Precise Mapping of Major Soil Productivity Indicators Using On-the-Go Soil Sensors

Contents:

Summary Points:

- On-the-go soil sensors are able to map soil texture, organic matter, and pH, along with topography
- A multi-sensor system effectively mapped a set of 10 fields across 6 states, delineating variability not detected by USDA soil surveys
- A proprietary fuzzy logic system that classifies productivity zones was able to estimate productivity differences
- Detailed quantitative soil maps and a novel classification approach are promising developments for improving the effectiveness of variable-rate inputs

Introduction

The challenge of accurately mapping soil variability has been an issue since the inception of precision farming, but has become even more critical as growers seek to vary seed populations and nitrogen. Conventional soil maps don't measure up; most USDA soil surveys were completed at a scale of 1:15,840 to 1:24,000, and did not identify areas smaller than 1-2.5 ha. Recent digitization improves access to the original maps, but with few exceptions fields have not been re-surveyed since the advent of GPS and other advanced precision agriculture technologies. As a result, most USDA surveys lack the quantitative and detailed geo-referenced soils data needed for optimizing VR population and nitrogen prescriptions. Grid sampling, while geo-referenced, is not typically conducted at the density needed. Studies have found the range of spatial dependence is shorter than the distances used in most grid sampling (Bianchini and Mallarino, 2002).

On-the-go soil sensors using GPS have the dense coverage needed to improve the delineation of soil boundaries (Adamchuk et al., 2004). The first commercialized on-the-go soil mapping system was for mapping soil electrical conductivity (Figure 1). Soil EC measurements correlate with soil properties that affect crop productivity, including soil texture, cation exchange capacity (CEC), drainage conditions, salinity, and subsoil characteristics (Grisso et al., 2009).

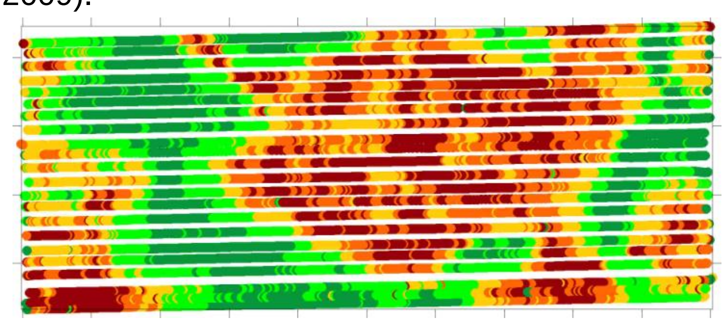


Figure 1. Soil EC mapping system and EC sensor coverage map

On-the-go soil pH sensing was commercialized nearly a decade ago with the introduction of the Veris Mobile Sensor Platform (Figure 2). Soil pH is an important factor in crop production. Nutrient usage, crop growth, legume nodulation, and herbicide activity are all affected by the pH of the soil. Studies have shown that within 1 ha grids, there is a wide range of pH values, often ranging from soils that call for lime to soils that are already extremely high in pH (Brouder et al., 2005). Recently, on-the-go soil organic matter mapping became commercially available with the Veris OpticMapper (Figure 3). Soil OM affects the chemical and physical properties of the soil and its overall health. It is a key component of structure and porosity, affecting moisture holding capacity, the diversity and biological activity of soil organisms, and plant nutrient availability. Topography and landscape position frequently exert a significant influence on soil properties and productivity, and can augment proximal soil sensing (Kitchen et al., 2003). With the advent of real-time-kinematic (RTK) and other high-grade GPS receivers, precise topographical measurements can be acquired simultaneously and co-located with proximal soil sensor readings. Recently, Veris Technologies introduced the MSP-3, a new multi-sensor platform that records soil EC, OM, and pH along with topography data (Figure 4).

Figure 2. Soil EC-pH Sensor.

Figure 3. Soil EC-OM sensor.

Figure 4. MSP-3: EC, OM, pH.

