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PROJECT FINAL REPORT

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- **Please note that making changes to the project without prior written consent from the funder(s) could constitute sufficient grounds for termination of funding.**
- This report must be a stand-alone report, *i.e.,* must be complete in and of itself. Scientific articles or other publications cannot be substituted for the report.
- A signed electronic copy of this report must be forwarded to the funders' representative on or before the due date, as per the investment agreement.
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Section A: Project overview

1. Project number: 2012F035R
2. Project title: Understanding Soil Variability for Effective Zone Management in Precision Agriculture –an evaluation of sensor based soil mapping tools
3. Abbreviations: Define ALL abbreviations used. Electrical Conductivity (EC); EM38-MK2 (EM38); Veris-MSP3 (Veris); All Terrain Vehicle (ATV); Nitrogen, Phosphorus, Potassium, Sulphur (NPKS); Farming Smarter (FS); Variable Rate (VR); Smoky Applied Research and Demonstration Association (SARDA); Normalized Difference Vegetation Index (NDVI); Power of Hydrogen (pH); Organic Matter (OM); Electromagnetic (EM); Unmanned Aerial Vehicle (UAV); Principle Components Analysis (PCA); Management Zone Analyst (MZA); Global Positioning System (GPS); Geographic Information System (GIS); Randomized Complete Block Design (RCBD); Near Infrared (NIR); Return on Investment (ROI) Precision Ag, Site-specific management, Electromagnetic induction sensors, EM38, Veris, On-farm research, Soil variability
4. Project start date: 2012/03/19
5. Project completion date: 2015/10/31
6. Final report submission date: 2016/01/04
7. Research and development team data

a) Principal Investigator: (Requires personal data sheet (refer to Section 14) only if Principal Investigator has changed since last report.)

Name	Institution
Ken Coles, M.Sc, P.Ag	Farming Smarter Association, Lethbridge

b) Research team members (List all team members. For each new team member, *i.e.*, joined since the last report, include a personal data sheet. Additional rows may be added if necessary.)

Name	Institution
Muhammad (Adil) Akbar, Ph.D., P.Ag., P.Eng.	Farming Smarter Association, Lethbridge
Lewis Baarda, M.Sc.	Farming Smarter Association, Lethbridge
Dennis Dey	Independent
Vance Yaremko	SARDA
Curt Walker	Ag Viser

Section B: Non-technical summary (max 1 page)

Farming Smarter initiated this study to compare performances of two soil EC sensors, EM38-MK2 (EM38) and Veris MSP3 (Veris). The study assessed soil EC mapping as a low cost alternative to grid soil sampling for estimating in-field soil variability. Additionally, the study assessed the capacity of soil sensors as well as other layers of mapped data to create zones for variable rate management applications.

The study showed that EM38 and Veris performance is accurate and consistent over both time and space. Soil EC maps from both sensors were found to be strong indicators of the presence of clay and soil moisture. However, the study revealed that mapped EC data could not be used for a direct estimation of the spatial distribution of plant macro-nutrients (NPKS).

The project tested five different zone delineation methods in each of the 10 fields studied. Zones were delineated using surface geography, grid soil samples, historic yield maps, EC, and composite (yield + EC) methods. All five methods had some level of success at identifying regions that yielded differently from one another. The composite (yield + EC) method was the most consistently effective at differentiating zones of productivity. However, the study was not able to identify a unique yield response to nitrogen for the zones identified. In other words, the optimal rates of nitrogen identified for different zones were not statistically different from one another. The upshot is that although zones derived from various data sources identified regions with consequence for yield, the study could not consistently identify an effective variable nitrogen management strategy for these zones. The study shows that variable rate technology requires a variable approach; there is not a universal method that will be effective in all circumstances. The zone delineation techniques tested had varying levels of success in different fields. Producers should be prepared to develop a specific VR strategy for each field, and are advised to evaluate strategies using methods developed by FS in this study.

This project provides a methodology for creating and testing management zones for VR practitioners. The study also challenges the viability of a formulaic approach to zone delineation and management. These study results provide producers information to make better decisions around investment on equipment or services for VR technology implementation. For those producers using VR technology, this study offers new guidelines on choosing an appropriate VR strategy and provides a method for producers to assess the efficacy of any particular strategy.

Section C: Project details

1. Background (max 1 page)

That soil variability exists within fields and can cause varying effects on crop yield is well known. Intensive sampling of soil properties can provide a useful description of the variation in soil properties, but carries a prohibitive cost. The recent confluence of GPS technology, soil sensors, and improved data management offers the ability to efficiently and precisely map certain soil properties within fields. However, we need a better understanding of crop production implications and response to variably managed inputs to benefit from these data.

Precision agriculture consulting companies typically use satellite images, historical yield maps, or terrain analysis to delineate areas in a field likely to have similar soil properties and response to management. Then they use representative soil samples to characterize different zones. This approach is efficient and widely used. However, questions regarding the accuracy and effectiveness of delineated zones require continued evaluation and improvement of this approach.

EC sensors provide one additional layer of data to improve zone delineation, crop response predictions, and prescriptions. Electromagnetic induction can map field variability in soil salinity and texture and may also detect variation in other soil properties (Corwin and Plant 2005; Triantafilis and Lesch 2005). The EM38 (www.geonics.com) and Veris (www.veristech.com) are the most widely used commercially available instruments. The EM38 instrument does not require soil-to-instrument contact and can quickly obtain readings with minimal disturbance. The Veris instrument uses soil-to-instrument contact to map EC. Recently-introduced models of the Veris machine also measure soil variability in organic matter (OM) and pH.

Recent work in Australia demonstrated that EM38 measurements and soil sampling can map fields based on soil factors that constrained yield (Taylor et al. 2007; Dang et al. 2011). The proposed framework to estimate the monetary value of site-specific management options included: (i) identification of potential management classes from EM38 measurements; (ii) measurement of the soil attributes generally associated with soil constraints in the region; (iii) grain yield monitoring; and (iv) simple on-farm experiments. This study used a similar framework to evaluate the value of sensor-based soil mapping tools for Alberta.

2. Objectives and deliverables (max 1 page)

2.1 Objectives

- **Objective 1:** Evaluate two sensor-based soil mapping tools (EM38-MK2, Veris-MSP3) for ease of use, accuracy, consistency, and utility
- **Objective 2:** Determine relationships between soil properties, soil moisture availability and crop yields for identified soil management zones
- **Objective 3:** Identify and evaluate protocols to delineate soil management zones based on multiple sources of information (farmer knowledge, yield maps, topography, remote sensing, soil mapping tools)
- **Objective 4:** Identify and test the top recommended management option for variable management
- **Objective 5:** Develop and deliver information about soil mapping tools and how best to use them to producers through a variety of communication mediums

2.2 Deliverables

Annual and final report based on findings:

- Recommend method(s) to obtain and use soil sensor maps to develop variable management prescriptions for agricultural fields in Alberta
- Estimate accuracy of sensors for different soil properties
- Estimate improvement in understanding of field variability in crop yields, soil moisture availability and crop water use efficiency through information derived from soil sensor maps
- Initial assessment of top variable management recommendations

Communication of the study's findings:

- Websites: www.farmingsmarter.com, www.areca.ab.ca, www.agric.gov.ab.ca
- Talks and tours: Western Canadian Precision Ag Conference, Farming Smarter Conference, Agronomy Update, Plot Hops, Farming Smarter Field School
- Other outlets: Farming Smarter magazine, newsletters, social media and popular press

3. Research design and methodology (max 4 pages)

3.1 Objective 1: Evaluate two sensor-based soil mapping tools (EM38-MK2, Veris-MSP3) for ease of use, accuracy, consistency and utility. The project evaluated the two soil sensors by using them to map agricultural fields and test the data. Recognizing that each field is unique, this project treated each study field as its own trial. Please note that the unique nature of each field occasionally necessitated subtle deviations in trial implementation. The research team gained hands-on experience in the field operation and calibration of the Veris and EM38 soil sensors.

3.1.1 Site Selection: The team selected ten trial fields from cooperators working closely with FS in Southern Alberta and with SARDA in the Peace River region in northern Alberta. We insisted that cooperators have the capacity for VR application of nitrogen while seeding as well as yield mapping at harvest.

3.1.2 Data Collection: The research team collected two types of data from each field. Mapped data are the georeferenced readings gathered from soil sensors or UAVs. Measured data are lab analyzed measurements of soil properties from physically sampled soil cores. Technicians collected both mapped and measured data concurrently at two separate times for each field.

3.1.3 Mapped Data: Mapped data collected included Veris (EC pH and OM), EM38 (EC), aerial imagery (NDVI), yield maps, and elevation.

3.1.3.1 EC Data: The research team conducted EC mapping only when soil moisture levels were normal and the temperature above freezing to protect against collection of poor or inaccurate data. Both sensors were operated together, the Veris attached to a tractor, and the EM38 in a plastic sled towed at a reasonable distance to avoid proximity to metals. The study mapped fields in 20 meter transects, a standard practice for soil EC mapping. An alternating transect mapping pattern allowed the operator to identify drift in measurement and ensure proper data collection.

3.1.3.2 Veris-MSP3: The Veris-MSP3 (Veris Technologies, 2015) is a tractor mounted sensor whose primary function in agriculture is to measure the apparent EC of soil. The Veris is a contact-based EC sensor and has three pairs of coulters designed to maintain contact with the soil. An electric current passes through the soil between each pair to measure the resistivity of the soil, which is then converted to an apparent EC value. The coulters are arranged so that the machine can measure EC at both 0.75 and 1.5 meter depths concurrently.

The Veris model (MSP3) used in this study can also collect OM and pH data. An optical sensor located at the rear of the machine measures OM by gauging soil reflectance in both visible and near infrared (NIR) wavelengths. Darker soil gathers higher OM readings and lighter soil gathers lower OM readings. The Veris collects soil pH data by physically digging into the soil and gathering surface soil samples on the go. A pair of probes measure and record the pH of soil samples then rinse themselves clean prior to the next sample. This sensor is not continuous; it takes a reading about every 30 seconds. The EC and OM sensors on the other hand are essentially continuous, providing a much denser coverage of mapped data. Operators tested and properly calibrated all three Veris sensors before mapping each field.

