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Management zone classification for variable-rate soil residual herbicide applications

Rose V Vagedes[1] · Jason P Ackerson[2] · William G Johnson[1] · Bryan G Young[1]

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Abstract

The use of soil residual herbicides, along with other practices that diversify weed management strategies, have been recommended to improve weed management and deter the progression of herbicide resistance. Although soil characteristics influence recommended application rates for these herbicides, the common practice is to apply a uniform dose of soil residual herbicides across fields with variable soil characteristics. Mapping fields for soil characteristics that dictate the optimal dose of soil residual herbicides could improve the efficiency and effectiveness of these herbicides, as well as improve environmental stewardship. The objectives of this research were to develop and quantify the accuracy of management zone classifications for variable-rate residual herbicide applications using multiple soil data sources and soil sampling intensities. The maps were created from soil data that included (i) Soil Survey Geographic database (SSURGO), (ii) soil samples (SS), (iii) soil samples regressed onto soil electrical conductivity (EC) measurements (SSEC), (iv) soil samples with organic matter (OM) data from SmartFirmer® (SF) sensors (SSSF), and (v) soil samples regressed onto EC measurements plus OM data from SmartFirmer® sensor (SSECSF). A modified Monte Carlo cross validation method was used on ten commercial Indiana fields to generate 36,000 maps across all sources of spatial soil data, sampling density, and three representative herbicides (pyroxasulfone, s-metolachlor, and metribuzin). Maps developed from SSEC data were most frequently ranked with the highest management zone classification accuracy compared to maps developed from SS data. However, SS and SSEC maps concurrently had the highest management zone classification accuracy of 34% among maps developed across all fields, herbicides, and sampling intensities. One soil sample per hectare was the most reliable sampling intensity to generate herbicide application management zones compared to one soil sample for every 2 or 4 hectares. In conclusion, soil sampling with EC_a data should be used for defining the management zones for variable-rate (VR) residual herbicide applications.

Keywords Variable-rate applications · Residual herbicides · Geostatistics · Monte carlo cross-validation · Soil sampling intensity · Electrical conductivity

Extended author information available on the last page of the article

Introduction

Best management practices (BMPs) for mitigating herbicide resistance in weeds include multiple cultural (row spacing, seeding rates, cover crops, competitive cultivars, etc.), mechanical (hand-weeding, tillage, mowing, burning, electrocution, etc.), and chemical (herbicide mode-of-action rotation, herbicide mixtures, residual herbicides) weed management practices to prevent the selection, dispersal and buildup of resistance genes in the soil seedbank (Norsworthy et al., 2012; Heap, 2014). The primary tactic for weed management in major agronomic crops since the 1990s has been the deployment of crops with tolerance to foliar (postemergence) herbicides such as glyphosate, glufosinate, dicamba, and 2,4-D (Dill et al., 2008; Kumar et al., 2020; Priess et al., 2022; Young, 2006). Consequently, these foliar herbicides became the primary weed management practice and growers were applying them at rates lower than what was stated on the herbicide label. The repeated use of the same foliar herbicide at reduced rates has contributed to the rapid evolution of weed species with resistance to these herbicides (Kumar et al., 2020; Priess et al., 2022; Heap, 2024), thereby reinforcing the need for more robust and diverse weed management strategies. Two specific practices encouraged through BMPs to mitigate herbicide resistance include: (i) applying herbicides at the full labeled rates and (ii) using residual herbicides (Norsworthy et al., 2012). The activity of a soil residual herbicide dependents on several soil characteristics including soil texture, organic matter (OM), and pH. Thus, residual herbicides must be applied rate that match field specific soil conditions to provide the greatest efficacy and deter the potential expansion of herbicide resistance. Most soil residual herbicide labels convey the importance of these soil factors on herbicide activity by recommending multiple application rate ranges for specific soil conditions.

Soil characteristics can vary within production fields as a result of soil forming factors such as glacial disturbance or deposits, water drainage, soil erosion, and historical agricultural use patterns. Therefore, a uniform herbicide application rate may result in portions of the field receiving inadequate or excessive rates of the active herbicide ingredient. Herbicides such as metribuzin, sulfentrazone, trifluralin, acetochlor, isoxaflutole, s-metolachlor, etc. are more likely to cause crop injury when higher than recommended rates are applied under certain soil conditions (Armel et al., 2003, Green & Obien, 1969, Hartzler et al., 1989, Johnson et al., 2012). Conversely, reduced weed control and an increased risk of herbicide resistance may occur when a lower than recommended dose is applied under particular soil conditions. Ideally, the optimal rate of the soil residual herbicide would be applied to all sections of the field. However, this would require mapping field spatial soil variability, with delineations for soil texture and/or OM levels into management zone. With these zones, variable-rate (VR) applications can be performed by applying multiple herbicide rates within a single field.

There are numerous data sources currently available within the United States that are used to map field spatial soil variability. These sources include: (i) Soil Survey Geographic database (SSURGO), (ii) intensive soil sampling, (iii) soil electrical resistivity sensors, and (iv) implement-mounted optical reflectance sensors using visible and near-infrared (VNIR) reflectance spectroscopy. For nearly the entire United States, the SSURGO data are provided for no cost, publicly-available, online soil database known as Web Soil Survey (WSS) by the United States Department of Agriculture Natural Resources Conservation Service (USDA-NRCS). Soils were mapped by visually delineating aerial photographs or digital images based on local geology, topography, vegetation, or landforms (Soil Science Division Staff, 2017). The accuracy of these delineated area boundaries was verified with a limited number of soil pedons. The sampling procedures varied by scale, sampling intensity, and year of data collection. For regional information, soil scientists have found that these pedons along with the knowledge of the soil-vegetation-landscape relationship provided sufficient data for generating soil survey maps (Soil Science Division Staff, 2017). However, these soil surveys generally do not provide an accurate representation of OM and soil texture at a field-scale level for site-specific management practices (Anderson-Cook et al., 2002; Nawar et al., 2017).

In recent decades, intensive soil sampling has increased in popularity to improve fertilizer management recommendations by obtaining more accurate maps of soil nutrients, OM, pH, and soil texture These samples are commonly collected in a zonal pattern or on a 0.5- to 4-ha grid pattern (Lange & Peake, 2020). However, these soil samples only provide information at the known locations within the field and do not represent the spatial soil variability continuously across the whole field. To obtain a continuous spatial representation of the soil variability with the soil samples, a common geostatistical method known as ordinary kriging is needed to interpolate the unknown area between sampling locations (Chabala et al., 2017; Brouder et al., 2005; Meul & Van Meirvenne, 2003). More recently, the combination of soil apparent electrical conductivity (EC_a) data and manually collected soil samples has been used to map the spatial soil variability and improve the accuracy of management zones for VR fertilizer application and soil mapping (Corwin & Lesch, 2005). Commercially, the more popular method for obtaining soil EC_a measurements is through direct soil contact using vehicle-mounted electrical resistivity sensors (Doolittle et al., 2002). These sensors record data points at a 1hz logging rate up to ground speeds of 24 km/h, providing between 20 and 40 EC_a readings per acre (Adhikari et al., 2009). These semi-continuous readings enable mapping spatial variability within the field at a level of detail that would not be possible with intensive soil sampling; however, it challenging to distinguish main causes spatial variability in EC_a readings.

The EC_a readings can be coupled with soil samples to determine the relationship between the EC_a and soil property values. Studies have shown soil EC_a to have a strong correlation to both clay content (Corwin & Lesch, 2005; Broge et al., 2004) and soil OM (Broge et al., 2004). Therefore, coupling EC_a and soil samples may improve the predictive accuracy of soil texture and OM between known soil samples when developing management zones for VR residual herbicide applications. The collected soil samples (target variable) and soil ECa (auxiliary variable) results can be utilized together to improve the accuracy of the predictions of unknown sampling locations using a geostatistical method known as regression kriging (Hengl et al., 2007). Guiding predictions with auxiliary variables such as EC_a have been shown to perform better than other geostatistical methods such as ordinary kriging (Knotters et al., 1995). Nevertheless, regression kriging does not perform well if there is a poor correlation between the target and auxiliary variable (Zhu & Lin, 2010). Additionally, for ordinary and regression kriging, a minimum of 100 samples are recommended to receive high predictive accuracy when using geostatistical methods (Webster & Oliver, 1992). However, a sampling intensity of 100 is not practical for managing agronomic inputs, including residual herbicides due to the labor and cost of soil sampling. For VR residual herbicides, 100 samples per field would be expensive because each sampling location requires laboratory data of soil particle size distribution and basic soil analysis to identify management zones. Further research is needed to determine if sampling densities currently adopted for soil fertility and health management (generally one sample per 0.5 to 4 hectares) can produce reliable VR residual herbicide management zones using geostatistics.