Field Trials: Ten fields in six states

In 2010-2012, ten research fields totaling over 400 ha in Alabama, Georgia, Illinois, Iowa, Kansas, and Nebraska were mapped with the Veris EC and OM sensors. Several fields included pH sensing as well. 88 soil cores from these fields were lab-analyzed for OM, CEC and pH and were used to calibrate and validate the sensor measurements. The objective of this study was to evaluate soil sensor performance on a broad range of soils.

The dense coverage provide by on-the-go soil sensors is best illustrated with sensor point data maps. Typically, more than 200 EC and optical measurements are collected per hectare along with 10-20 pH sensor readings per ha. Figure 5 shows soil CEC, OM, and pH maps estimated by the multiple sensors for one of the fields in this study. The data have been collected at an adequate spatial scale to show pass-to-pass repeatability. The spatial structure of the soil properties is discernible without interpolating or other manipulation.

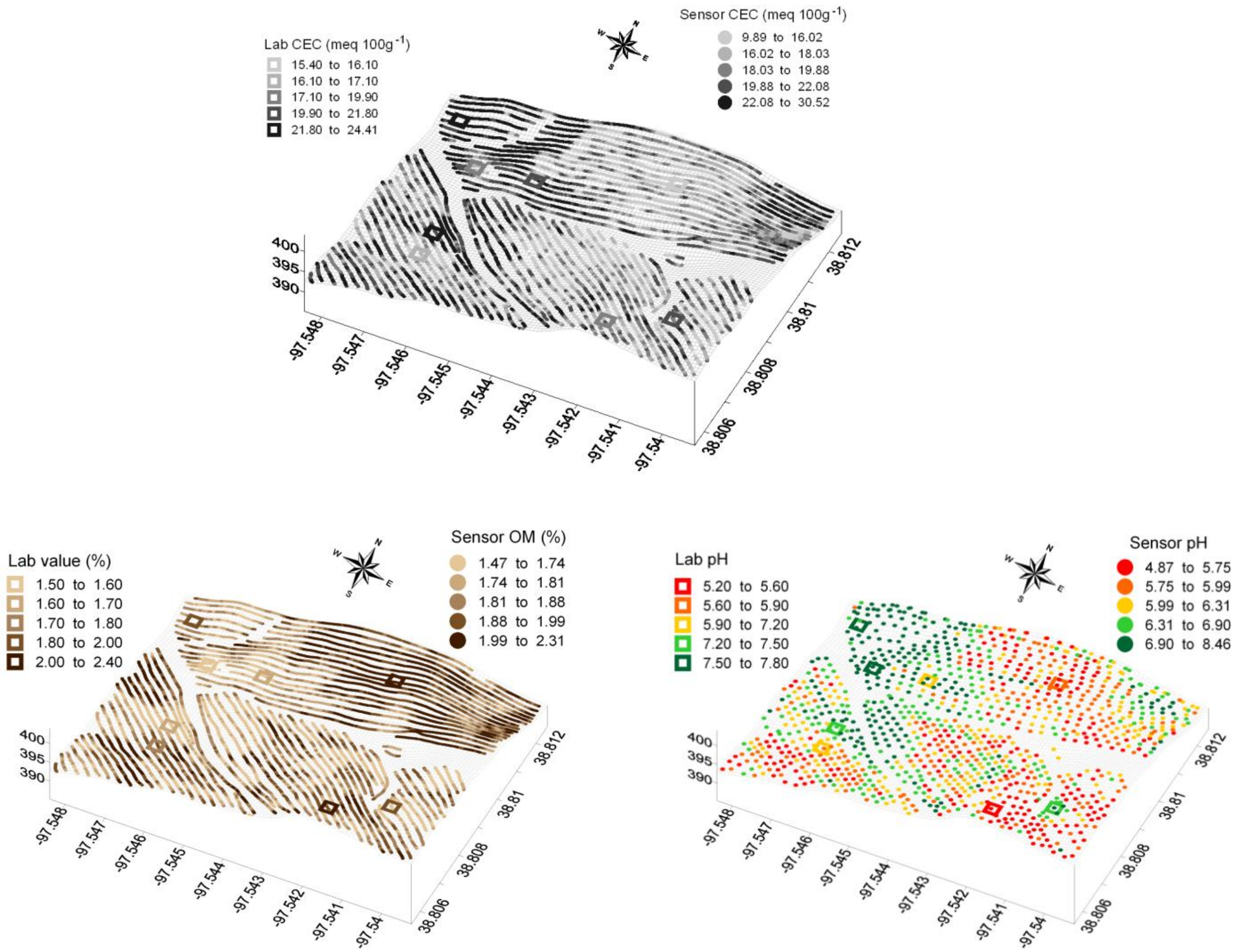
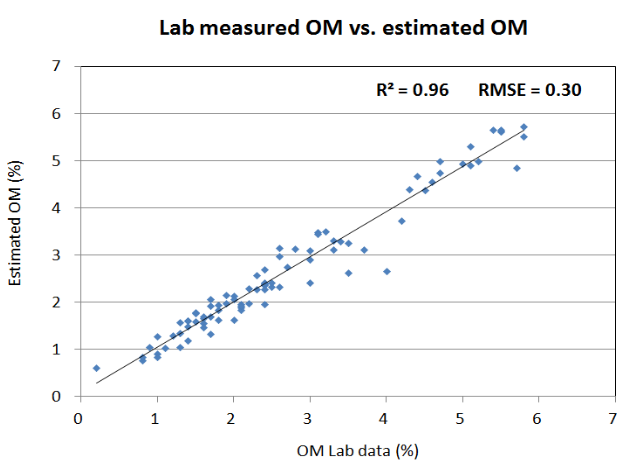
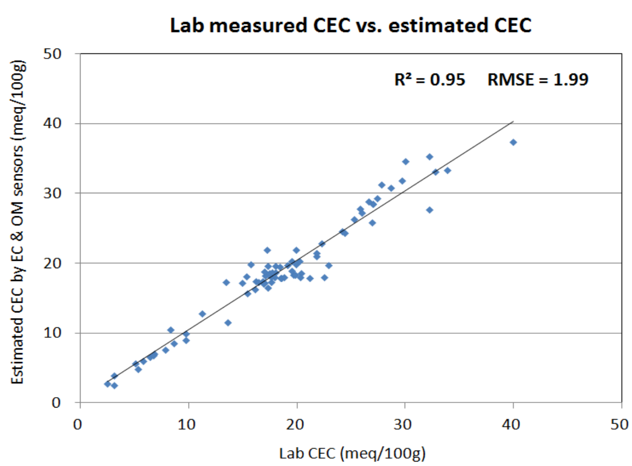