3.1.3.3 EM38-MK2: The EM38 (Geonics Limited, 2015) measures the apparent EC of soil as well. The EM38 is a non-contact sensor that uses electromagnetic induction to detect soil EC. The instrument creates an EM field then detects, records, and converts variations in this EM field to apparent EC as the sensor moves across the soil. The EM38 model (MK2) used in the study is a dual-dipole sensor with the capacity to measure both shallow and deep soil EC concurrently. The horizontal dipole reacts to soil properties nearer to the surface (0.75 meters), while the vertical dipole reacts to soil properties attached to soils at depth (1.5 meters). The EM38 takes measurements almost continuously while towed across the field.

The EM38 is highly sensitive to elements outside of the soil such as metals, atmospheric moisture, or nearby EM fields. The operator properly calibrated and tested the instrument before mapping each field, re-calibrating the EM38 every few hours to mitigate the risk of measurement drift as conditions changed.

3.1.3.4 Aerial Imagery: The study collected aerial imagery for some of the fields in the study. Aerial imagery was collected with a fixed-wing UAV. The data collected were used to generate red light NDVI values for the fields surveyed.

3.1.3.5 Yield Data: The researchers collected 3-5 years of yield data for each field according to industry standard. All yield data were cleaned to eliminate outliers, inliers, and data points in error.

3.1.3.6 Elevation: The research team gathered elevation data concurrently with EC mapping. The on-board RTX GPS receiver recorded elevation in each field and generated elevation maps with a reported 4cm horizontal accuracy and 10cm vertical accuracy.

3.1.4 Measured Data: The study collected georeferenced soil cores from each field in a stratified five acre grid pattern, resulting in 32 samples collected for each 160 acre field. In cases where a designated sample location was inaccessible, either a nearby location was used or that sample location was omitted. At each location, two soil cores were collected. The first core was divided into three depths, 0-15cm, 15-30cm, and 30-60cm, and analyzed for the major soil nutrients (NPKS) as well as OM, pH and EC at each depth. The second soil core was divided into four segments, 0-30cm, 30-60cm, 60-90cm, and 90-120 cm, and was analyzed for soil texture using the hydrometer method, as well as soil moisture content.

<u>3.2 Objective 2: Identify and evaluate protocols to delineate soil management zones based on multiple sources of information.</u> The study addressed this objective using three separate statistical procedures. The first was a pair of correlation analyses. A global correlation matrix measured the similarity of spatial patterns in pairs of mapped data layers. A second local correlation matrix measured the spatial relationships between layers of mapped data and measured soil sample data. Next, the project used PCA to gain a deeper understanding of the relationships between mapped layers, as well as to identify key variables for zone delineation. Finally, the project used cluster analysis as an objective means of creating management zones from these data.

3.2.1 Scale and Grid Polygon Geography: The investigation used seeder width to determine an appropriate spatial resolution for data analysis. The upper limit on spatial resolution is constrained by seeder width, as this is the finest scale at which a cooperator can respond to field variability with their equipment. Data trials by the research group showed spatial patterns beginning to dissolve at a spatial resolution coarser than 2 seeder widths. The study therefore created a layer of grid cells sized between 1 and 2 widths of the cooperators' seeders for each field. All data collected were nested into these grid cells for analysis.

3.2.2 Correlation Analysis: The project team used a correlation analysis to compare each layer of data to every other layer of data. SAS Analytics Software statistical procedures were used to assess correlations with a probability level of $p<0.5$ across all analyses. Pearson correlation was determined for each pair of variables. Two separate correlation analyses were completed. The first one compared every pair of mapped variables for each field and the second compared every layer of mapped data to each element in the measured soil sample data.

3.2.3 Principal Components Analysis (PCA): The project used PCA to identify variables among the mapped data layers that would contribute the most to our understanding of variability in each field mapped. PCA reduces the number of observed interdependent variables in a large data set to a relatively smaller set of transformed and independent new variables. These new variables account for most of the variance in the observed variables and are not correlated with one another. For this study, PCA primarily identified the mapped data layers that represented the maximum amount of variability across time and space. These data layers were then used for creating management zones.

3.2.4 Cluster Analysis: Cluster analysis is a statistical procedure for grouping similar data into distinct classes or clusters. Potential management zones for the project field sites were created with Management Zone Analyst (MZA) computer software using a fuzzy c-means unsupervised clustering algorithm. The clustering procedure assigns a value to each grid cell, objectively determining both zone boundaries and the optimal number of zones on the basis of the distribution of the data.

<u>3.3 Objective 3: Determine relationships between soil properties, soil moisture availability and crop yields for identified soil management zones.</u> The project addressed many of the components of objective 3 using the procedures outlined for objective 2. The correlation matrices and PCA analysis help to understand relationships between all the layers of data collected.

<u>3.4 Objective 4: Identify and test the top recommended management option that could be variably managed</u>. The research team used five different delineation methods to divide each of the 10 study fields into management zones. The study then tested each of these delineation methods.

3.4.1 Creating Management Zones: The delineation methods applied in each field were surface geography, grid soil sampling, historic yield, mapped EC and composite.

Surface Geography: Zones were created using a subjective assessment of visual spatial differences in terrain, moisture, salinity, etc.

Grid Soil Sampling: Soil sample nitrogen measurements were spatially interpolated using the kriging method. Resulting values were divided equally into three zones.

Historic Yield: All available yield maps were normalized, then pooled to create an average normalized yield map. Resulting values were divided into three zones equally.

EC: A single EM38 deep EC map was put through a cluster analysis procedure to objectively determine zone boundaries and number of zones.

Composite: A single representative EM38 deep EC layer and a single representative yield layer were pooled and put through a cluster analysis procedure to objectively determine zone boundaries and number of zones.

4.2 Testing Management Zones: The project used VR equipment to treat each field with a range of nitrogen rates at time of seeding in an RCBD trial design. The researchers collected a harvest yield map from the GPS monitors of each cooperator after harvest. Technicians then used GIS technology to “draw” each delineation method on top of this yield map. Yield response to nitrogen for each zone was identified by collecting yield data where a selected zone overlapped with a selected rate of nitrogen. Yield response curves for all zones in each delineation method were generated from these data. For each delineation method 2-3 response curves were generated, each representing yield in a particular zone.

The research team analyzed the response curves for each zone delineation method in two ways. First, the curves were assessed to determine if mean yield values were significantly different from one another. Zones with significantly different mean yields would indicate that the zones created and their soil properties have implications for productivity. Second, the curves were assessed to determine if the slopes were significantly different from one another. Curves with different slopes respond to nitrogen differently and can therefore be managed using different optimal rates of nitrogen.

4. Results, discussion and conclusions (max 8 pages)

Note: Project results are the aggregation of findings obtained in ten discrete fields. Given the complexity and depth of the analysis, this report will not cover the specific patterns and responses observed in individual fields, but will focus on aggregate results.

4.1 Objective 1: Evaluate two sensor-based soil mapping tools for ease of use, accuracy, consistency, and utility. The research team found that the EM38 was easier to use and produced higher quality EC data than the Veris. However, both sensors produced highly effective mapped EC data. EC maps from both sensors were consistent over space, time, and across sensors. The study also found that although EC data were dependable for mapping the texture and moisture of soil, they were not effective predictors of soil nutrient properties such as NPKS. The specific results leading the research team to these conclusions are detailed in the following sections.

4.1. Calibration: The researchers calibrated each sensor against the manufacturer standard criteria. Operators closely monitored EC readings from both sensors for calibration drift, and mapped EC in alternating transects to aid in detection of drift. Additionally, where conditions changed or logistical challenges slowed the mapping of a field, the operators re-calibrated sensors. Highly consistent EC readings attained in different locations, times, and conditions indicate that field calibration protocols were effective and that the instruments performed according to specifications.

4.2 Ease of Use. The research team gained hands on experience in the operation and calibration of both the Veris and EM38 EC sensors. One key difference identified was the EM38's ability to produce quality EC maps under a range of conditions. The Veris, requiring contact with the soil, was susceptible to weaker performance due to stubble, surface debris, firm soil, or uneven terrain. The EM38 is lighter, easier to transport, and only requires a small truck or ATV to tow, whereas the Veris-MSP3 requires a tractor. The research team found calibration of the EM38 challenging to learn, but easy to implement. Conversely, Veris calibration was relatively simple, but cumbersome and time consuming to implement. Considering each sensor's strengths and weaknesses, this study found the EM38 to be easier to operate.

4.3 Accuracy Consistency and Utility: Given that accuracy, consistency, and utility are related and largely interdependent concepts, the project investigated all three concurrently. The backbone of this component of the study includes the global and local correlation analyses performed on spatial data for each field that examine spatial relationships between mapped layers and measured soil properties.

4.3.1 Global Correlation: The project measured correlations between all available layers of mapped data for each study field. Technicians mapped each study field twice over the course of the project yielding nearly 20 mapped EC layers for each sensor. There were a few instances where mapped EC layers were omitted from analysis due to accuracy concerns. The study found correlations between layers of mapped EC data to be almost universally significant and strong. The average Pearson correlation value ($p<0.05$) between EC layers was 0.69, indicating a large strength of association between the variables. The research team further examined mapped EC layers by assessing their performance over time and by profile depth. Table 1 shows average correlation values between mapped EC layers according to time, depth, and sensor. Notable observations regarding relationships by depth, time, and sensor are discussed in the following sections.

4.3.1.1 EC by Profile Depth: The analysis showed extremely strong correlations between deep and shallow EM38 EC measurements mapped at one time, with an average Pearson correlation of 0.93. Veris readings mapped at one time also had a very high average Pearson correlation of 0.81. When examined across time, a similar pattern is evident where EM38 shallow and deep correlations are slightly stronger than Veris shallow and deep correlations. Finally, deep EC correlations across sensors averaged 0.66 and shallow correlations averaged 0.65. This analysis demonstrates that relationships between shallow and deep EC readings are extremely strong, although slightly stronger for the EM38 than for the Veris. Ultimately, the study found little difference between shallow and deep EC readings from either sensor and that either would be effective for understanding soil variability.