One of the more recent commercially-available sources used to map spatial soil variability are optical reflectance sensors using VNIR reflectance spectroscopy, such as SmartFirmer® sensors (Precision Planting, Tremont IL). These sensors provide high resolution spatial soil data with the convenience of being fast, cost-effective, and nondestructive (Mouazen et al., 2020). The SmartFirmer® sensors are attached on the back of the seed trencher on a planter so the soil passing along the sides of the sensors can be measured for soil moisture, temperature, crop residue, furrow uniformity, and OM (Liu et al., 2021). Published field data, albeit limited, has shown that the OM predictions with VNIR sensors in the seed furrow generally underestimate the soil sampled OM levels (Conway et al., 2022). Therefore, further evaluation is needed to determine if the predictions provided by planter-mounted optical reflectance sensors are reliable sources for mapping spatial OM variability for VR residual herbicide applications.

Previous VR soil residual herbicide studies have focused on weed control, crop injury, or herbicide savings compared to uniform rate applications (Kurt, 2011; Gundy & Dille, 2022; Williams & Mortensen, 2000). The only known study to compare data sources and methodology of documenting spatial soil variability for VR residual herbicide applications was conducted by Gundy and Dille (2022). In this research, intra-field soil variability was documented using soil EC_a across the field and soil samples collected with a 1-ha sampling scheme to generate field specific algorithms (Gundy & Dille, 2022). However, this study focused on evaluating weed control and herbicide savings between the two algorithms: algorithm 1 using only OM soil data and algorithm 2 using OM and soil texture data. If growers want to optimize the herbicide efficacy, reduce the risk of crop injury, and further prolong the development of herbicide-resistant weeds, it is important to understand how the soil data currently available can be used for VR residual herbicide applications and which methods are the most reliable for documenting spatial soil variability.

The objectives of this study were to (1) quantify the reliability of five different combinations of spatial soil data sources from SSURGO, soil samples, electrical resistivity sensors, and planter-mounted VNIR sensors for predicting the spatial variability of soil texture, OM, and residual herbicide management zones; and (2) determine the impact of soil sampling intensity on the management zone classification accuracy for VR applications of soil residual herbicides.

Methods and geostatistical analysis

Data collection

In the spring of 2021 in the United States, a survey was conducted across ten commercial Indiana fields within Benton, Daviess, Fulton, Franklin, Johnson, Rush, St. Joseph, and Warren Counties (Fig. 1). All fields included soil EC_a data collected using a Veris 3100 (Veris Technologies Salina, KS, USA) vehicle-mounted, soil electrical resistivity (ER) sensor equipped with six electrodes (two transmitting and four receiving). A 15-m spacing was used between pass with the sensor while traveling at an average of 16 km/h. EC_a readings

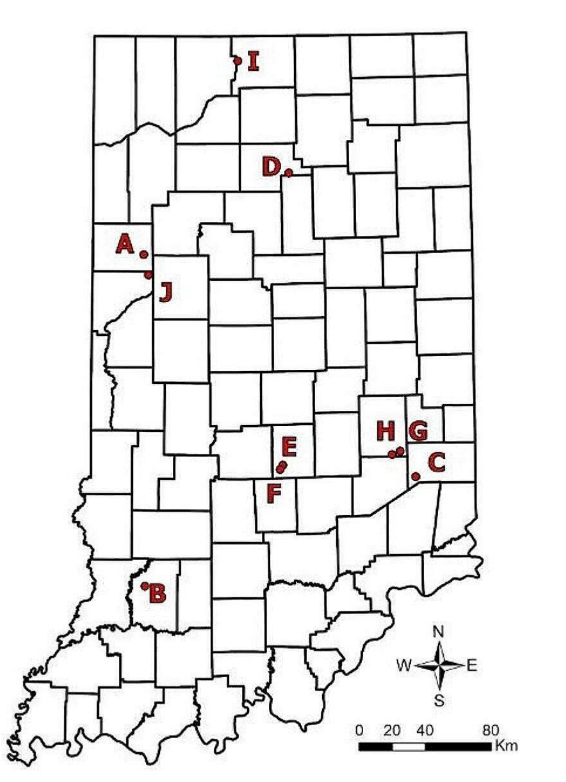

Fig. 1 Locations of (**A**) Benton, (**B**) Davies, (**C**) Franklin, (**D**) Fulton, (**E**) Johnson 1, (**F**) Johnson 2, (**G**) Rush 1, (**H**) Rush 2, (**I**) St. Joseph, and (**J**) Warren County fields within the state of Indiana

(mS/m) were collected at a 1 hz logging rate by determining the difference in current flow emitted from the transmitting to the receiving electrodes at shallow (0 to 30 cm) and deep (0 to 90 cm) depth. Only shallow measurements were used for analysis since the upper portion of the soil profile has the greatest interaction with residual herbicides.

The digital SSURGO data were downloaded from the website WSS (Soil Survey Staff, 2021) and processed in Microsoft Access using the .mdb file to link all the attribute data tables. All information provided in the .mdb files were linked to corresponding shapefiles using the Soil Data Viewer 6.2 Add-in in the geographic information system (GIS) software, ArcMap (Esri, Redlands, CA, USA). Soil texture and OM data used for developing management zones for VR residual herbicides were selected from the "Soil Health-Organic Matter" and "Soil Health-Surface Texture" properties sections of the WSS website (see Appendix A in Supplement Information).

Before developing the soil sampling stratums for stratified random sampling, all extraneous EC_a values suspected to be the cause by metal debris, interference from a rock, poor soil-to-electrode contact, etc. were manually removed from dataset. A sampling point was labeled extraneous and removed if it was +/-15 mS/m from all surround data points. The prepared EC_a dataset was then divided into three strata using quantile classification (Fig. 2) with 20 samples randomly assigned within each stratum, totaling 60 georeferenced points locations within each field. These georeferenced samples were used to guide an automatic Wintex 1000 soil sampler (WintexAgro, Saint Bancroft, IA, USA) mounted on a

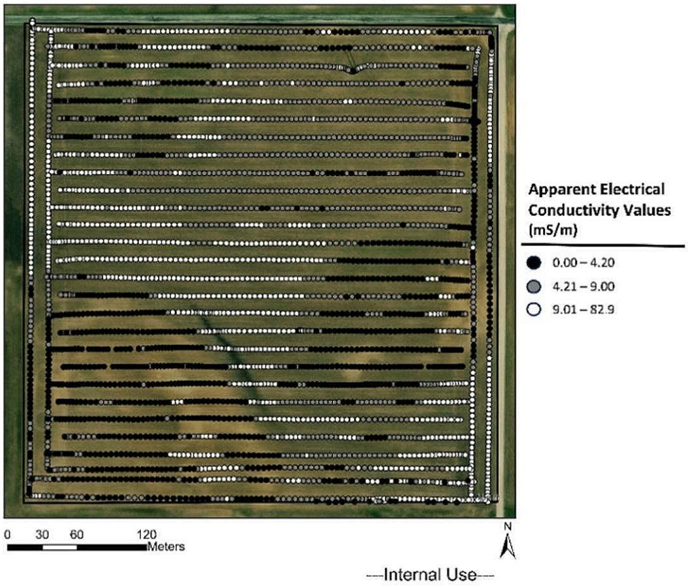

Fig. 2 Example of quantile classification of apparent electrical conductivity (EC_a) values at the Daviess County field with ArcGIS Pro World Imagery basemap

Table 1 Particle and organic matter content analysis from soil samples collected in 2021 from ten commercial fields within Indiana[1]

Field	Size	Sand Content		Silt Content		Clay Content		Organic Matter	
		Min	Max	Min	Max	Min	Max	Min	Max
	ha	%							
Benton	26	19	69	20	56	9	35	0.8	5.1
Daviess	17	45	92	3	32	3	23	0.6	3.7
Franklin	17	11	38	41	66	16	31	1.1	2.7
Fulton	26	21	88	15	48	6	31	1.2	9.1
Johnson 1	24	17	45	22	60	15	37	1.6	4.3
Johnson 2	14	16	52	23	60	19	35	1.5	2.8
Rush 1	25	9	45	40	60	15	43	2	5.1
Rush 2	21	12	36	41	43	18	43	2	4.3
St. Joseph	23	46	76	2	45	5	23	1.8	52.6
Warren	25	16	66	23	57	9	33	1.6	35.6

[1]Samples were analyzed at a commercial soil testing lab for particle size analysis using a hydrometer method and the basic soil fertility tests such as organic matter [loss on ignition (Combs & Nathan, 2012)], soil pH, buffer pH, cation exchange capacity, and selected macronutrients

UTV equipped with global positioning system (GPS) and Wide Area Augmentation System (WAAS) correction to collect a composite sample with 15 cores using a 2-cm diameter soil probe to a depth of 15 cm within a 0.5-m^2 area. These samples were sent to a commercial soil testing lab for particle size analysis using a hydrometer method and OM was measured by loss on ignition (Combs & Nathan, 2012; Table 1).