Figure 5. Calibrated Veris MSP-3 sensor maps (KS1 field)

The calibration results for OM, CEC, and pH are shown in Figure 6 and Table 1. Sensor readings were well correlated with lab-analyzed measurements; errors were typically less than .3% OM, 2 meq 100g^{-1} CEC and .45 pH. Many fields had correlation coefficients over .90 R^2, with lower correlation scores on fields with low variability.





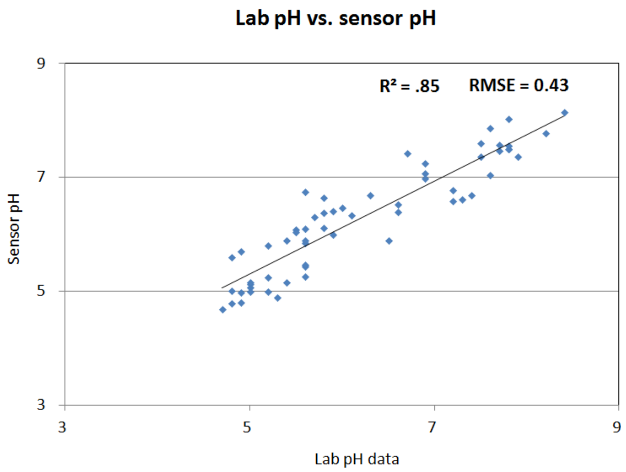


Figure 6. Soil OM, CEC, and pH scatter plots with combined data for all fields.

Table 1. Calibration results for all fields.