4.3.1.2 EC by Time: The project found that the EM38 demonstrated stronger spatial relationships than the Veris among EC maps gathered at separate times in the same location. Correlation analysis of EC data collected at separate times yielded an average Pearson value of 0.76 for EM38 data, and 0.69 for Veris data. This indicates that spatial patterns detected were slightly more consistent over time for the EM38 data than for the Veris. The relationship between Veris data and EM38 data collected at different times yields an average correlation value of 0.60, demonstrating a high level of temporal consistency in mapped EC data regardless of the sensor used.

4.3.1.3 EM38 vs Veris: The study found the EM38 to be more consistent over time, and across shallow and deep profile measurements. However, the gap in performance between the two sensors is small enough and the relationship between EC maps generated strong enough, that either sensor would be effective considering the parameters of this research project.

4.3.2 All Mapped Data Layers: The global correlation analysis also gauged relations between all layers of mapped data acquired for each study field. Table 2 shows the percentage of instances in which each pair of mapped variables resulted in a correlation that was both significant ($p<0.05$) and strong (Pearson>0.4). The project found a highly variable network of relationships among mapped data layers with results at times fluctuating significantly from one field to another. Notable trends observed in the cases of pH and OM data, elevation data, and yield data are discussed below.

4.3.2.1 pH and OM: The study found that correlation between mapped EC (Veris or EM38) and pH and OM data mapped by the Veris was rare and weak, with acceptable correlations found in only 7/90 instances for pH and only 3/87 instances for OM. Thus, mapped EC data could not explain variability in pH and OM as mapped by the Veris, nor predict spatial patterns of those variables in soil.

4.3.2.2 Elevation: The analysis found that mapped elevation correlated with mapped EC data in 42% of instances, almost all of which were negative. EM38 EC data correlated strongly with elevation in 63% of instances, while Veris EC data did so in only 24% of instances. These results indicate a possible inverse relationship between EC measurements and elevation, likely reflecting the relationship between elevation and soil texture in many locations. The EM38 data exhibited this trend with greater strength and consistency than the Veris data.

4.3.2.3 Yield: The analysis showed a great deal of variability in relationships between yield and other data layers. As an aggregate, yield correlated with EC data in roughly 20% of instances. This fluctuated significantly by year, however, with instances of correlation in excess of 30% for 2010 and 2013 yield data and as low as 0% across the board for 2012 yield data. This shows how variable yield patterns can be from year to year. In fact, yield maps from various years only had strong correlations to one another in 10% of instances project-wide. Elevation correlated strongly with yield data in 26% of instances. This places significant limits on the capability of soil sensor or elevation data to predict grain yield in a given field in a given year. Although relationships between yield and other data were rare, both EC and elevation correlated to specific yield maps more often than other yield maps from the same field. This indicates that these data layers may be more effective predictors of grain yield than historic yield data.

4.3.2 Local Correlation: The study used correlation analysis to compare mapped sensor data to measured soil properties. Table 3 shows the frequency of correlation between mapped EC data and measured soil data by identifying significant ($p>0.05$) and strong (Pearson>0.4) correlation instances.

The researchers found relationships between mapped and measured data to be highly variable, over both location and time. The strength and frequency of correlations between mapped data and measured clay content and moisture indicate a significant relationship between those variables. This analysis suggests that correlations for most other variables were too few to render reliable conclusions for practical and operational purposes.

The study found a relationship between mapped EC data and soil texture (especially clay), with strong and significant correlations in 25% of instances. Correlation with soil moisture occurred slightly less often at around 20% of instances. There was a weak and rare relationship between mapped EC and measured pH, EC, and OM in the soil. With the exception of sulfur, mapped EC data correlated with measured soil macronutrients (NPKS) in very few circumstances. Sulfur correlated with EC in the range of 25% of instances.

4.3.2.1 Challenges: The intention of this analysis is to give a sense of the coarse accuracy of the soil sensors. The lack of on point data collection, particularly in the case of the local data, may place limits on the strength of this analysis. The strength of the correlations that do exist, however, supports the argument that Veris and EM38 EC maps are effective predictors of clay content and soil moisture. This trial is better designed to examine accuracy of EC data than it is OM and pH data. EC data has a 60ft spatial range and does not need to be measured on point to be considered accurate. Whereas OM and pH (as well as NPKS) must be mapped at a higher resolution to effectively assess accuracy.

4.2 Objective 2: Determine relationships between soil properties, soil moisture availability, and crop yields for identified soil management zones. The study addresses most of the elements of this objective in other sections of the report. The relationships between soil properties, mapped variables and crop yields are closely examined in section 4.1. Performance of identified soil management zones in the context of both productivity and response to nitrogen are discussed at length in section 4.4.

The study used soil samples to examine the soil properties of the management zones created. This analysis found that soil properties tied to management zones closely mirrored the results of the correlation analysis described in the summary of objective 1. Management zones built using EC, for example, tended to contain soil with different soil moisture and texture properties for each zone. The soil management zones used in this study did not, however, effectively differentiate soil nutrient properties.

4.3 Objective 3: Identify and evaluate protocols to delineate soil management zones based on multiple sources of information. The project focused on two elements in developing protocols for zone delineation: 1) Which data sources to use, and 2) How to effectively use these data to create zones. PCA identified key data layers for zone delineation and cluster analysis objectively defined zones.

4.3.1 Principal Component Analysis: The research analysts ran a PCA for each of the 10 study fields, incorporating all data layers available for each field. Input variables for the PCA process therefore differed from field to field due to subtle differences in data collected in each field. PCA results were quite similar for all 10 fields. The EC variable loaded strongly on the first factor in all instances, indicating that EC accounts for the most unique variability among the data layers collected and is a key variable. The specific variables loading on the second factor fluctuated from field to field, but most often yield data was the next most significant layer following EC in the PCA process. The other notable result of the field by field PCA procedure was that OM data occasionally loaded onto the same factor as yield. This indicates a relationship between the two variables where they tend to account for the same variability in some fields. Ultimately the PCA process objectively identified two key data layers, EC and yield, for zone delineation.

4.3.2 Cluster Analysis: The study used cluster analysis to objectively divide input data into management zones. Cluster analysis groups data into clusters that have similar properties. The process objectively determines into which zone each datum belongs and suggests an ideal number of zones to create. This zone delineation strategy is specific to each individual field, while maintaining the rigor of an objective and repeatable process. There are a number of specific protocols that tailor the analysis to the specific data. The researchers, using a trial and error strategy, developed an effective protocol for the input data. The study found cluster analysis effective for creating zones using data that were not normally distributed, such as EC, or for combining multiple variables. The study did not apply cluster analysis to surface geography or grid soil sample delineation methods as the input data in those cases were not raw data. Similarly, cluster analysis was not applied to yield data, as the team instead tested the common industry practice of using average normalized yield divided into three equal zones.

4.4 Objective 4: Identify and test the top recommended management option that could be variably managed. The project generated response curves documenting the response of yield to increasing rates of nitrogen for each zone in all five different methods of zone delineation. The research team examined these curves to assess the effectiveness of each delineation method. There are two scenarios that indicate meaningful or useful zones. The first is if the mean yields of identified zones differ significantly. The second is if crop yield response to nitrogen differs for each zone. The five different zone delineation methods tested were surface geography, grid soil sampling, historic yield, EC and a composite of yield and EC.

4.4.1 Yield Productivity of Delineated Zones: The study had reasonable success identifying zones that yielded differently. All five delineation methods differentiated at least two zones whose yields were significantly different in at least 70% of instances (Figure 1). This suggests that zones created by all five methods were related to soil properties with real implications for yield. The composite method (EC and yield) most consistently identified zones that yielded differently, being the only method that did not fail to differentiate regions of productivity in any of the research fields. The remaining four delineation methods failed to do so in at least 20% of cases. The grid soil sample method appeared least successful. Although this method often differentiated some regions of the field that produced differently, in only 20% of cases all zones had significant yield differences. The other four methods identified significant yield differences for all zones in 50% or more of instances. While all five zone delineation methods were reasonably effective at differentiating productivity, the composite method was most consistently effective.

4.4.2 Yield Response of Delineated Zones: The study had limited success in identifying zones with differing yield responses to nitrogen. Among the 50 zone delineations tested over 10 research fields, there was only one instance where the slopes of all the response curves were statistically different from one another (Figure 2). This instance occurred with the grid soil sample method. The research team identified statistically different response curve slopes for 2 of 3 zones in 12% of instances. Across all zone delineations tested, 86% of instances had no statistically significant difference between response curves for different zones. The project expected to find unique responses to nitrogen in at least those zones that had significantly different yield means, but this was not the case. Effective yield prediction did not lead to effective yield response differentiation.

4.4.3 Challenges The research team had a few challenges assessing effectiveness of delineated zones. One challenge involved selecting nitrogen rates that adhered to what cooperators were comfortable applying. In some cases, this limited the number and range of rates applied.

However, the study found that when an ideal number and range of nitrogen rates were applied, there was still a very low success rate. For fields that fewer rates were applied, yield response curves were not statistically different even at a coarse level. It stands to reason that any optimal rates identified in the study would need to lie within a range that a cooperator would be comfortable with to be useful.

<u>4.5 Conclusion</u> This project had a strong focus on collection and analysis of on-farm data. The researchers found it easy to gather large quantities of data. Converting that data into tangible knowledge proved more challenging. Data and analysis must provide information that is consistently reliable in order to be used for good decision making. The knowledge generated by this study provides strong guidelines for collection, analysis, and application of spatial on-farm data. It also places limitations on the on the ways data can facilitate good management decisions. The implications of the study results are summarized three sections: 1) data and soil variability, 2) data and yield prediction, and 3) zone delineation and VR management.