Additionally, OM data from the 2020 planting season were collected from SmartFirmer® sensors (Precision Planting, Tremont IL) on two of the ten fields; Franklin and Rush 1 county field. The sensors were spaced 3-m apart on a 12-row corn planter traveling approximately 9 km/h.

Map development

Three single active ingredient soil residual herbicides that are used in soybean were selected based on the maximum possible number of management zones that could be generated within a field according to the herbicide label (Table 2). The number of possible management zones for each herbicide was three for pyroxasulfone (Anonymous, 2022c), six for s-metolachlor (Anonymous, 2022a), and ten for metribuzin (Anonymous, 2022b). The labeled application rate structure for these three herbicides were used throughout the study to develop the management zones for VR residual herbicide applications.

The methodology used to generate maps for each field, herbicide, and sampling intensity with manually collected soil samples was structured based on the general concepts of cross validation. Cross validation is one of the most popular methods for data resampling used to estimate the accuracy of models by splitting the original dataset into two categories: a training set and testing set (Berrar, 2019). Training sets are used to train the models, while the test sets are used to evaluate the output from the trained model. The cross-validation method that was used as the baseline for this study was the Monte Carlo cross validation (MCCV), also known as repeated random subsampling validation. MCCV works by randomly selecting a defined number of test samples (k) and the remaining samples are used for the training set (Ramezan et al., 2019). Testing sets from MCCV are randomly selected with replacement, similar to bootstrapping (Fig. 3A). However, to ensure there are enough samples in the training set to compare the effects of sampling intensity on management zone classification accuracy for VR residual herbicide applications, a modified version of Monte Carlo cross validation (mMCCV) was required for this study. The MCCV was modified by splitting the training set further into two categories: (i) training set- used and (ii) training set-unused (Fig. 3B). This allows for multiple combinations of a defined sample size (determined by sample intensity) to be evaluated with consistent testing samples. After sev-

Table 2 Summary of herbicides used to develop management zone for variable rate residual herbicide applications based on the maximum possible number of management zone defined by the herbicide label

Herbicide	Organic matter	Herbicide rate by textural class[2]		
		Coarse	Medium	Fine
			(g a.i. ha^{-1})	
pyroxasulfone	All	91–128	119–183	146–210
s-metolachlor	<3% OM	1,071 – 1,424	1,424-1,788	1,424-1,788
	≥3% OM	1,424	1,424-1,788	1,788-2,142
metribuzin	<2% OM	Do Not Use	400–533	533–666
	2–4% OM	400	533–666	533–932
	≥4% OM	400	666–799	1,065
	Muck[1]	Do Not Use	Do Not Use	Do Not Use

[1] Muck soils were defined as any soil with organic matter (%) greater than 12 to 18% depending on clay content (%)

[2] Information derived from herbicide labels: pyroxasulfone (Anonymous, 2022c), s-metolachlor (Anonymous, 2022a), and metribuzin (Anonymous, 2022b)

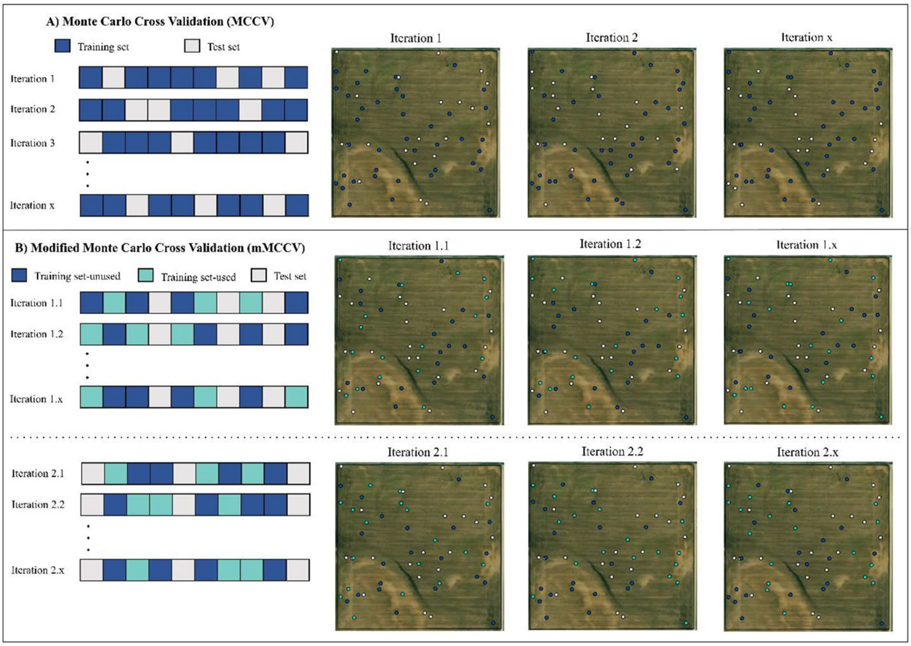

Fig. 3 (**A**) The Monte Carlo cross validation (MCCV) works by randomly selecting the training and test data sets with replacement. (**B**) A modified version of MCCV was used in this study to evaluate the effect of sampling size on soil texture, organic matter, and herbicide management zone classification accuracy. This was performed by splitting the training set into two categories: used and unused. Samples from the Daviess County field were used as an example

eral iterations occur using a particular testing set, all testing and training sets were pooled together, redistributed, and repeated. Additionally, not all combinations of training and testing sets was processed. The modified cross-validation process is summarized into eight steps (Fig. 4) and explained in greater detail in the following sections. This process was used to generate 36,000 maps across all ten fields to determine the most reliable sampling intensity and source for most agricultural fields.

Selecting samples for testing and map development (Fig. 4: steps 1 and 2)

Sixty samples were collected within each field to ensure enough samples for the testing and training datasets. The testing dataset refers to the samples that were used to confirm whether the OM, soil texture, and management zone prediction were accurate to the true values or class assignment. The number of testing samples was dependent on the field size in order to have approximately one sample per 0.8-hectare. The remaining soil samples were used to develop VR residual herbicide management zones at varying sampling intensities using spatial soil data collected from soil samples, EC, and VNIR OM data. The number of samples selected for the low, medium, and high sampling intensity were determined so there would be one sample per 4, 2, and 1 hectare, respectively. The total number of samples were rounded to a multiple of 3, if necessary, to ensure an equal number of samples were assigned to all three strata for stratified random sampling (Table 3). Maps at the low sam-

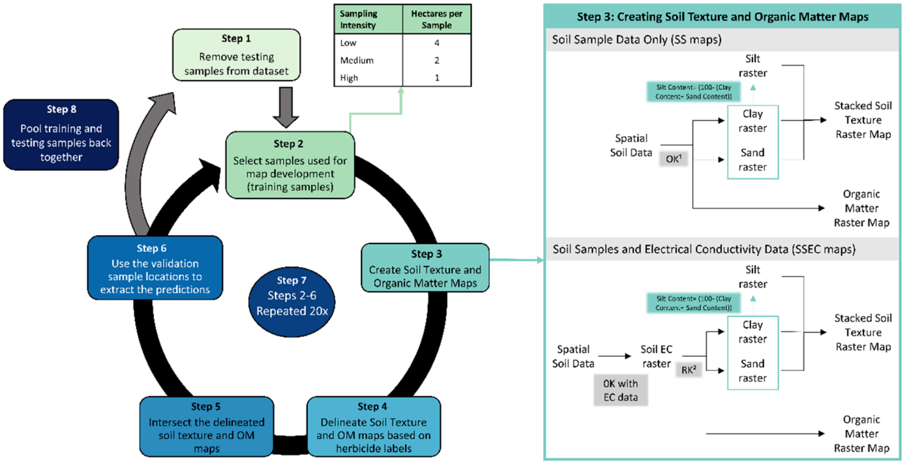

Fig. 4 Workflow for developing management zones for variable rate residual herbicide applications using soil samples alone (SS maps) or soil samples plus electrical conductivity (EC) data (SSEC maps). [1]Ordinary Kriging (OK) was performed with the desired soil data. [2]Regression Kriging (RK) was performed using the interpolated EC_a raster with the desired soil data

Table 3 Number of samples used for developing variable-rate residual herbicide maps at each sampling intensity based on field size and the number of samples used for validating the accuracy of the maps

Field	Sampling intensity[1]			Validation samples
	Low	Medium	High	
	No.			
Benton, Fulton, Johnson 1, Rush 1, St. Joseph, Warren	6	12	24	30
Rush 2	6	9	21	27
Daviess, Franklin	6	9	18	21
Johnson 2	NA[2]	6	15	18

[1] Number of samples used for map development at a low, medium, and high sampling intensity so each sample covered approximately 4-, 2-, and 1 ha, respectively.