	OM (%)			CEC (meq 100g^{-1})			pH		
Field	Range	R^2	RMSE	Range	R^2	RMSE	Range	R^2	RMSE
AL	1.1-3.5	0.86	0.22	5.1-13.6	0.84	0.76	-	-	-
GA	.08-1.6	0.82	0.14	2.5-5.3	0.75	0.38	-	-	-
IA1	2.4-5.7	0.84	0.48	15.3-33.9	0.84	2.59	5.6-7.8	0.58	0.45
IA2	2.8-5.8	0.92	0.29	15.7-30.0	0.88	1.65	5.2-7.9	0.77	0.47
IL1	0.2-5.1	0.94	0.31	8.3-40.0	0.94	1.92	6.3-8.3	0.82	0.34
IL2	4.4-5.1	0.54	0.18	26.9-40.0	0.66	2.85	5.0-8.0	0.98	0.15
KS1	1.5-2.4	0.44	0.2	15.4-24.4	0.93	0.77	5.2-7.8	0.89	0.31
KS2	1.0-2.8	0.78	0.21	13.4-22.5	0.17	1.89	4.7-7.8	0.67	0.18
NE1	1.4-4.0	0.92	0.25	-	-	-	5.6-8.2	0.94	0.25
NE2	1.0-2.4	0.81	0.23	-	-	-	5.4-8.4	0.91	0.34

Soil sensor maps vs. alternative soil maps

Comparing the USDA soil survey with soil sensor maps, as shown in Figure 7, uncovers several limitations with the soil survey. While the USDA map accurately delineates the sandy soil in the 88B Sparta, it allows several sizeable inclusions in the highly productive 125 Selma clay loam and 447 Canisteo loam. The soil survey lists the OM range for Selma at 4-6 % and the Canisteo at 4-8 %. Calibrated proximal sensors mapped OM areas of <1 % included within the both of these soil types. These deviations from the survey-listed OM and CEC could seriously affect the performance of practices such as variable rate corn population and nitrogen on the sandy, low OM soils contained within these survey units.

Soil survey inclusions and errors can present a serious problem if inputs are varied according to the expected productivity within a map unit. Even for a 1 ha inclusion, the minimum for a fine-scale survey, the included soil represents a ~100 m × 100 m area. A large 24 row planter would make at least five passes through that inclusion, potentially metering a severely sub-optimal rate for the inclusion. Proximal soil sensors are typically operated on 15-20 m transects, which more closely matches the capability of farm equipment to apply inputs site-specifically. With GPS and proximal soil sensors the location of changes in soil properties can easily be mapped within 1-2 m. Sensor maps reflect the spatial pattern of soil as a continuum, identifying soil transitions precisely whether they occur gradually or suddenly, while soil survey lines can only depict soil differences as abrupt boundaries.