4.5.1 Data and Soil Variability: The project was unable to effectively account for the variability of most soil properties using the data layers collected. Spatial relationships between various data layers were inconsistent and tended to vary from field to field. Using any one variable to predict the spatial pattern of another is unlikely to yield consistent or repeatable results. The study does not recommend using any of the data variables studied to predict variability in soil properties. Although mapped data such as EC, pH, OM, yield or satellite imagery are relatively cheap and easily attainable, this study shows that they are not effective predictors of macro-nutrients (NPKS) in the soil.

Soil EC, however, demonstrated consistent and repeatable relationships to the presence of clay and soil moisture in the study fields. The project found some differences between Veris and EM38 performance, but both produced EC maps that effectively predicted location soil texture and soil moisture. While other variables such as weather or management practices can change from year to year, EC remains relatively stable over time. Not only did the PCA highlight EC as a key factor in soil variability, but the correlation analysis showed EC patterns to be highly consistent over space and stable over time. Additionally, EC is relatively cheap, easy to acquire and has a longer shelf life than other variables. The research team recommends EC as an effective tool to better understand soil variability.

4.5.2 Data and Yield Prediction: The study found spatial correlation between yield and most other study variables to be weak and rare. The study expected to find a relationship between measured soil properties and grain yield, but did not. The coarse 5-acre grid resolution of collected soil samples may have limited the study's ability to detect such relationships. The higher resolution mapped data offered a limited, if inconsistent, improvement over soil sample data for yield prediction. Mapped EC performed the best when it came to yield prediction. However, the results were quite variable from year to year and from field to field. In fact, the study found yield patterns highly variable from year to year, with yield data layers rarely strongly correlated to one another.

There are a number of factors that may account for the limited correlation between yield and other variables. First, accurate yield data maps are difficult to collect. Limited spatial coverage, use of multiple combines, calibration errors, variable swath widths, or inconsistent harvest geography can all obfuscate yield map patterns. Second, spatial variability of yield constraints other than soil properties, such as localized weather events or non-uniform management practices can influence yield patterns. Finally, temporal variability in yield patterns themselves makes grain yield difficult to predict. The yield pattern for a wet year, for example, may vary significantly from the yield pattern for a dry year.

This led the research team to conclude that accurate and consistent grain yield prediction using the variables studied is unlikely. The relative, if inconsistent, success of EC for yield prediction likely lies in the consistency of this variable. The implications of mapped EC may change over time with variations in weather patterns and crops grown, but the pattern is highly consistent. Mapped EC is a stable variable that provides a strong base for understanding soil variability.

For these reasons, EC may be effective for understanding soil variability and productivity. Although mapped EC data could not consistently explain variability in grain yields, adding context through additional data layers or weather information would likely improve its performance.

4.5.3 Zone Delineation and VR Management: The project created and tested five unique zone delineation strategies for each study field. The innovative use of PCA identified EC and yield as key variables to be used for zone delineation. Considerable effort was expended to ensure that delineation methods were objective and repeatable, and therefore as universal as possible in their application to multiple fields. The study analyzed the yield of created zones, paying particular attention to the mean yield and yield response to nitrogen for each zone. Although results varied from field to field, strong aggregate conclusions came from the analysis.

The project had reasonable success at identifying zones with statistically different mean yields. Although all five methods were successful in this regard, the grid soil method was the least successful, while the yield and EC composite map was the most successful. These results indicate that the data collected did relate to properties in the soil with implications for yield. The study showed that mapped data can identify zones of productivity. The project had expected to encounter a larger gap in the efficacy of delineation methods than the results showed. For example, there was very little difference in success between the rigorous composite approach and the rather imprecise surface geography method. Some of the success of the composite method is likely due to the use of multiple variables – hedging our bets so to speak. Some of its success also likely comes from the identification of yield and EC as key variables.

However, the project was largely unsuccessful in identifying zones that had unique responses to nitrogen. Response curve slopes were only statistically different for all zones identified in one instance across all the fields and delineation methods tested. This indicates that grain yields in the zones identified did not respond differently to nitrogen. Therefore, there was no statistically unique optimal nitrogen rate identified for each zone. Although meaningful zones can be identified, it appears unlikely that a consistent and effective nitrogen application strategy could be developed to manage each zone optimally and uniquely.

4.5.4 Summary: The study determined that variable rate technology requires a variable approach. Temporal and spatial variability in soil properties, yield, weather and other factors produce a complex and dynamic system that is difficult to understand, predict and manage. Additionally, every field is unique and responds differently to various management strategies. There is no magic formula or universal approach that can consistently identify meaningful and manageable zones.

The project advises VR practitioners to evaluate zone delineation methods with the on-farm research design used in this project. This allows for an objective evaluation of any VR management approach in any field. When developing a VR strategy, design zones using an objective, and therefore repeatable technique so that results attained are also repeatable. The project suggests that in most cases, mapped EC would be the most useful data for understanding the variability of soil properties. Yield data is also an effective variable, but its efficacy can be limited by data quality and temporal variability in yield patterns. Producers are advised to take meticulous care to ensure yield data are accurate and dependable.

Finally, the analysis had minimal success identifying unique, optimal nitrogen rates for a number of strategies in 10 different fields in Alberta. These results challenge the validity and effectiveness of universal approaches to VR nitrogen management. The dynamic nature of crop production, temporal variability in weather, difficulties in measuring soil variability, and the scale at which we can respond to variability all challenge our capacity to manage soil variability in a meaningful way. More academic work is needed in this area. Until then, it would be difficult to recommend variable rate nitrogen application as a consistently effective crop management strategy.

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6 Project team (max ½ page)

Describe the contribution of each member of the R&D team to the functioning of the project. Also describe any changes to the team which occurred over the course of the project.

- Ken Coles, M.Sc. P. Ag. (General Manager and Team Leader)
  - Ken provided overall leadership and coordination of the project as a Team Leader; facilitated the project team for successfully completing the project; prepared extension material for information and dissemination purposes and made presentations in producers' gatherings and conferences
- Dr. Muhammad Akbar, P. Ag. P.Eng. (Research Director & Geomatics/Precision Ag Scientist)
  - Dr. Akbar provided scientific and technical supervision of the project; provided professional advice and support on the commissioning and operation of soil EC sensors; assisted in designing and conducting field trials; conducted data analysis, interpretation and reporting; prepared presentations, interim and final project reports on the study's findings and mentored project team in all aspects of the application of geomatics and spatial and statistical analysis techniques pertinent to the project
- Lewis Baarda, M.Sc. (GIS Analyst)
  - Lewis supervised and coordinated all the field operations and data gathering activities; conducted data compiling and analysis; assisted in preparation of final project report; prepared extension material for information and dissemination purposes and made presentations in producers' gatherings and conferences

7 Benefits to the industry (max 1 page; respond to sections *a)* and *b)* separately)

a) Describe the impact of the project results on the Alberta or western Canadian agriculture and food industry (results achieved and potential short-term, medium-term and long-term outcomes).

The project results increase chances for producer success when developing their own VR strategies and provide tools to evaluate that strategy. The study produced strong guidelines for data to use and how to delineate management zones that will improve a producer's odds of establishing meaningful and manageable zones. Additionally, the on-farm research model developed gives any VR practitioner the necessary tools to evaluate the efficacy of VR strategies on their own fields. The study found that universal strategies for zone delineation were largely ineffective. In the short-term, this should initiate work into improving existing formulaic strategies and increasing ability to tailor VR strategies for specific fields.

The study contributed to a better understanding of spatial relationships between different layers of data collected in a number of fields in Alberta. More research in this area is sorely needed in the medium-term. The study found many layers, including yield, to be quite variable, and thus difficult to predict. Unpredictable impacts on crop production, such as weather and its relationship to in-field variability, need further exploration. Crop production is so dynamic with so much spatial and temporal variability, that it is unlikely to either predict yield or create manageable spatial zones consistently with existing techniques. A long-term paradigm shift where field uniqueness gets more focus and an effective evaluation tool is embedded into VR strategies would improve the likelihood of developing techniques with measurable benefits.

b) Quantify the potential economic impact of the project results (*e.g.,* cost-benefit analysis, potential size of market, improvement in efficiency, etc.).

This study begs for close scrutiny of VRT strategies that can cost between $4 and $15/acre for mapping, zone delineation, and prescription writing. Study results showed the VR strategies tested mostly unable to identify unique optimal nitrogen rates for zones identified. It is unlikely that the strategies tested would help a producer reduce nitrogen inputs and associated costs. Considering VRT consultation costs represent a substantial investment, producers could use the study template to calculate ROI. The study provides an effective template for unbiased evaluation of this investment by any producer with VRT capability. Additional costs would include investment in VR equipment, training and qualified labour.

8 Contribution to training of highly qualified personnel (max ½ page)

Specify the number of highly qualified personnel (*e.g.*, students, post-doctoral fellows, technicians, research associates, etc.) who were trained over the course of the project.

Staff from FS and SARDA gained invaluable knowledge regarding the use and capability of soil EC sensors and about the complexities, advantages and limitation of these technologies. Over the 3-year study, Farming Smarter employed the following people who were engaged in many different components of this project:

- About six post-secondary students
- Two interns
- One international student
- Two Masters
- One PhD

9 Knowledge transfer/technology transfer/commercialisation (max 1 page)

Describe how the project results were communicated to the scientific community, to industry stakeholders, and to the general public. Please ensure that you include descriptive information, such as the date, location, etc. Organise according to the following categories as applicable:

a) Scientific publications (*e.g.*, scientific journals); attach copies of any publications as an appendix to this final report

- No scientific publications to this point

b) Industry-oriented publications (*e.g.*, agribusiness trade press, popular press, etc.); attach copies of any publications as an appendix to this final report

- Farming Smarter Magazine, Fall 2014, 16-17
- Farming Smarter Magazine, Spring 2016, 18-19
- Top Crop Manager, Western Edition, March 2016, 20-25
- The Western Producer, March 3, 2016, 75

c) Scientific presentations (*e.g.*, posters, talks, seminars, workshops, etc.); attach copies of any presentations as an appendix to this final report

- No scientific presentations to this point

d) Industry-oriented presentations (*e.g.*, posters, talks, seminars, workshops, etc.); attach copies of any presentations as an appendix to this final report

- FS AGM; Feb 28, 2013 – Ken Coles presentation (61 attendees)
- Field School; June 25-27, 2013 – Ken Coles presentation (~ 300 attendees)
- SARDA July 10, 2013 - open house (3 attendees)
- FS Conference; Dec 3-4, 2013 - Lewis Baarda presentation (200 attendees, 300 registrants)
- FS AGM; Feb 27, 2014 – Ken Coles VRT presentation (61 attendees)
- Field School; June 24-26, 2014 – Field implementation of on-farm research protocol was demonstrated (over 250 attendees)
- One-to-one meetings; March - June 2014 – Ken Coles, Lewis Baarda, and Adil Akbar continued to share knowledge from the VRT project (over 50 attendees)

- FS Conference; Dec 8-9, 2015 – Lewis Baarda full VRT results (288 attendees)
- Tactical Farming Conference; Feb 10-11 2016 – Lewis Baarda and Adil Akbar VRT techniques and results (75 attendees)
- FS AGM; Feb 25, 2016 – Lewis Baarda VRT key findings (65 attendees)
- Canadian Association of Farm Advisors; Apr 28, 2016 – Lewis Baarda innovations in precision agriculture (15 attendees)

e) Media activities (*e.g.*, radio, television, internet, etc.)