[2] Insufficient number of samples at a low sampling intensity in Johnson 2 County field to fit semivariogram models used for ordinary and regression kriging.

pling intensity for Johnson 2 County field were not developed since only three samples were available for map development, which was not sufficient for fitting semivariogram models used for kriging.

Creating soil texture and organic matter layers (Fig. 4: step 3)

Once the samples used for map development were selected, the spatial point data (soil samples, electrical conductivity, and SmartFirmer® OM data) were used to determine the soil texture and OM data across the entire field. This step was not required for the SSURGO data since earlier methods conducted in ArcMap already provided continuous soil data across the field area as a shapefile. For all other sources, whole field data were generated using ordinary and regression kriging to interpolate the unknown area between the georeferenced sampling locations. To successfully perform kriging, the autocorrelation, or the relationship of a measured value at a known location to the neighboring locations, was quantified using semivariogram models (Webster & Oliver, 1992). Semivariogram models were used to calculate the weighted values based on the distance of the sample location to the predicted location, the spatial relationship of the measured values, and the fit of the model to the measured values. When using geostatistics, such as kriging, accurate interpolations of the predictive variables rely on the fitness of the semivariogram model fit. However, fitting each semivariogram to the best model (spherical, exponential, Gaussian, Matérn, etc.) and parameters (range, nugget, sill) would be difficult in this study due to the large volume of maps being generated.

Preliminary work was completed to determine the best semivariogram model for this study. For St. Joesph County field, four training sample sets were selected at a low and high sampling intensity to see which models were the best for clay content data interpolated with and without EC_a data (see Appendix B in Supplement Information). These four training sample sets were also subjected to the entire workflow shown in Fig. 4 to determine how each model impacts that accuracy of the management zones for VR applications of s-metolachlor. From the work on the St. Joseph County field, the exponential and Matérn semivariogram model were most frequently a best fit to the data and provided the highest management zone classification accuracies. Although the fit and accuracy of the exponential and Matérn semivariogram models were similar, ultimately, the Matérn model was selected since it resulted in the processing loop used for the mMCCV method shown in Fig. 4 to terminate less frequently than the exponential semivariogram model. This is likely from the Matérn model being a generalization of multiple theoretical semivariogram models and having an incorporated smoothness parameter that provides more flexibility in the model (Minasny & McBratney, 2005). Therefore, all electrical conductivity, OM, clay content, and sand content data were fitted to a Matérn semivariogram models using gstat package in R version 4.1.1.

Soil texture and OM layers were then developed using the fitted Matérn semivariograms for ordinary and/or regression kriging on a 10-meter grid to interpolate the spatial point data across the entire field. For developing soil texture and OM raster layers using only soil samples, ordinary kriging was performed on sand, clay, and OM content. The silt content raster layer was then created by summing the sand and clay values of the corresponding grid cell [i] and subtracting from 100 (Eq. 1).

$$silt\,[i] = (100 - (clay\,[i] + sand\,[i]) \tag{1}$$

The sand, silt, and clay raster layers were then stacked together using the raster package in R (Hijmans, 2022). This was conducted so each cell was assigned a sand, silt, and clay value to determine the soil texture type.

Soil texture and OM raster layers generated from soil samples and EC_a raster layer were created using regression kriging. The EC_a data were used as an auxiliary variable to guide the predictions between the known sampling points. First, the EC_a data were converted to a raster layer using ordinary kriging. From the EC_a raster, a linear model is determined to extract the residuals at all sampling locations. Similar to the methods described earlier, the silt content raster was developed by subtracting the sum of the sand and clay values from 100. The sand, silt, and clay raster layers were then stacked into one raster to define the soil texture type present in the field.

OM data collected from the planter-mounted VNIR sensors, were interpolated using ordinary kriging. The two fields containing this data were Franklin and Rush 1 County. Since VNIR sensors do not collect data on soil particle size, spatial information on sand, silt, and clay content was still required to define management zones for VR residual herbicide applications. Two variations of soil texture maps were developed based on the method described above: (1) with soil samples alone using ordinary kriging and (2) with soil samples plus EC_a using regression kriging. For sources of spatial soil data, the next step was to delineate the interpolated soil texture and OM raster layers based on the pyroxasulfone, s-metolachlor, and metribuzin labels (Table 2).

Classifying soil texture and organic matter layers (Fig. 4: step 4 and 5)

All soil residual herbicides included in the study have the 12 soil texture types (STT) subdivided into three broad classifications as defined by each individual herbicide label: coarse, medium, and fine. These three soil classifications will be referred to as herbicide textural classes (HTC) for the remainder of the paper. The soil texture raster layers were then assigned to the appropriate HTC based on the residual herbicide label.

Similarly, the soil OM raster layers were delineated based on the soil residual herbicide labels. For metribuzin, applications on muck soils are not recommended. According to the organic soil material criterion listed in Soil Survey Staff (1999), muck soils are defined as any soil with organic carbon values greater than $12+0.1$ (*% clay content*) when the clay is less than 60% or organic carbon content is greater than 18% when clay content is greater than 60% (Fig. 5). Since OM is a combination of organic carbon, soil humus, and nutrients, a conversion factor can be used to calculate the organic carbon content needed to define muck soils from the OM raster layers. Most research investigating the conversion factors between organic carbon and organic matter have found 1.724 and 2.5 to be acceptable (Nelson & Sommers, 1983), with a factor of 2 being most accurate under the assumption that OM is 50% carbon (Pribyl, 2010). For this study, a conversion factor of 2 was used for calculating organic carbon levels.

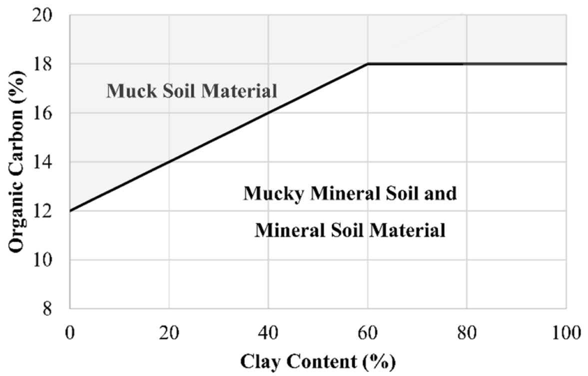

Fig. 5 Soils that fall within the gray area are defined as muck soils based on the clay-organic carbon content relationship defined by Soil Survey Staff (1999)

Once the soil texture and OM layers were reclassified, the layers were intersected together using the sf package in R (Pebesma, 2018) to generate desired management zones. For the remainder of the article, management zones for all fields were developed with spatial soil data from the SSURGO data, soil samples alone using ordinary kriging (SS), and soil samples with EC_a data using regression kriging (SSEC). For the two fields with VNIR OM data from the SmartFirmer® (SF) sensor, two additional sources were included: 1) one created with a soil texture raster generated with ordinary kriging (SSSF) and another using a soil texture raster from regression kriging with the EC_a data (SSECSF). The SSSF and SSECSF sources were only evaluated with s-metolachlor and metribuzin since pyroxasulfone does not have restraints on application rate based on OM levels.

Validating map accuracies and resampling (Fig. 4: step 6–8)

To confirm the accuracy of the STT, HTC, OM, and management zone predictions, the testing samples withheld from map development were used to extract the predictions at known sampling locations (Fig. 4: Step 6). Since the dataset devoted to map development contains more samples than what was needed for each sampling intensity, Steps 2 through 6 were repeated 20 times, selecting a new combination of samples with each pass. Once Step 7 was completed, all testing and map development samples were pooled back together. Then a new combination of the testing set was selected and steps 2 through 7 were repeated. All steps were conducted in R using a series of loops and functions (Fig. 4). Every time the loops reached Step 6, the information extracted at the testing sampling sites were exported into spreadsheets and saved for further analysis.