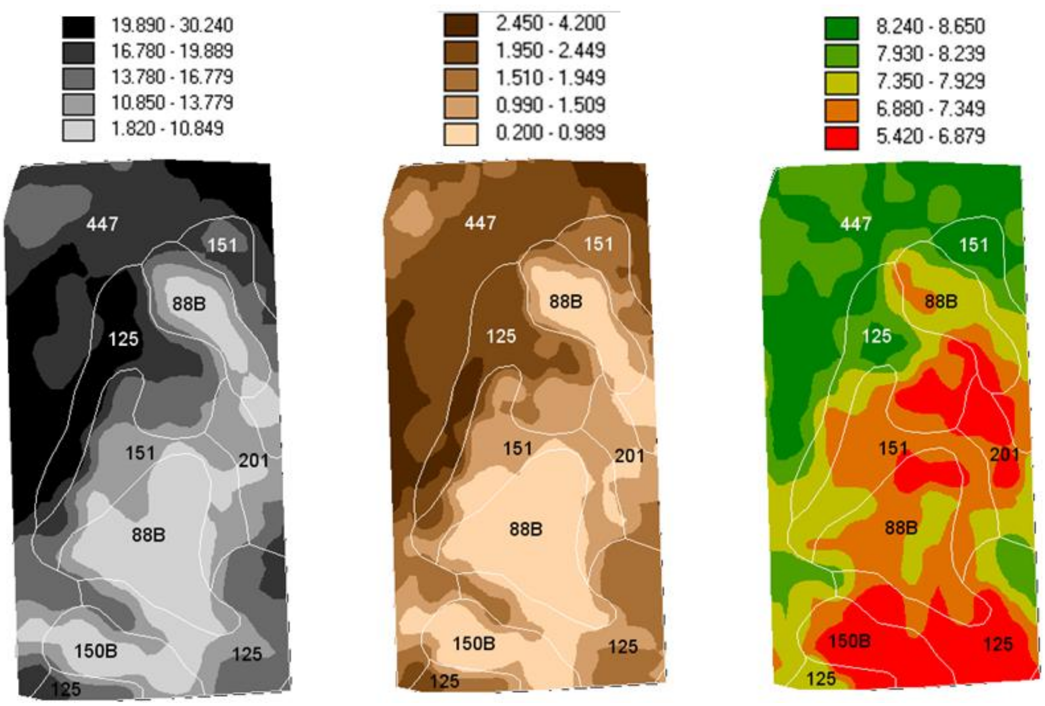


Figure 7. Soil survey overlaid on CEC, OM, and pH sensor maps

The variations within 1 ha grids are similar to that found with other variability studies; wide variations are present within most of the 1 ha grid cells (Figure 8).

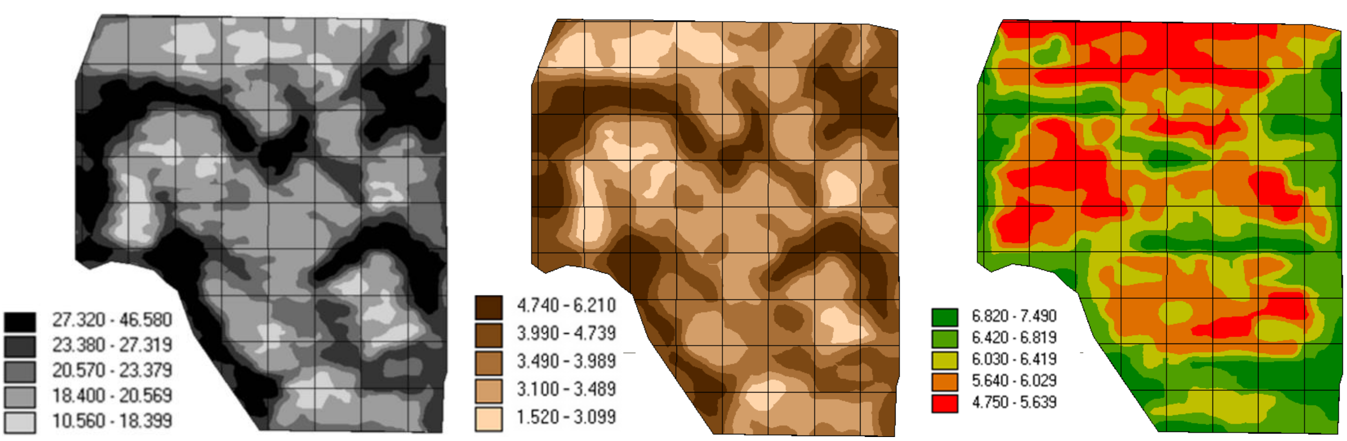


Figure 8. Veris MSP-3 CEC, OM and pH maps for IA1 with 1 ha grid cells overlaid.

Productivity Index

The soil properties precisely delineated on these maps relate to productivity and provide a rationale for varying inputs such as seed and nitrogen. In many cases, the organic matter map may drive the prescription; differences in organic matter often relate to historical biomass production and as a result can be effective in predicting future productivity. Variations in soil water holding capacity between contrasting soil texture zones may also be a key driver of variable rate applications. In many cases, however, estimating productivity is not as linear. For example, a high OM zone may represent lower productivity if it coincides with the heaviest clay, but could indicate highly productive soil in the more loamy sites. Or, high CEC soils may be productive, but only if high in OM. The EC, OM, and pH sensors generate the quantitative, geo-referenced data required to differentiate these combinations.