- Project was reported and discussed by Ken Coles in numerous video clips posted on the Farming Smarter and YouTube websites. Farming Smarter with partner applied research associations also continued to communicate the findings of this project in 2015 to the producers and the agricultural industry via extension and government websites, such as www.farmingsmarter.com, www.agric.gov.ab.ca, through talks and tours during Farming Smarter Conference, Agronomy Update, Crop Walks, Diagnostic Field School, as well as from other outlets including Farming Smarter magazine, Newsletters, social media and the popular press. Farming Smarter's staff was also be available for advice upon request on one-to-one basis.

f) Any commercialisation activities or patents

- None

N.B.: Any publications and/or presentations should acknowledge the contribution of each of the funders of the project, as per the investment agreement.

Section D: Project resources

1. **Provide a detailed listing of all cash revenues to the project and expenditures of project cash funds in a separate document certified by the organisation's accountant or other senior executive officer, as per the investment agreement.** Revenues should be identified by funder, if applicable. Expenditures should be classified into the following categories: personnel; travel; capital assets; supplies; communication, dissemination and linkage (CDL); and overhead (if applicable).
2. **Provide a justification of project expenditures and discuss any major variance (*i.e.*, ± 10%) from the budget approved by the funder(s).**
3. **Resources:**
   Provide a list of all external cash and in-kind resources which were contributed to the project.

Total resources contributed to the project		
Source	**Amount**	**Percentage of total project cost**
Agriculture Funding Consortium	172550	%
Other government sources: Cash	61567	%
Other government sources: In-kind	5075	%
Industry: Cash	30728	%
Industry: In-kind	76892	%
Total Project Cost	**346842**	**100%**

External resources (additional rows may be added if necessary)		
Government sources		
Name (no abbreviations unless stated in Section A3)	Amount cash	Amount in-kind
Alberta Agriculture		5075
Alberta Opportunity Fund	43096	
Municipalities of Alberta	18469	
Industry sources		
Name (no abbreviations unless stated in Section A3)	Amount cash	Amount in-kind
A&L Laboratories		30000
Veris		9000
Alberta Canola Producers	15000	
Alberta Barley Commission	7756	
Producer Co-operators		22891
Precision Ag Consulting Companies		15000

Year	Source	Type	Personnel	Travel	Capital Assets	Supplies	CDL*	Overhead	Total/year
1	ACPC	Cash						15000	15000

2012	Gov't	Cash							
		In-kind							
	Industry	Cash							
		In-kind							
Total Year 1								**15000**	**15000**
2 **2013**	ACPC	Cash	29398	1924		1497	3849	8329	44997
	Gov't	Cash	10385	680		529	1360	7064	20018
		In-kind					1650		1650
	Industry	Cash	5188	340		264	679	3529	10000
		In-kind	10500					14500	25000
Total Year 2			**55471**	**2944**		**2290**	**7538**	**33422**	**101665**
3 2014	ACPC	Cash	30133	1972		1535	3945	18813	56398
	Gov't	Cash	10644	697		542	1394	7241	20518
		In-kind					1691		1691
	Industry	Cash	5318	348		271	696	3617	10250
		In-kind	10763					14863	25626
Total Year 3			*56858*	*3017*		*2348*	*7726*	*44534*	*114483*
4 2015	ACPC	Cash	30887	2022		1573	4044	17629	56155
	Gov't	Cash	10911	714		556	1428	7422	21031
		In-kind						1734	1734
	Industry	Cash	5451	357		278	714	3708	10508
		In-kind	11032					15234	26266
Total Year 4			*58281*	*3093*		*2407*	*6186*	*45727*	*115694*
Grand Total			**170610**	**9054**		**7045**	**21450**	**138683**	**346842**

Section E: Research Team Signatures and Authorised Representative's Approval

The Principal Investigator and an authorised representative from the Principal Investigator's organisation of employment MUST sign this form.

Research team members and an authorised representative from their organisation(s) of employment MUST also sign this form.

By signing as an authorised representative of the Principal Investigator's employing organisation and/or the research team member's(s') employing organisation(s), the undersigned hereby acknowledge submission of the information contained in this final report to the funder(s).

Principal Investigator

Principal Investigator	
Name: Ken Coles, M.Sc. P.Ag	**Title/Organisation:** General Manager/Farming Smarter Association, Lethbridge
Signature: Ken Coles	**Date:** **2016-06-03**
Principal Investigator's Authorised Representative's Approval	
Name:	**Title/Organisation:**
Signature:	**Date:**

Research Team Members (add more tables as needed)

1. Team Member	
Name: Muhammad (Adil) Akbar, Ph.D., P.Ag., P.Eng.	**Title/Organisation:** Research Director/ Farming Smarter Association, Lethbridge
Signature: Adil Akbar	**Date:** **2016-06-03**
Team Member's Authorised Representative's Approval	
Name:	**Title/Organisation:**
Signature:	**Date:**

2. Team Member	
Name: Lewis Baarda, M.Sc.	**Title/Organisation:** GIS Analyst/ Farming Smarter Association, Lethbridge
Signature:	**Date:**
Team Member's Authorised Representative's Approval	
Name:	**Title/Organisation:**
Signature:	**Date:**

3. Team Member	
Name: Vance Yaremko	**Title/Organisation:** Manager/ SARDA, Falher
Signature: Vance Yaremko	**Date: 2016-06-16**
Team Member's Authorised Representative's Approval	
Name:	**Title/Organisation:**
Signature:	**Date:**

Section F: Suggested reviewers for the final report

Provide the names and contact information of four potential reviewers for this final report. The suggested reviewers should not be current collaborators. The Agriculture Funding Consortium reserves the right to choose other reviewers. Under *Section 34* of the *Freedom of Information and Protection Act (FOIP)* reviewers must be aware that their information is being collected and used for the purpose of the external review.

Reviewer #1

Name:

Position:

Institution:

Address:

Phone Number:

Fax Number:

Email Address:

Reviewer #2

Name:

Position:

Institution:

Address:

Phone Number:

Fax Number:

Email Address:

Reviewer #3

Name:

Position:

Institution:

Address:

Phone Number:

Fax Number:

Email Address:

List of Appendices Attached

Appendix A: Tables and Figures

Table 1: Average Pearson Correlation Values Between Mapped EC Layers

		Time 1				Time 2			
		EM38 Deep	**EM38 Shallow**	**Veris Deep**	**Veris Shallow**	**EM38 Deep**	**EM38 Shallow**	**Veris Deep**	**Veris Shallow**
Time 1	**EM38 Deep**		0.93	0.64	0.60	0.80	0.77	0.61	0.56
	EM38 Shallow	0.93		0.67	0.67	0.74	0.73	0.63	0.60
	Veris Deep	0.64	0.67		0.82	0.61	0.60	0.65	0.66
	Veris Shallow	0.60	0.67	0.82		0.56	0.61	0.69	0.76
Time 2	**EM38 Deep**	0.80	0.74	0.61	0.56		0.93	0.66	0.53
	EM38 Shallow	0.77	0.73	0.60	0.61	0.93		0.69	0.64
	Veris Deep	0.61	0.63	0.65	0.69	0.66	0.69		0.81
	Veris Shallow	0.56	0.60	0.66	0.76	0.53	0.64	0.81	

Table 2: Percentage of Instances in Which Correlations Between Data Layers Were Both Significant ($p<0.05$) and Strong (Pearson>0.4)

	EM38 Shallow	EM38 Deep	Veris EC Shallow	Veris EC Deep	pH	OM	Elevation	Yield 2010	Yield 2011	Yield 2012	Yield 2013	Yield 2014	Total Yield
EM38 Shallow	86%	97%	94%	97%	5%	0%	63%	29%	17%	0%	31%	10%	19%
EM38 Deep		100%	90%	90%	6%	4%	64%	17%	33%	0%	22%	11%	14%
Veris EC Shallow			100%	100%	11%	6%	25%	33%	0%	0%	38%	14%	21%
Veris EC Deep				100%	8%	4%	24%	44%	14%	0%	21%	40%	21%
pH					29%	11%	13%	20%	25%	0%	38%	43%	24%
OM						17%	15%	0%	25%	11%	0%	11%	9%
Elevation								25%	50%	0%	33%	40%	26%
Yield 2010									0%	50%	0%	50%	
Yield 2011										25%	0%	0%	
Yield 2012											0%	0%	
Yield 2013												0%	
Yield 2014													
Total Yield													10%

Table 3: Frequency and Percentage of Correlations Between Mapped EC Data and Measured Soil Properties