Statistical analysis

The accuracy of the STT, HTC, and management zone classification was determined by calculating the percentage of testing samples accurately predicted by the maps. The classification accuracies were analyzed using an analysis of variance (ANOVA) with the stats package in R (R Core Team, 2021). The means were separated using Tukey-Kramer's Honest Significant Difference (HSD) at a significance level of 0.05. When analyzing the effect of sampling intensity on classification accuracy, a one-way ANOVA was setup by filtering the dataset by field, herbicide, and source of spatial soil data. To determine the effect of source of spatial soil data on classification accuracy, a one-way ANOVA was performed after filtering the dataset by field, herbicide, and sampling intensity. The effect of the number of possible management zones on the herbicide label was conducted similarly by filtering the dataset by field, then pooling the data across sampling intensity for a given source. Data analysis was conducted by each field due to an interaction with sampling intensity, source of spatial soil data, or herbicide. To quantify the reliability of individual sources of spatial soil data and sampling intensities across all fields, the frequency that a source or sampling intensity was either the most accurate (denoted by an (A) or (a) from Tukey- Kramer's HSD) was quantified as a percentage of the total observations.

To determine whether the HTC were under-, over-, or accurately predicting, the HTC were first assigned to a numeric value (1 = coarse, 2 = medium, and 3 = fine). The numeric values of the actual HTC were then subtracted from the predicted HTC. Therefore, values less than zero implied that the predictions underestimated the true textural class, equal to zero meant they were the same, and values greater than zero indicated predictions were overestimated. For each iteration, the frequency of the testing samples under-, equally, and over-estimated were calculated and subjected to ANOVA to determine any difference between the sources of spatial soil data for predicting HTC.

The accuracy of the OM predictions was determined by calculating the difference between the predicted and measured OM values. The data were subjected to a two-sided t-test analysis at an alpha equal to 0.05 for determining whether the values were different from zero. The mean error (ME) was calculated to determine if the predicted OM values tended to over-, under-, or equally predict the actual OM values. The measured OM values were derived from the testing samples withheld from map development. The predicted OM values were extracted at the locations of the georeferenced testing samples and precision of the OM predictions was determined with root mean squared error (RMSE). There was less variance between the predicted and measured OM values when the RMSE was smaller, meaning the predictions were more precise.

Pearson's correlation coefficient (r) and coefficient of determination (R^2) were conducted between EC_a values and several soil properties (OM, clay, silt, and sand content) to determine the relationship between these variables. Lack of relationship between soil EC_a data and soil properties, such as clay content and OM, can affect the prediction accuracy of maps developed with regression kriging.

Results and discussion

Soil texture type (STT) and herbicide textural class (HTC) predictions

The mapping accuracy for each source of spatial soil data was evaluated based on the percentage of samples in the testing (or validation) dataset that were accurately predicted within each map. The frequency of SS, SSEC, and SSURGO maps having the highest-ranking STT classification was 62%, 72%. and 28%, respectively (see Appendix C: Table C1 in Supplemental Information). The frequency of SS, SSEC, and SSURGO maps having the greatest rank of accuracy for HTC was 59%, 62%, and 3.4%, respectively (see Appendix C: Table C2 in Supplemental Information). Maps developed using SSEC were among the most accurate soil data sources for STT and HTC.

Accurate predictions of HTC as specified on individual herbicide labels is critical for VR residual herbicide applications. For all fields, the HTC accuracy of the SS and SSEC maps was greater than the classification accuracy for STT (Table 4). Misclassified STT often fell within the same HTC as the measured soil sample, which resulted in greater predictive accuracy for HTC. For the SSURGO maps there were two fields, Franklin and Fulton County, where an increase in classification accuracy was not observed from STT to HTC. In these fields, the misclassification of the STT fell outside of the HTC of the collected soil sample, resulting in no improvement in classification accuracy. Additionally, for the SS and SSEC maps, the highest sampling intensity was the most accurate sampling intensity for predicting HTC at 90 and 100% of the fields, respectively.

Since the maps made at the high sampling intensity most frequently had the greatest HTC accuracy, the high sampling intensity was used to determine whether the HTC predictions

Table 4 Comparison between classification accuracy of soil texture type (STT) and herbicide textural class (HTC) for sources of spatial soil variability and sampling intensity (if applicable)[1]

Field	Soil class	Mean classification accuracy by source of spatial soil data and sampling intensity[23]						
		SSURGO	SS			SSEC		
			Low	Medium	High	Low	Medium	High
			(%)					
Benton	STT	8.3 b	50 b	52 b	55 b	55 b	57 b	58 b
	HTC	65 a	61 a	63 a	64 a	69 a	70 a	71 a
Daviess	STT	17 b	47 b	49 b	54 b	58 b	63 b	62 b
	HTC	38 a	100 a	100 a	100 a	98 a	99 a	99 a
Franklin	STT	62 a	85 b	85 b	86 b	81 b	82 b	84 b
	HTC	64 a	86 a	87 a	89 a	82 a	84 a	85 a
Fulton	STT	57 a	78 b	78 b	78 b	78 a	78 b	78 b
	HTC	57 a	83 a	82 a	83 a	83 a	83 a	83 a
Johnson 1	STT	8.3 b	57 b	62 b	62 b	52 b	55 b	57 b
	HTC	55 a	80 a	82 a	82 a	80 a	79 a	80 a
Johnson 2	STT	30 b	--	33 b	36 b	--	36 b	38 b
	HTC	40 a	--	63 a	66 a	--	68 a	69 a
Rush 1	STT	43 b	42 b	43 b	47 b	41 b	45 b	43 b
	HTC	62 a	73 a	75 a	75 a	78 b	76 a	81 a
Rush 2	STT	30 b	39 b	40 b	38 b	37 b	41 b	41 b
	HTC	42 a	55 a	54 a	51 a	57 a	58 a	57 a
St. Joseph	STT	22 b	74 b	77 b	79 b	70 b	75 b	78 b
	HTC	48 a	76 a	80 a	83 a	72 a	77 a	82 a
Warren	STT	10 b	44 b	45 b	48 b	46 b	52 b	58 b
	HTC	25 a	58 a	59 a	61 a	61 a	66 a	70 a

[1] Abbreviations: SSURGO, Soil Survey Geographic Database; SS, soil samples alone; SSEC, soil samples with electrical conductivity (EC) data, STT; soil texture type; HTC; herbicide textural class

[2] Low, medium, and high sampling intensity means each sample covers approximately 4-, 2-, and 1 ha, respectively.

[3]The mean classification accuracy is the average percent of validation samples that were correctly predicted from the maps developed from each source of spatial soil data and sampling intensity. Classification accuracy means within a column followed by the same letter are not significantly different according to Tukey's HSD (α=0.05). Classification accuracy means are not compared across fields.

were being under-, equally, or over-estimated for each source of spatial soil data. When misclassification of the HTC occurred, the SSURGO data tend to overestimate the textural class (Table 5). Overestimating the HTC could result in a higher application rate being assigned to a management zone, which increases the possibility of crop injury. Whereas the SS and SSEC maps tended to underestimate in 7 out of the 10 fields. Daviess County field was the only site where none of the maps underestimated the HTC across all sources of spatial soil data. This occurred because the actual HTC was classified as coarse; therefore, the predictions could only be equally or overestimated. At the Daviess County field, the SSURGO data overestimated 45% of the testing samples since the source indicated a medium HTC when the actual HTC was coarse.