There is a need to improve the efficiency of combining and analyzing soil layers; enabling zone creation and decision-making without excessive time and grower involvement, especially for fields without yield maps or other grower history. Fuzzy logic is a promising technique for soil classification (McBratney and Odeh, 1997). Veris Technologies has developed a fuzzy clustering procedure for site-specific productivity zones which uses soil property data obtained from on-the-go soil sensors, along with generalized grower input (Kweon, 2012). In this approach, growers (or crop consultants) simply describe the texture, OM level, pH, and topography of their ideal soils, and of their least productive soils. They have a wealth of empirical information on which to base their assessments. Yield maps are certainly valuable information, but even without multiple years of high quality yield data, growers have observed visual differences in crops and yield monitor display readings from many fields harvested during their farming careers. Growers already make these types of assessments as they set overall yield goals, make land acquisition decisions, and perform other management functions. Once the productivity rules are in place, the Veris software program mines the soil sensor data to identify areas matching the input, and classifies each sensor data point in the field on a 0-1 productivity scale.

This novel approach to multi-layer data fusion represents an exciting development in precision agriculture. Fuzzy logic is being used in many industries to deal efficiently with complex, interacting factors. The unique aspect of the Veris process is that while it draws on the vast knowledge base of growers, it doesn’t require their valuable time or specific spatial knowledge of each field in order to create zones. Once a productivity rule has been established for a familiar field, that rule can be extended to other, similar fields. The approach is customizable for different fields; for example, a grower may establish different rules for upland and river bottom fields. The classification process is individualized, yet automated.

An example of the output Productivity Map along with the sensor input maps is shown in Figure 9. For this field, the highest productivity was set for high OM, medium CEC, gently sloping soils as those would best represent productive loams. There were two low productivity criteria: one, concave topography areas having extremely high OM, EC and pH, which would be heavy, poorly drained, alkaline soils. The other low productivity sites were sandy knolls--very low OM and low CEC soils found on sloping and convex topography. Other areas between these extremes were rated based on the fuzzy classification system. For example, areas with medium to high OM with medium pH would be expected to have higher productivity than similar soils with high pH. On the maps in Figure 9, the sites marked with an X highlight locations that have highly contrasting soil properties, yet have similar productivity expectations, based on the criteria set for this field.