EC Sensor	Profile depth	Statistics	Clay	Sand	Silt	Moisture	EC	OM	pH	Nitrogen	Phosphorus	Potassium	Sulfur
EM38	Deep	Correlations	11	9	9	7	4	5	5	2	1	1	10
		Percentage	29%	24%	24%	18%	11%	13%	13%	5%	3%	3%	26%
	Shallow	Correlations	10	8	8	9	5	4	4	3	0	2	10
		Percentage	26%	21%	21%	24%	13%	11%	11%	8%	0%	5%	26%
Veris	Deep	Correlations	9	9	9	6	8	2	5	2	1	4	9
		Percentage	24%	24%	24%	16%	21%	5%	13%	5%	3%	11%	24%
	Shallow	Correlations	9	6	6	7	8	2	5	1	1	3	9
		Percentage	24%	16%	16%	18%	21%	5%	13%	3%	3%	8%	24%

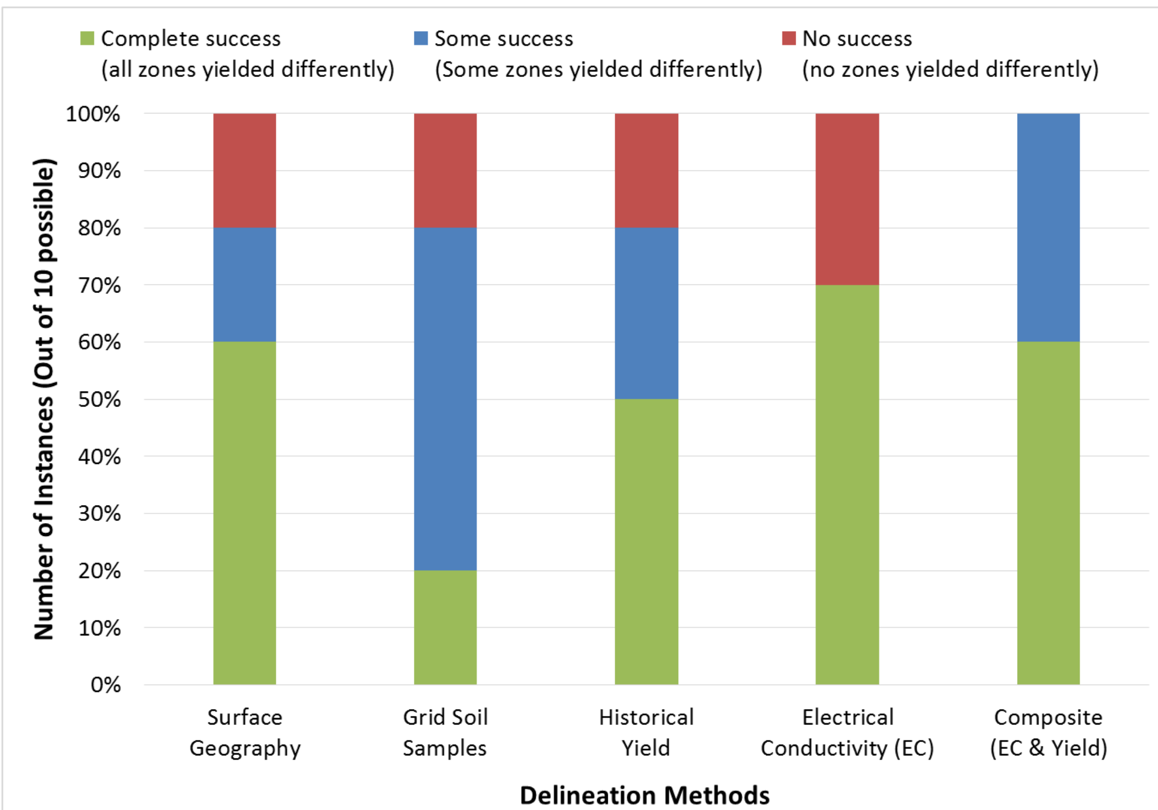


Figure 1: Success rate and performance comparison of the five zone delineation methods investigated in this study for identifying within-field zones of different yield potentials.

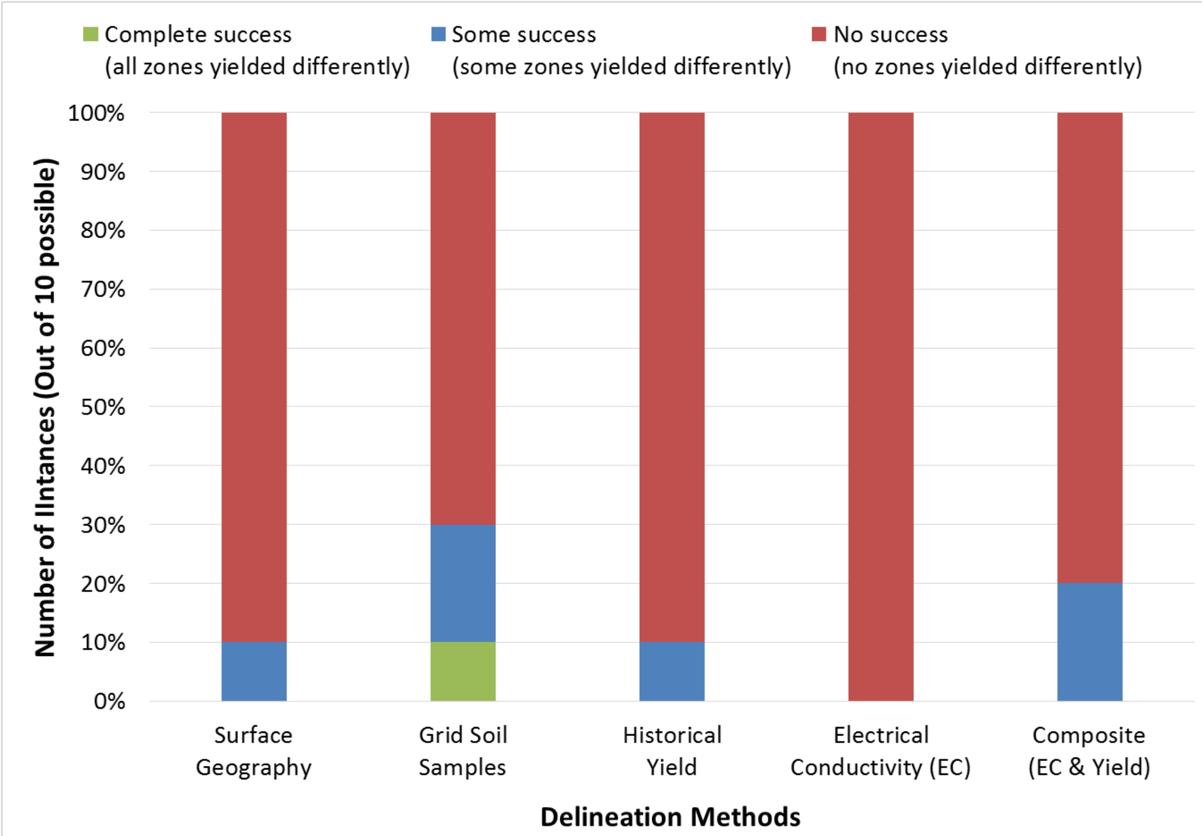


Figure 2. Performance comparison of the five zone delineation methods with respect of the success rate for showing yield response to nitrogen fertilizer.

Appendix B: Publications

1. Farming Smarter Magazine, Fall 2014, 16-17
2. Farming Smarter Magazine, Spring 2016, 18-19
3. Top Crop Manager, Western Edition, March 2016, 20-25
4. The Western Producer, March 3, 2016, 75

Keep on-farm trials simple and focused

Random and replicated is the key // BY LEE HART

Ken Coles leads a sandbox discussion at the Farming Smarter Field School. PHOTO: C LACOMBE

The belief that a test strip, is a test strip, is a test strip isn't necessarily the proper way to approach doing your own on-farm trials to determine if a new product or a new treatment is making a difference according to Ken Coles, general manager with Farming Smarter.

Yes, admittedly even a basic test plot or check strip is of more value than doing nothing, says Coles, but at the same time, with just a bit more planning, farmers can develop on-farm trials that produce meaningful results.

Farmers, interested in using new products or applying new treatment rates have long heard the advice from extension specialists "leave a test strip."

"And the general advice is still valid," says Coles, "But leaving a single drill or sprayer width strip down the field, for example, may not provide that much useful information. The same goes with dividing a field in half and providing the treatment on one-half and not the other. It might give you some indication of whether a treatment was effective, but it also leaves room for error."

Farming Smarter made a point of discussing the pros and cons of on-farm trials during its annual Field School in June. The applied research organization created three different sandbox scenarios that showed varying soil types and topographical conditions commonly found in cropland.

Coles, Lewis Baarda, Farming Smarter precision ag specialist and Dr. Adil Akbar, Farming Smarter research director worked with small groups of producers at each station and explored scenarios with producers. "If you had a field with these varying conditions, how would you plan your on-farm trials?"

HOMOGENOUS AREAS

"And it is going to be different for every field," says Coles. "One of the important things you do as your planning is to select a homogenous area of the field to conduct the on-farm trial."

For example, a field with a large low lying, saline area here, an area of sandy soil there and an area of windblown hill top there, plan the trial so plots or test strips are within one of those zones — a relatively homogeneous area.

KEEP IT SIMPLE

All three Farming Smarter extensions specialists emphasized three key elements when planning on-farm trials — keep it relatively simple and layout plots so they are random and replicated.

"Whether it is an on-farm trial or formal research, often the challenge is to keep it simple," says Coles. "Take a step back. Be focused and clear on the question you want to answer with this on-farm trial and don't complicate it by trying to do too many things — answer too many questions — from your test strips."

He also urges producers to use appreciable increments when measuring different treatments. If, for example, a producer conducts a trial to determine an optimum fertilizer rate, Coles doesn't recommend having a test plot that is only 10 pounds heavier than the farmer's conventional rate. He considers it too small an increase to produce statistically relevant results.

"Again if you're looking at fertilizer rates, have one plot that is the conventional 100 per cent rate, but then put in a plot that is a 50 per cent lower rate and another that is 50 per cent higher rate in the test strip" says Coles. "It is going to give you a much better indication of which treatment is the optimum rate."