Table 5 Average percent of validation samples that were under, equally, or over predicted for herbicide textural class (HTC) among SS, SSEC, and SSURGO maps[1]

Field	Source[1]	Accuracy of HTC predictions[2]		
		Underestimated	Equal	Overestimated
		Mean % of validation samples		
Benton	SS	17 Ab	76 Aa	7.6 Bc
	SSEC	11 Bb	80 Aa	9.2 Bb
	SSURGO	13 ABc	65 Ba	22 Ab
Daviess	SS	0.0 Ab	100 Aa	0.0 Bb
	SSEC	0.0 Ac	98 Aa	1.7 Bb
	SSURGO	0.0 Ab	55 Ba	45 Aa
Franklin	SS	14 Ab	85 Aa	0.7 Ac
	SSEC	14 Ab	85 Aa	0.5 Ac
	SSURGO	14 Ab	86 Aa	0.0 Ac
Fulton	SS	12 Ab	88 Aa	0.1 Cc
	SSEC	10 Ab	85 Ba	5.4 Bc
	SSURGO	8.3 Ac	67 Ca	25 Ab
Johnson 1	SS	12 Ab	84 Aa	3.4 Bc
	SSEC	12 Ab	84 Aa	3.8 Bc
	SSURGO	8.5 Bc	61 Ba	31 Ab
Johnson 2	SS	32 Ab	66 Ba	2.1 Bc
	SSEC	29 Bb	69 Aa	1.9 Bc
	SSURGO	17 Cb	67 ABa	17 Ab
Rush 1	SS	9.7 Bc	77 Ba	14 Ab
	SSEC	11 Bb	84 Aa	5.0 Bc
	SSURGO	37 Ab	63 Ca	0.0 Cc
Rush 2	SS	27 Ab	51 Ba	23 Ab
	SSEC	26 Ab	58 Aa	17 Bc
	SSURGO	37 Ab	45 Ca	18 ABc
St. Joseph	SS	13.1 Bb	82.6 Aa	4.3 Bc
	SSEC	16.2 Ab	81.2 Aa	2.6 Cc
	SSURGO	15.6 Abc	46.1 Ba	38 Ab
Warren	SS	14 Bc	62 Ba	24 Bb
	SSEC	9.6 Cc	71 Aa	19 Cb
	SSURGO	20 Ac	31 Cb	50 Aa

Abbreviations: SSURGO, Soil Survey Geographic Database; SS, soil samples alone; SSEC, soil samples with electrical conductivity (EC) data

Sample size equals 40 for SS and SSEC for each herbicide and 6 for SSURGO

[1] Predictions at the high sampling intensity were used for the SS and SSEC maps.

[2]Means within a column followed by the same uppercase letter (ABC) are not significantly different and means within a row followed by the same lower-case letter (abc) are not different according to Tukey's HSD ($\alpha=0.05$). Means are not compared across fields.

Organic matter predictions

The accuracy and precision of the OM predictions across all sampling intensities and sources of spatial soil data were summarized (Table 6). Results from the mean error (ME) and t-test were used to evaluate the accuracy of the OM predictions. Fields with a negative ME value indicates that the OM predictions on average underestimated the actual OM levels at each testing sampling location across all iterations of the mMCCV. Conversely, positive ME values indicate an overestimation of the actual OM levels occurred on average at the testing sampling locations. The SSURGO data overestimated the predicted values in eight out of ten fields, whereas OM predictions generated by maps with SS, SSEC, and SF underestimated the actual OM levels across all sampling intensities, except Rush 2 and St. Joseph County fields. OM predictions from the SF sensor have been reported to generally underestimate OM levels (Conway et al., 2022).

Table 6 Precision and accuracy of the predicted organic matter (OM) values comparison to the collected and measured OM values with each field by source and sampling intensity (if applicable)

Field	Statistics[2]	Mean ME and RMSE of OM by source of spatial soil data and sampling intensity[1]							
		VNIR	SSURGO	SS			SSEC		
				low	**medium**	**high**	**low**	**medium**	**high**
Benton	ME (%)	--	0.85	-0.19	-0.27	-0.26	-0.24	-0.18	-0.18
	RMSE	--	1.39	1.22	1.21	1.17	1.07	1.02	0.98
	Sample size	--	60	2400	2400	2400	2400	2400	2400
Daviess	ME (%)	--	0.31	-0.06	-0.08	-0.03	-0.001	-0.05	-0.07
	RMSE	--	0.83	0.69	0.67	0.61	0.63	0.55	0.50
	Sample size	--	42	1680	1680	1680	1680	1680	1680
Franklin	ME (%)	-0.19	-0.11	-0.14	-0.17	-0.16	-0.17	-0.16	-0.17
	RMSE	0.31	0.3	0.35	0.34	0.33	0.37	0.35	0.33
	Sample size	3280	42	1640	1640	1640	1640	1640	1640
Fulton	ME (%)	--	0.12	-0.08	-0.12	-0.17	0.03	0.02	-0.01
	RMSE	--	12.2	1.52	1.46	1.34	1.76	1.43	1.24
	Sample size	--	60	2400	2400	2400	2400	2400	2400
Johnson 1	ME (%)	--	0.27	-0.07	-0.05	-0.04	-0.06	-0.03	-0.05
	RMSE	--	1.16	0.71	0.65	0.61	0.76	0.67	0.61
	Sample size	--	60	2400	2400	2400	2400	2400	2400
Johnson 2	ME (%)	--	-0.05	--	-0.05	-0.1	--	-0.07	-0.11
	RMSE	--	0.62	--	0.29	0.29	--	0.3	0.29
	Sample size	--	36	--	1440	1440	--	1440	1440
Rush 1	ME (%)	-0.24	0.08	-0.04	-0.13	-0.18	-0.1	-0.12	-0.14
	RMSE	0.59	1.02	0.73	0.64	0.56	0.68	0.61	0.53
	Sample size	4640	60	2320	2320	2320	2320	2320	2320
Rush 2	ME (%)	--	0.52	0.08	0.07	0.07	0.06	0.1	0.09
	RMSE	--	5.15	0.42	0.44	0.44	0.5	0.49	0.44
	Sample size	--	60	2400	2400	2400	2400	2400	2400
St. Joseph	ME (%)	--	3.07	-0.32	0.81	0.54	1.31	0.93	0.69
	RMSE	--	18	9.47	7.02	5.53	13.25	10.74	6.91
	Sample size	--	60	2400	2400	2400	2400	2400	2400
Warren	ME (%)	--	3.14	-0.86	-0.6	-0.47	-0.7	-0.91	-0.53
	RMSE	--	10.6	6.04	5.53	4.95	6.03	5.52	4.67
	Sample size	--	60	2400	2400	2400	2400	2400	2400

[1] Low, medium, and high sampling intensity means each sample covers approximately 4-, 2-, and 1-hectare, respectively

[2]Abbreviations: SSURGO, Soil Survey Geographic Database; SS, soil samples alone; SSEC, soil samples with electrical conductivity (EC) data; VNIR, organic matter data from a planter-mounted visible near infrared sensor; ME, mean error; RSME, root mean squared error.

Although, most of the ME values differed from zero, most of the predictions were less than 1% from the actual OM levels. A difference of 1% or 0.5% might seem small but can become problematic for delineating the field area for VR residual herbicide applications. For example, if the true OM level at a particular field location is 2.4%, being off by 0.5% could affect whether that area gets assigned to the appropriate management zone for a herbicide such as metribuzin. Depending on the HTC, this error could result in the field area being assigned a rate from the OM levels < 2% OM class opposed to the 2–4% OM class (Table 2). This area would be assigned a lower application rate that would potentially result in a shorter duration or extent of residual weed control (Grey et al., 2013; Knezevic et al., 2009). Conversely, being assigned a management zone with a higher OM level would increase the herbicide application rate and potentially increase the risk of crop injury from the herbicide (Szmigielski et al., 2009). Both scenarios would be considered an illegal application since the herbicide was not delivered according to the herbicide label.

The precision of the OM predictions was indicated by the RSME values (Table 6). The closer the RMSE value is to zero, the more accurate the source/sampling intensity. Alternatively, RMSE can be interpreted as the standard deviation of the error. For the SS and SSEC maps, the RMSE values decreased as the number of samples included in the map development process increased. Therefore, the variance between the predicted and actual OM values was decreased by increasing the number of samples used for spatially predicting the OM levels within a field. In five out of the ten fields the SSURGO data did not differ from the sampled OM results following a t-test analysis. This can be explained by the large RMSE that indicated a relatively greater variance between the predicted and actual OM values. Additionally, in nine out of the ten fields, the variance between the predicted and actual OM values was the greatest with the SSURGO OM maps compared with the SS, SSEC, and SF OM maps. The more variance between the predicted and actual OM levels increases the risk of the field area being assigned the wrong management zone.

Management zone classification

Due to significant interactions between fields and sampling intensity or source of spatial soil data, alternative methods were used to quantify the most reliable sources and sampling intensities across all fields. For quantifying the reliability of the low, medium, and high sampling intensities, the frequency that an individual sampling intensity was the most accurate was calculated as a percentage of the total fields. The complete set of data means, and statistical results can be found in Appendix C: Table C3-C5 in Supplemental Information; however, a summary of these results are shown in Tables 7 and 8.

