'22.7"N and 98°06'58.1"W) was 50 m west relative to the 2016 field site to avoid flooding in lower elevation areas. This field was cultivated one month before planting to control early-season weeds and received a burndown two weeks before planting. Grain sorghum was planted in 0.76 cm rows on May 25. A second burndown and PRE applications were applied on May 27. Grain sorghum heads were hand harvested from the center two rows for length of entire plot and shelled. Shelled grain was weighed and tested for moisture and yield was calculated at 13.5% moisture.

2017 – Manhattan

In June of 2017, grain sorghum was no-till planted in 0.76 cm rows at the K-State Agronomy Department's Ashland Bottoms Research Farm approximately 10 km southwest of Manhattan (39°07'36.0"N and 96°38'05.9"W). Plot size was 4.6 m wide by 45.7 m long. A burndown was applied one week prior to PRE treatments that were applied May 22. Throughout the season there were no weeds to access herbicide efficacy, therefore grain yield, harvested by combine, was the only data collected for this location.