Random and replicated are concepts farmers haven't commonly used for on-farm trials, says Baarda. "They think about making a machine width strip treatment down the field or splitting a field in half, but both of those approaches leaves too much room for error," he says. "In both cases you'd have to ask if any difference you saw in yield, for example, is due to treatment applied or is it due to variations in the field.'

> **"Whether it's an on-farm trial or formal research, often the challenge is to keep it simple."**
>
> — Ken Coles

It takes some planning, but using the fertilizer rate example, select an area of the field that is relatively consistent — homogenous — and make at least three replicated strips at least a drill width wide and within each strip have a one plot at the standard 100 per cent rate, another at the 50 per cent less rate, and another at the 50 per cent higher.

To create the randomness, in the next strip alter the order of the treatment so perhaps the first plot is 50 per cent less, the next is 50 per cent higher and the third is the 100 per cent standard. And in the third strip, alter the order of the various treatments again.

"So you are laying out your plots in an area of the field that has relatively similar conditions," says Coles. "But with three test strips, you replicate those treatments and then by staggering the treatments within the test strips you create the randomness. With today's precision farm technology, it is relatively easy to layout the treatments and to measure the results at harvest."

Whether evaluating a new variety, a new herbicide product or a different fertilizer rate, any yield difference that stands out through those replicated treatments should be a solid figure.

"It takes some planning and preparation ahead of time," says Baarda. "You have to select the area, plan the layout and plan how you will collect the data. You have to expect a certain amount of sacrifice in the process — it is going to take time and, depending on treatments, it might affect yield, but producers can have confidence in the results from a properly planned and measured trial." —

On-farm Data Requires Scrutiny

BY LEWIS BAARDA

PHOTOS: FARMING SMARTER

Understanding land is a big component of farming. What better way to understand your land than to interact with it. To feel it, to dig holes in it, to scrutinize its performance. There is something to be said for rolling up your sleeves and turning a handful of soil through your fingers.

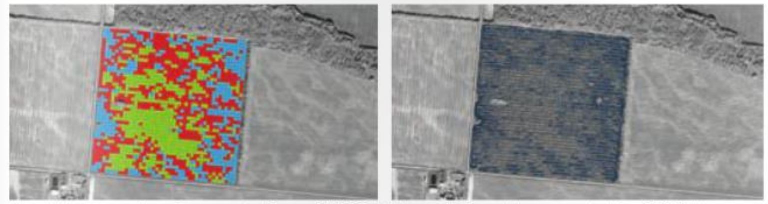
Recent innovations provide farmers with a new set of tools to understand land. Georeferenced yield maps, aerial imagery and soil sensors offer a cost effective alternative to rigorous grid soil sampling. These layers of information collect data at a high density (as many as 50,000 data points in 160 acres of land). This density allows these layers of data to account for variability in a field at a scale that traditional grid soil sampling cannot approach. With all this data, however, comes the challenge of gleaning knowledge that can help guide decisions at the farm level.

Farming Smarter waded into the world of big data three years ago when it began a study on soil sensors and variable rate technology. The study focussed on soil sensors, specifically those measuring soil electrical conductivity (EC), the Veris and EM38. The team gathered a number of additional layers of data for the 10 fields analyzed including aerial imagery, yield maps and soil samples.

Large datasets must be filtered. Just because data are available and accurate doesn't mean they should be used to guide management in the field. Data must be taken in the context of the information it can divulge. Yield data, for example, identifies the productivity of various regions of a field. This may imply something about the soil properties in these regions, but it does not directly tell us how much nitrogen or clay is present in the region. For this, an inference must be made using available data and knowledge.

The primary objectives of the study were to ascertain what meaningful information can be gleaned from all the data collected and to determine if the information obtained is useful to make effective management decisions. To achieve this, available data layers were vetted to identify those that best accounted for spatial variability among the fields studied. Additionally, mapped data layers were compared to measured data from soil samples to determine if relationships to soil properties were present. This information guided selection of data used to delineate zones.

The study tested five different methods of zone delineation, each based on different input data layers. A number of different data



Above left: A management zone image generated from raw EM38 EC data. Above right: The raw data map generated from EM38 EC data.
PHOTOS: FARMING SMARTER

layers were found to be successful at identifying zones that yielded significantly differently. Across the 10 fields studied, the delineation of zones using a combination of EC and yield data was the most effective in this regard. This indicates that mapped field data can effectively identify zones with different soil properties.

However, identifying a unique optimal nitrogen rate for each of these zones proved to be more challenging. With very few exceptions, the study found that the yield response to nitrogen did not tend to differ significantly from one zone to another.

These results indicate that while the data gathered for the study could be used to identify zones of productivity, it was a challenge to identify unique optimal rates for each zone. So while the study was able to use available data to better understand soil and yield variability, it had very limited success in outlining a clear management response to this information.

One big challenge with mapped data is that every field is different. Data layers may have different implications from one field to another. And while there may not be a universal strategy for identifying and managing zones, every strategy can be tested using deliberate on farm research. The best way to use data to understand land is to roll up you sleeves and reach into the data stream. Feel it, test it and scrutinize its performance.

PHOTOS COURTESY OF FARMING SMARTER.

MAPPING VARIABILITY

An on-farm study looks at soil sensor data for identifying variable rate management zones.

by Carolyn King

Variable rate nitrogen applications have the potential to save money and improve crop yields. But what is the best way to come up with variable rate management zones that provide economic benefits to the farmer? Could soil sensor maps be a practical data source for identifying meaningful management zones? Those are some of the questions Alberta researchers are answering through a major on-farm precision agriculture study.

The idea for this study was sparked a few years ago when Ken Coles, general manager of Farming Smarter, saw some electrical conductivity (EC) sensors at a precision agriculture conference. He was intrigued by the possibility of using these sensors as an alternative to grid soil sampling for mapping in-field soil variability. "The idea is that we can't do grid soil sampling to the level of accuracy needed to manage variable rate inputs effectively, plus soil sampling is expensive. So if we can run a soil sensor over a field and get the same or better information, then maybe there is value in it," he says.

Lewis Baarda, GIS analyst with Farming Smarter, compares the two approaches. He explains that a grid soil sampling system with one sample every five acres would provide 32 data points for a quarter section, and the lab analysis for nitrogen, phosphorus, potassium and sulphur would cost about $1,600. An EC sensor service could produce an EC map of a quarter section with about 50,000 data points for a cost of about $880. EC data tend to be good at predicting soil texture and soil moisture content.

But Coles wanted to do more than compare EC sensor maps and grid soil sampling maps for creating management zones; he wanted to evaluate if those zones were actually meaningful and useful for variable rate management. He says, "Creating management zones based on soil information and then creating a prescription map is not that hard. The challenging part is verifying whether your variable rate management is actually paying for itself. That is really what I wanted to do with this study."

Coles also wanted to do the study as on-farm research, which added another level of variability. He notes, "Just finding the right co-operators to work with is challenging, and even when we have the right people, we still have human error issues or lack of priority issues. So, not only are we going into a complex environment where we have no control over the variables, but we are literally studying variability and we also have human and equipment and scale variability."

Starting in 2012, he teamed up with Baarda and Muhammad

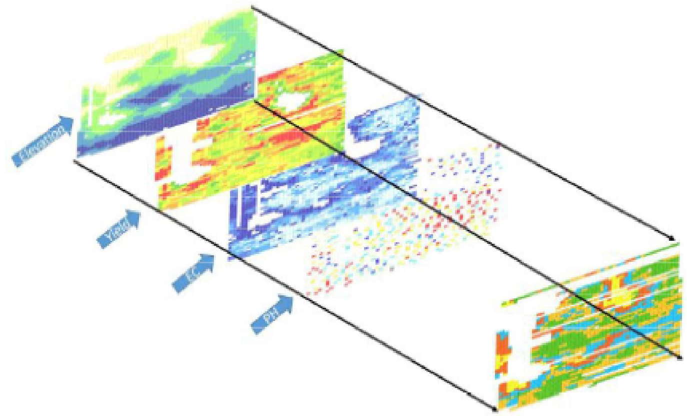
ABOVE: **The researchers hooked together the Veris MSP3 and EM38-MK2, pulling the two soil sensors across each field at the same time to compare the data.**

(Adil) Akbar, precision agriculture specialist and research director with Farming Smarter, to conduct the study on 10 farm fields. The fields are located in southern Alberta, the Drumheller area and the Peace Region (in co-operation with the Smoky Applied Research and Demonstration Association).

Because of the study's complex objectives, quite a few steps were required in the data collection and analyses for each field, including: conducting soil sensor mapping and grid soil sampling; determining how strongly the EC maps matched up with the soil sample data, yield maps and other data sources; delineating field zones based on these different data sources; conducting a nitrogen fertilizer rate/yield response trial; determining which zone map best predicted yield variability across the field; and determining which zone map provided the best basis for variable rate nitrogen applications.

With funding from Alberta's Agricultural Initiatives Program, Farming Smarter was able to purchase two EC sensors: the EM38-MK2 and the Veris MSP3. The researchers hooked together the two sensors and pulled them across each field, using Farming Smarter's onboard RTX-DGPS sensor for georeferencing and elevation recording.

"The EM38 has been around for a long time; they used to use it to map salinity and it's quite effective for that," Coles says. The EM38 does not require direct contact with the soil to take EC readings. It is pulled over the field's surface and takes measurements every few seconds. It can measure EC at depths of 0.75 and 1.5 metres at the same time.



The study compared several data layers, including electrical conductivity (EC) data from soil sensors, for understanding in-field variability.

The Veris organic matter sensor measures the soil's optical reflectance, basically how dark or light the soil is, and those reflectance data are converted to organic matter content by Veris. The pH sensor directly measures soil pH using an on-the-go chemical test, taking a soil sample, testing it and then taking the next sample, while the Veris moves across the field. The pH and organic matter sensors provide fewer data points per field than the 50,000 points generated by the EC sensors.

Soil sampling followed a five-acre grid, with 32 samples for each 160-acre field. The samples were analyzed for nitrogen, phosphorus, potassium, sulphur, organic matter, pH, EC, moisture content and texture.