Management zone classification accuracy across sampling intensity

For all herbicides, the high sampling intensity (~ 1 sample per ha) was the highest-ranking sampling intensity for the management zone classification accuracy (Table 7). These results align with other studies that evaluated the effect of sampling intensities on predication accuracy of various soil properties using kriging (Saurette et al., 2022; Li, 2010). For SS maps with pyroxasulfone, the medium sampling intensity had an identical frequency for having the highest management zone classification accuracy as the high sampling intensity. Overall, the low sampling intensity was unreliable for classifying management zones, particularly for s-metolachlor and metribuzin. By decreasing the number of samples used for kriging, each sample was interpolated to a larger surrounding area, ultimately, leaving more room for error when predicting the appropriate management zone. Additionally, it was challenging to get a well fitted semivariogram model for clay, silt, sand, and OM content (see Appendix B: Table B3 and Table B4 in Supplemental Information). Even at a high sampling

Table 7 Frequency of individual sampling intensity having the most accurate management zone classification accuracy across all fields[1]

Herbicide	Source[3]	Highest management zone classification accuracy frequency by sampling intensity[2]		
		Low[2]	Medium	High
		% of fields		
pyroxasulfone	SS	80	90	90
	SSEC	60	70	90
s-metolachlor	SS	20	80	100
	SSEC	30	90	100
metribuzin	SS	50	60	90
	SSEC	40	80	100

[1] For each herbicide, the frequency of an individual sampling intensity having with the greatest accuracy was determined by quantifying the number of fields denoted with an "A" from Tukey- Kramer's HSD from Appendix C: Table C3-C5 in Supplemental Information and dividing by the field sample size of 9, 10, and 10 for low, medium, and high sampling intensities, respectively.

[2]Low, medium, and high sampling intensity means each sample covers approximately 4-, 2-, and 1 ha, respectively.

[3] Abbreviations; SS, soil samples alone; SSEC, soil samples with electrical conductivity (EC) data.

Table 8 Frequency of individual source of spatial soil data with the highest ranking for accuracy across all combinations of herbicide and sampling intensity for all fields, and fields grouped by similar characteristics[2]

Source	Frequency of highest management zone classification accuracy by field grouping				
	All fields[1]	**Group 1**	**Group 2 A**	**Group 2B**	**Group 3**
	% of total observations				
SS	72	59	94	92	58
SSEC	79	85	70	83	100
SSURGO	33	24	21	17	33
SSSF	--	--	--	--	75
SSECSF	--	--	--	--	75

[1] Field Group 1: fields that have a significant relationship between electrical conductivity and organic matter data; Field Group 2 A: fields without a relationship between electrical conductivity and organic matter data, Field Group 2B: All group 2 A fields excluding St. Joseph County; Field Group 3: fields with organic matter data from planter-mounted VNIR sensor.

[2] The frequency of an individual source of spatial soil data having with the greatest accuracy was determined by quantifying the number of observations denoted with an "a" from Tukey- Kramer's HSD from Appendix C: Table C3-C5 in Supplemental Information and dividing by the total number of observations of 87, 54, 33, 24, and 12 for All Fields, Group 1, Group 2 A, Group2B, and Group 3, respectively.

intensity (15 to 24 samples depending on field size), the number of samples used for kriging were lower than what is recommended for interpolating soil variables at a field-scale level (Saurette et al., 2022; Brouder et al., 2005; Kerry et al., 2010). Further research should investigate sampling intensities covering less than 1 ha per sample to determine if sampling intensities greater than what was tested in this study can provide better management zone classification accuracy.

Although the reliability of the management zone classification was the greatest at the high sampling intensity, there were several scenarios where management zone classification accuracy was not impacted by sampling intensity. The factors contributing to these results include: (1) the level of spatial soil variability present within a field and (2) the possible number of management zones on the herbicide label. There were three fields that saw no difference in management zone classification accuracy across all sampling intensities: Daviess, Franklin, and Rush 2 County field (see Appendix C: Table C3 in Supplemental Information). These three fields had very little spatial variability for HTC which resulted in similar management zone classification accuracies across all sampling intensities. Franklin County field was the only location that was not impacted by sampling intensity for pyroxasulfone, s-metolachlor, and metribuzin (see Appendix C: Table C3 through Table C5 in Supplemental Information). This resulted from Franklin County field being nearly homogeneous in both soil texture (100% of field was medium HTC) and OM (1.1–2.7% OM). Therefore, a VR application would only be required for metribuzin at the Franklin County field. The herbicide that was impacted the least by sampling intensity was pyroxasuflone since management zones were defined by soil texture only. Despite finding some scenarios where lower sampling intensities can provide similar management zone classification accuracies as the high sampling intensity, there is no way of knowing whether a low or medium sampling intensity will provide enough spatial soil data for VR residual herbicide applications without physically taking all the soil samples at a higher sampling intensity. Another challenge with intensive soil sampling for VR residual herbicide applications is cost. Current, intensive soil sampling methods are generally collecting soil samples for a basic soil analysis which includes data on OM, soil pH, buffer pH, cation exchange capacity, and select macronutrients. The methods used in this study require soil analysis on soil particle size which is approximately double the cost of a basis soil analysis. However, the cost for soil particle size analysis is a one-time expense since soil texture changes very little over time.

Management zone classification accuracy across source

Across all fields, SSEC was more frequently among the highest-ranking sources for classifying all herbicide management zones and sampling intensities than SS and SSURGO (SSEC = 79%, SS = 72%, and SSURGO = 33%; Table 8). The SS and SSEC maps were concurrently highest-ranking sources 34% of the time (data not shown). Since the relationship of the soil variables (target variables) to the EC_a data (auxiliary variable) has been proven to influence the predictive accuracy of regression kriging, the fields were split into two groups based on the results of the correlation analysis (Table 9). Group 1 contained all the fields that had a significant relationship between EC_a and OM which included Benton, Daviess,

Table 9 Pearson correlation coefficient (r) and coefficient of determination (R2) between apparent electric conductivity and clay content or organic matter (n = 60)[1]

Field	Clay content		Organic matter	
	r	R^2	r	R^2
Benton County	0.78*	0.61	0.81*	0.66
Daviess County	0.8*	0.64	0.78*	0.6
Franklin County	0.32*	0.1	0.45*	0.2
Fulton County	0.52*	0.27	0.44*	0.2
Johnson County 1	0.72*	0.51	0.15	0.02
Johnson County 2	0.34*	0.11	0.09	0.01
Rush County 1	0.75*	0.57	0.50*	0.24
Rush County 2	0.5*	0.25	-0.02	0.0
St. Joseph County	-0.13	0.02	-0.13	0.02
Warren County	0.37*	0.14	0.50*	0.25

[1]Significance (*) at an alpha level of 0.05.

Fulton, Franklin, Rush 1, and Warren County fields. From this group of fields, SSEC was the most accurate source nearly 25% and 60% more than SS and SSURGO, respectively (Table 8).

The correlation analysis also indicated that four out of the ten fields did not have a relationship between EC_a and OM content (Johnson 1, Johnson 2, Rush 2, and St. Joseph County fields). When there was not a significant relationship between EC_a and OM, the frequency of SS maps being ranked the most accurate source was greater than SSEC maps (94% and 70%, respectively; Group 2 A fields in Table 8). However, this large difference between SS and SSEC maps in the Group 2 A fields was largely influenced by one field, St. Joseph County, which did not have a significant relationship between clay or OM content with the EC_a data. The lack of relationship between clay and OM content could possibly be from the low clay content (<23% clay content) and the wide range in OM levels (1.8–52.6% OM). Together, these soil conditions could have negatively impacted the relationship to the EC_a data. Other soil variables such as soil moisture could have affected the relationship, however, we are unable to determine the impact of soil moisture on EC_a since spatial soil moisture data was not collected. When the St. Joseph field was excluded, the frequency of each source having the highest classification accuracies was 92% for SS maps followed by 83% for the SSEC maps. Additionally, the SS and SSEC maps were concurrently among the most accurate sources 75% of the time for Group 2B (data not shown). Including EC_a data in map development when neither clay nor OM content have a relationship to EC could increase the risk of misclassifying management zones and reduce the overall classification accuracy for VR residual herbicides. However, the only way to know whether the soil parameters will have a relationship to EC_a is by collecting the data first. This would have a negative financial impact to the growers since they risk paying for data that is not needed. For the two fields with SF OM data (Group 3), the SSSF and SSECSF were the most accurate source 75% of the time. Similar to Group 2 A fields, the Franklin and Rush 1 County fields had the highest management zone classification accuracy with SSEC maps more frequently than the SS maps. Both fields have significant relationships of clay and OM content with EC_a (Table 9), which could contribute to the improved management zone classification accuracy with the SSEC maps.