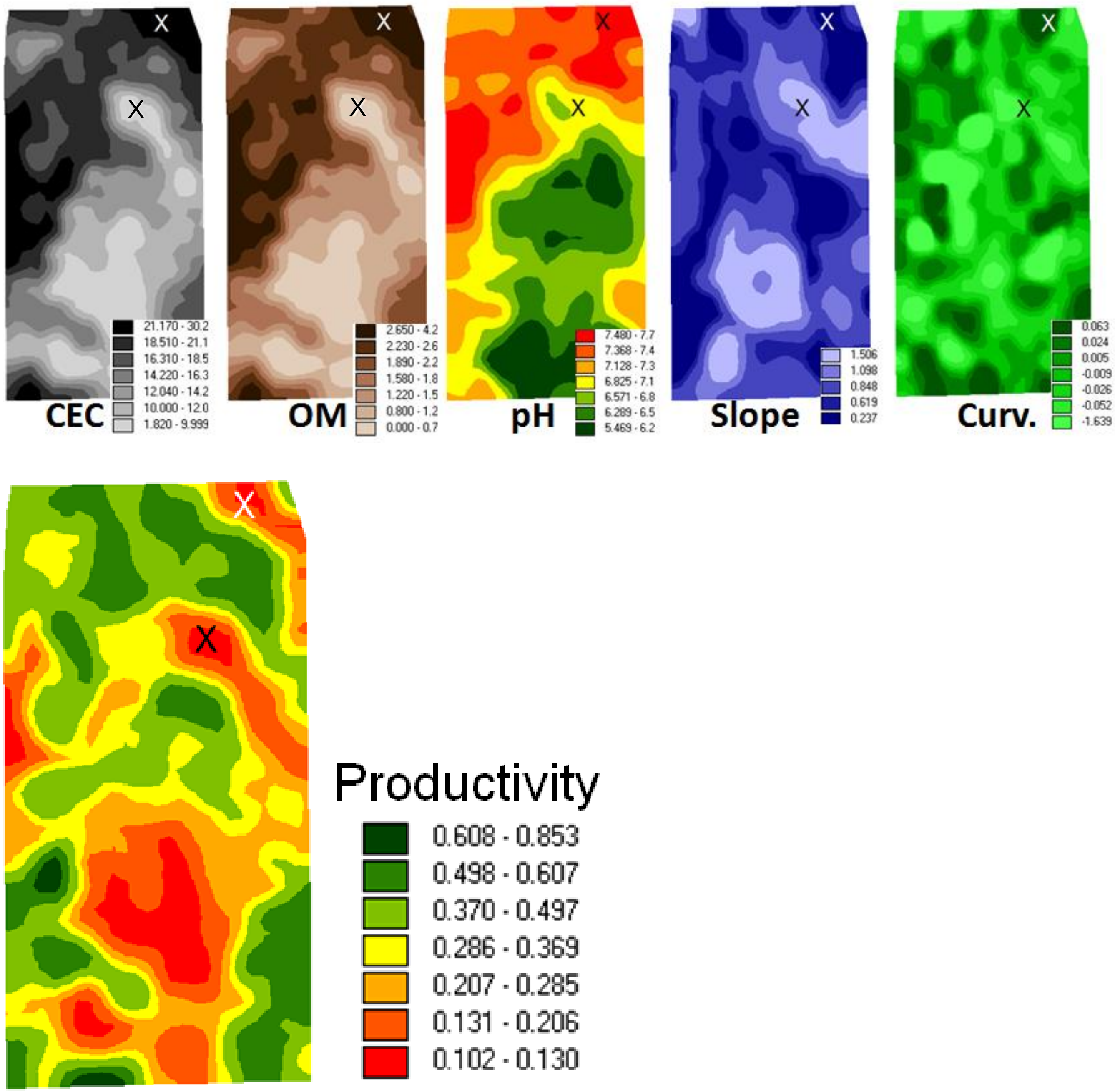


Figure 9. Veris fuzzy clustering on IL1: input layers (above) productivity map (below).

Conclusion

This ten field study provided an opportunity to evaluate a multi-sensor platform in a variety of soil types and field conditions. On-the-go soil sensor measurements correlated well with lab-analyzed soil samples, and sensor maps showed small-scale variability not detected with USDA soil surveys or at conventional grid sampling scales. A fuzzy logic system that classifies productivity zones was able to estimate productivity differences based on sensor data and decision rules for the field. The wealth of detailed, geo-referenced, and quantitative soil information provided by the sensors, coupled with a proprietary fuzzy classification approach are promising developments for improving the effectiveness of several variable-rate inputs.

References

Adamchuk, V.I., J.W. Hummel, M.T. Morgan, S.K. Upadhyaya. 2004. On-the-go soil sensors for precision agriculture. Comput. Electron. Agric. 44:71–91.

Bianchini, A.A. and A.P. Mallarino. 2002. Soil-sampling alternatives and variable-rate liming for a soybean–corn rotation. Agron. J. 94(6):1355–1366.

Brouder, S.M., B.S. Hofmann, and D.K. Morris. 2005. Mapping soil pH: Accuracy of common soil sampling strategies and estimation techniques. Soil Sci. Soc. of Am. J. 69:427–441.

Grisso, R., M. Alley, D. Holshouser, and W. Thomason. 2009. Precision farming tools: Soil electrical conductivity. Virginia Cooperative Extension. http://pubs.ext.vt.edu/442/442-508/442-508.html

Kitchen, N.R., S.T. Drummond, E.D. Lund, K.A. Sudduth, G.W. Buchleiter. 2003. Soil electrical conductivity and other soil and landscape properties related to yield for three contrasting soil and crop systems. Agron. J. 95:483–495.

Kweon, G. 2012. Delineation of site-specific productivity zones using soil properties and Topographic attributes with a fuzzy logic system. Biosys. Eng. 112:261-277

McBratney, A. B., & Odeh, I. O. A. 1997. Application of fuzzy sets in soil science: fuzzy logic, fuzzy measurements and fuzzy decisions. Geoderma, 77, 85–113.

Veris technologies

601 N. Broadway
Salina KS, 67401 (785) 825-1978
www.veristech.com