The co-operators provided yield data collected by their on-combine yield monitors. Baarda notes, "Although the standard practice is to use at least three to five years of yield maps to define productivity zones, in most cases it was a challenge to gather even three years with good spatial coverage."

The research team scanned each field twice with the two EC sensors, usually in the spring and the fall

The Veris MSP3 is a mobile sensor platform with three sensors: EC, pH and organic matter. Its EC sensor requires soil contact so it has coulters that maintain soil contact as the equipment is pulled across the field. Like the EM38, this sensor measures EC at both 0.75 and 1.5 metres deep.

The research team scanned each field twice with the two EC sensors, usually in the spring and the fall.

Coles adds, "Finding good yield map data is really difficult. There are many reasons for that. One reason is that people don't save the data; they don't take the time to transfer it to their computer. Another reason may be that they have two or three combines on the field at the same time, which makes it challenging to stitch the data together. Or it could be they didn't calibrate it properly."

For each field, the researchers created zone maps using five different data sources: EC sensor data; historical yield data from the co-operator; grid soil sample data; a visual depiction of the field's main terrain features; and a composite of yield and EC sensor data. This composite method was included because an objective procedure called principal component analysis identified EC and yield as the two variables, among all the data collected, that best accounted for spatial variability in the 10 fields.

At each field, they conducted a replicated, randomized nitrogen fertilizer rate/yield response trial. The nitrogen fertilizer was applied at seeding. The specific nitrogen rates used in each trial depended in part on what the cooperating farmer wanted to do; usually fewer than five rates were used. The researchers measured the variations in grain yield response and determined the nitrogen rate/yield response curves.

Next, they laid each zone map over the yield response results and determined which of the five zone delineation methods worked best for predicting in-field yield variations and for predicting zones for variable rate nitrogen applications.

Highlights of results

As you can probably imagine, the study involved huge amounts of data that required complex analysis. Akbar, Baarda and Coles are currently finalizing the study's report, and they hope to also publish some scientific papers.

In terms of the performance of the EC sensors, Baarda says, "Our EC data from the Veris and the EM38 were highly consistent with each other. Also, the spring EC map was always highly consistent with the fall EC map. We could almost take one EC layer and say that's what the EC map is [for the field] because those patterns don't change over time and they don't change between the sensors." The researchers also found that the EM38 was easier and less costly to use than the Veris for mapping EC.

Overall, the EC sensor data tended to be strongly correlated with the soil sample data for sand and clay content and soil moisture content, although the strength of the correlations varied from field to field. So, EC sensor maps can give farmers a better understanding of the soil variability in their fields.

However, the EC sensor maps didn't necessarily predict the spatial patterns in some of the other soil sample data, like nitrogen (N), phosphorus (P), potassium (K), sulphur (S), pH and organic matter. According to Baarda, scale issues could be a factor in the weakness of some of these correlations.

"We're comparing about 30 data points from soil sampling to about 50,000 from the EC sensors. The [weaker] relationships can get obscured because of the different scales of the datasets. So, even though we don't see a relationship to N, P, K and S, we can't necessarily say that those macronutrients don't correlate to EC. But we get a sense that they probably don't correlate as strongly as we'd need to make a management response to them." So the EC sensor maps are not a reliable way to directly estimate variable nutrient rates.

The study also showed grain yield could not be predicted directly from just the EC sensor maps. The correlations with yield were weak or did not exist. Various factors might have contributed to these poor correlations, including the challenges in obtaining good yield data.

Another key finding was the surprising amount of year-to-year variation in the yield patterns. "I think people have a sense that yield patterns are more static than they actually are. Some parts of those spatial patterns are consistent, but statistically those patterns change more than I would have thought," Baarda says. "So it's important to have at least three to five years of yield data; the more years you have, the more it helps to balance out the outlier years."

The strength of the correlations among the various other data layers – such as elevation, yield, soil nutrients, soil texture, the pH sensor and the organic matter sensor – also varied from field to field.

Because of the field-to-field differences, the different zone delineation techniques had different levels of success depending on the field.

For predicting yield potential, the composite method – pairing up yield and EC sensor data – was the best of the five methods for delineating zones. "In 100 per cent of the instances, the composite method was the most successful in differentiating within-field zones of different yield potentials. So the zones created by pairing EC and yield were meaningful: they predicted where we would have high and low productivity based on the information we had before the growing season," Baarda explains. "The other four delineation methods failed in differentiating any productivity zones in 20 to 30 per cent of the instances and had varying combinations of complete and/or partial success in the remaining instances."

He adds, "Some of the composite method's success is likely due to the use of multiple variables – hedging our bets so to speak. Some of its success also likely lies in the fact that we objectively identified yield and EC as key variables for zone delineation."

None of the delineation methods were very successful in identifying zones that could be managed differently for nitrogen in ways that would benefit the farmers economically.

According to Coles, the next step in this research would be to add more layers of data to the analysis, such as remote sensing data from satellites and data from other in-field sensors.

Some take-home messages

"Our big message is there is no single data layer that can be guaranteed to tell you what you need to know to variably manage inputs," Baarda says. He emphasizes that zone management is a process – each field is unique and you have to be prepared to invest some time in understanding the field's variability and figuring out what works best for that particular field.

If you're interested in experimenting with variable rate applications, Coles recommends starting with just a few layers of data.

Baarda thinks an EC sensor map could be a good option for one of those layers. "Not only is EC mapping cheaper than grid soil sampling, but it has a longer 'shelf life.' In our experience, EC doesn't tend to change over time, so a field could be mapped for EC once, and in most circumstances, that data would be relevant for a number of years." Although the sensors don't provide the data on nutrient levels that you can get from soil sample analysis, the sensor maps do indicate variations in other soil properties, especially soil texture.

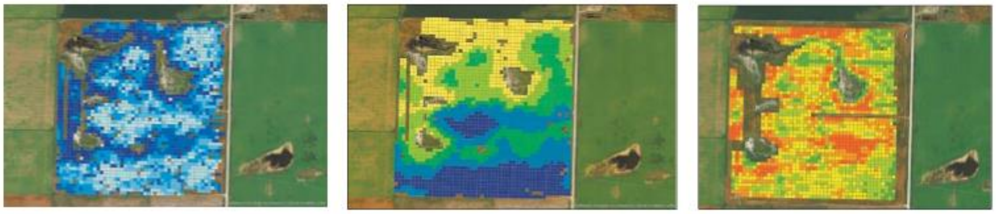
If you want to use your yield monitor data in identifying management zones, then try to ensure the reliability of that data. For instance, be sure to download the yield data from your combine and save it so you can accumulate as many years of data as possible. If you're using two separate combines on the same field, then consider calibrating them in the same way. If you're calculating the average yield pattern for a field based on several years of data, exclude any years where the data are skewed because of some external factor, like hail damage on half of the field.

And no matter what data layers you use and what zone delineation method you test, Coles suggests that your on-farm study design should include the steps needed to allow an objective evaluation of whether or not your approach is actually helping you economically.

Coles concludes, "There are lots of people doing variable rate agriculture but very few who are effectively testing and verifying the success." He adds, "More academic work in this area is sorely needed."

The study was funded by the Alberta Canola Producers Commission, Alberta Barley and Farming Smarter.

For more on soil management, visit topcropmanager.com.



The most valuable data layers are those with the highest correlation. Shown here are electrical conductivity, left, topography and yield maps of the same field. | LEWIS BAARDA/ FARMING SMARTER PHOTO

TECHNOLOGY

Information overload: making sense of precision ag data

BY RON LYSENG
WINNIPEG BUREAU

CALGARY — The constant introduction of newer and better data-collection technology can leave many precision farmers and consultants scratching their heads.

There's not much point in wasting time or money logging field data that will never be used, says Lewis Baarda, a GIS specialist with Farming Smarter in Lethbridge.

Baarda analyzed various types of data maps last year with the goal of determining which might be the most valuable.

The Farming Smarter team figured that maps with the highest correlation to each other held the best information about what the soil can do. Maps that were way out of the ballpark probably had little or no value.

"We started with 15 layers of field data, and that was a real mess," Baarda told the recent Tactical Farming conference in Calgary.

Different coverage, gaps, overlaps and shifting GPS points all made the stack of 15 layers even more of a mess, he added.

They eventually whittled down the list to four meaningful maps that had good visual correlations. The finalists included electrical conductivity, yield, organic matter and topography.

Yield maps should theoretically provide the most valuable information, and sometimes they do. Other times they're worse than nothing.

"Yield maps have a strong correlation to the others, but you can't always trust them," Baarda said.

"If your yield monitor isn't quite perfect when the crop is ready to combine, do you go combining anyway or do you waste time fixing the monitor? It's not viewed as an essential part of the combine, and that's why the data isn't always reliable.

"Organic matter is useful if there's good data, but I'm not sure we can always trust the data. Topography is a simple one to get with your GPS.

"EC can provide good information, but for us it was a real challenge to get the EC hooked up to a computer and then hook that computer up to GPS so we could get everything working together on the same map. Operationally, that takes technical expertise that not everyone has."

The Veris EC mapping trailer has been on the market for 20 years. Most agronomists agree electrical conductivity can be useful, but few farm supply outlets have a Veris or Em38. Baarda speculated that the technical hurdles of getting it all work together might be the problem.

However, the struggle to get it to all work together extends far beyond EC and yield maps. Baarda said little of the data that's been collected over the years is ever used.

"There's a good reason for that," he said.

"The software out there is not user-friendly. It's not flexible. You spend $8,000 or $10,000 for a monitor in your combine and what do you get? Five functions. It's a challenge to do much more than just look at maps. Your smartphone can let you do that. Integrating meaningful data is difficult.

"Instead of collecting a pile of data layers you can't use, I'd urge farmers to pick just a small number of maps their software can handle. Two or three or four, maximum. Keep it simple. If I had to pick just two, I'd go with yield and EC. If you pay to have EC data mapped, that data should be good for five to 10 years."

For more information, contact Baarda at 403-381-5118 or visit www.farmingsmarter.com.

ron.lyseng@producer.com