Overall, soil samples alone were reliable for classifying management zones for pyroxasulfone, s-metolachlor, and metribuzin. The risk of reducing the management zone classification accuracy by including the EC_a data with soil samples is less than 20% and 86% of the time SSEC maps achieve similar or better classification accuracies compared to SS maps (data not shown).

Management zone classification accuracy across herbicides

In general, as the number of possible management zones on the herbicide label increased, the classification accuracy decreased, resulting in lower classification accuracies for metribuzin that has a possibility of ten different management zones (Table 10). There were a few instances where the classification accuracy increased between s-metolachlor and metribuzin: Rush 1 County with SS, SSEC, SSSF, and SSECSF; Rush 2 County with SS and SSEC; and Warren County with SSURGO. Lower management zone classification accuracies for s-metolachlor were the result of the actual and predicted OM being at or near 3% OM, which is the cutoff defined on the herbicide label (Table 2). Interestingly, many of the

Table 10 Mean management zone (MZ) classification accuracy[1] for herbicides with a different number of unique soil parameters for a specific application rate: pyroxasulfone (3), s-metolachlor (6), and metribuzin (10)

Field	Source[3]	Mean MZ classification accuracy by maximum number of management zones[2]		
		3	6	10
		(pyroxasulfone)	(s-metolachlor)	(metribuzin)
		(%)		
Benton	SSURGO	73 a	63 b	40 c
	SS	63 a	58 b	35 c
	SSEC	71 a	63 b	47 c
Daviess	SSURGO	38 a	38 a	37 a
	SS	100 a	93 b	72 c
	SSEC	99 a	90 b	86 c
Franklin	SSURGO	63 a	58 b	17 c
	SS	83 a	83 a	44 b
	SSEC	83 a	83 a	48 b
	SSSF	--	83 a	45 b
	SSECSF	--	83 a	46 b
Fulton	SSURGO	70 a	68 a	37 b
	SS	87 a	68 b	44 c
	SSEC	83 a	70 b	42 c
Johnson 1	SSURGO	63 a	48 b	33 c
	SS	81 a	63 b	52 c
	SSEC	78 a	59 b	54 c
Johnson 2	SSURGO	43 a	43 a	27 b
	SS	64 a	64 a	46 b
	SSEC	67 b	70 a	49 c
Rush 1	SSURGO	63 a	58 a	17 b
	SS	76 a	50 c	68 b
	SSEC	77 a	58 c	68 b
	SSSF	--	48 b	69 a
	SSECSF	--	47 b	71 a
Rush 2	SSURGO	45 a	0.0 b	0.0 b
	SS	55 a	31 b	53 a
	SSEC	57 a	34 b	57 a
St. Joseph	SSURGO	75 a	40 b	37 b
	SS	80 a	73 b	57 c
	SSEC	78 a	67 b	48 c
Warren	SSURGO	23 a	10 c	20 b

Table 10 (continued)

Field	Source[3]	Mean MZ classification accuracy by maximum number of management zones[2]		
		3	6	10
		(pyroxasulfone)	(s-metolachlor)	(metribuzin)
		(%)		
	SS	59 a	46 b	45 b
	SSEC	66 a	53 b	42 c

[1] The mean classification accuracy is the average percent of validation samples that were correctly predicted from the maps developed from each source of spatial soil data.

[2] For each field, the classification accuracy was averaged across sampling intensity for each herbicide x source combination. Classification accuracy means within a row followed by the same letter are not significantly different according to Tukey's HSD ($\alpha=0.05$).

[3] Abbreviations: SSURGO, Soil Survey Geographic Database, SS, soil samples alone, SSEC, soil samples with electrical conductivity (EC) data, SSSF, soil samples with organic matter data from planter-mounted visible and near-infrared (VNIR) sensor, SSECSF, soil samples with EC plus with planter-mounted VNIR sensor organic matter data. Sample size equals 120 for SS, SSEC, SSSF, and SSECSF for each herbicide and 2 for SSURGO for each herbicide.

predicted OM levels were less than 0.25% OM different from the actual OM levels (data not shown). Although, the intra-field soil variability can be extremely small, there is still a risk of reducing the herbicide efficacy and crop safety by applying a uniform application. Previous research has shown that when a pendimethalin application rate for coarse soil was selected and applied across three different soil types (coarse with 1.9% OM, medium with 2.4% OM, and medium with 6.2% OM), the percent of weed control was 94%, 77% and 57%, respectively (Metcalfe et al., 2018). The soils with higher clay content and organic matter did not receive a high enough dose to achieve effective weed control. However, when the application rate was selected based on the medium texture soils, the percent weed control was increase to 91% and 82% on the medium soils with 2.4% and 6.2% OM, respectively. This demonstrates that weed control can be optimized when soil residual herbicide rates were selected based on the soil properties.

Conclusions

For this study, we focused on the impact that the source of spatial soil data, sampling intensity, and herbicide label have on the accuracy of delineating the management zones for VR residual herbicide applications. Our study validates that commercial fields have inherent field variability that translates to multiple management zones for soil residual herbicide applications. For developing the management zones for VR residual herbicide applications, the highest management zone classification accuracies and lowest RMSE for the OM predictions occurred most frequently with a high sampling intensity of approximately one sample per hectare. However, the low and medium sampling intensities often provide similar management zone classification accuracy as the high sampling intensity.

Additionally, management zones delineated from SSEC maps had higher prediction accuracy with the HTC, lower RMSE with the OM predictions, and were most frequently the most accurate sources of spatial soil data for herbicide management zone classification.

The inclusion of EC_a data provided increased or similar classification accuracy compared to the SS maps 86% of the time. Therefore, the addition of EC_a data is encouraged whenever there is a relationship to at least clay content, to capture the variability that is not provided by soil samples alone. However, since there is no way to know whether the EC_a and soil parameters will have a relationship, there is a small risk that inclusion of the EC_a data could lower the management zone classification accuracy. Although the OM predictions from the planter-mounted VNIR sensor underestimated the true OM level more than SS and SSEC prediction, this technology or future adaptations of these sensors, may provide a cost-effective alternative for the purpose of developing prescription maps for VR soil residual herbicides. Lastly, we recommend that SSURGO data be avoided for variable-rate residual herbicide applications since that data was consistently unreliable for spatial soil data when developing herbicide management zones, especially for soil OM content.

Future considerations

These data have shown that the spatial soil variability within Indiana fields justifies VR residual herbicide applications. Further investigation should focus on determining if the rates on the herbicide label vary enough to justify VR residual herbicides in terms of economics and field performance of the VR herbicide applications for weed control and crop safety. As shown in Table 2, some herbicide management zones share similar rate structures meaning that a field may be treated as a uniform application despite having multiple management zones. The VR application of certain soil residual herbicides may be a significant opportunity to enhance weed management and reduce environmental impact. However, some herbicides with few management zones on the product label and overlapping herbicide rate ranges across the listed management zones on the label may limit the utility and impact of VR applications. Thus, herbicides with the greatest range in application rate across the labeled management zones (e.g. metribuzin) should be the target for further research and potential commercial adoption.

Additionally, conservative parameters were used on the semivariograms for ordinary and regression kriging to ensure computation efficiency for the thousands of maps developed for this study. Overall, the conservative parameters resulted in poorly fitted semivariograms that lacked spatial autocorrelation which is important for regression kriging. This was especially noticeable at the low sampling intensity. However, training set D in Supplemental Information Figure B4 shows that the gaussian semivariogram was well fitted but had no impact on the management zone classification accuracy. It may be possible that the management zone classification accuracy was impacted by the samples selected with the training set more than the variogram model. More research is needed on the semivariogram parameters and/or alternative models to fully understand the potential impact of semivariograms on VR residual herbicide management zones.

Regarding the spatial data provided by the planter-mounted VNIR sensor, additional research should be conducted to determine whether the soil moisture and temperature data collected simultaneously with the OM data can be used as an auxiliary variable for regression kriging when delineating management zones for VR residual herbicide applications.

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Authors and Affiliations

Rose V Vagedes[1] · Jason P Ackerson[2] · William G Johnson[1] · Bryan G Young[1]

✉ Rose V Vagedes
rvagedes@purdue.edu

[1] Purdue University, West Lafayette, IN, USA

[2] Soil Health Institute, Morrisville, NC, USA