Using Yield and Soil Electrical Conductivity (EC) Maps to Derive Crop Production Performance Information

Eric D. Lund
Colin D. Christy
Paul E. Drummond
Veris Technologies
Salina KS
(785) 825-1978
www.veristech.com

ABSTRACT

Of the various factors that affect crop yield, soil water-holding capacity is usually a significant contributor. Soil electrical conductivity (EC) measurements in non-saline soils are driven primarily by soil texture and soil moisture. Those same factors correlate highly to the soil's water-holding capacity. Thus, an EC map can serve as a proxy for soil water-holding capacity, resulting in soil EC and yield maps that frequently exhibit similar spatial patterns. Numerous commercial EC mapping systems are being used in precision agriculture, and many of the maps generated by these units are being layered in a GIS with yield data in an attempt to explain yield variability. A common tool being employed in yield-EC analyses is bi-variate linear regression. While this analysis frequently explains a larger percentage of yield variability than is explained by other available layers of soil sample information, it ignores the more complex relationships between soil physical properties and yield. Moving to a non-linear curve-fit may improve the correlation co-efficient but rarely explains more than 50% of the yield variability within a field. This paper presents an analysis technique that sorts through the cloud of yield data points to establish a yield benchmark for each soil EC level. Further analysis generates maps that can be used to investigate areas that are performing below the benchmark.

Keywords: soil electrical conductivity, EC, GPS, yield, GIS, precision agriculture, boundary line, yield goal, benchmark

MATERIALS AND METHODS

Measuring soil EC

The two primary methods of measuring soil conductivity are by electromagnetic induction (EMI) or by means of direct contact. Contact methods use at least four electrodes that are in physical contact with the soil to inject a current and measure the voltage that results (Figure 1). On the other hand, EMI

Presented at the 5th International Conference on Precision Agriculture 2000

does not make contact but instead uses a transmitter coil to induce a field into the soil and a receiver coil to measure the response. Research has shown that the two methods produce similar results (Sudduth, et al., 1998). The robust construction, freedom from metal interference, and elimination of daily calibration are some of the characteristics of the direct contact method that make it practical for widespread use in agriculture. The EC data used in this paper have been collected with the direct contact method, using a Veris® mobilized soil EC mapping system. As the Veris cart is pulled through the field, one pair of coulter-electrodes injects a current into the soil, while the other coulter-electrodes measure the resulting voltage (Figure 1). Although the coulter-electrodes only need to penetrate the soil a few centimeters, the signal arrays penetrate up to 80 cm deep into the soil. The system records these conductivity measurements and geo-references them using a GPS. When used on 15 to 20m swaths at speeds up to 12 k/h, the system produces between 40 and 100 samples per ha. Two models are available: the 3100 which measures two depths of EC simultaneously, 0-25 cm and 0-80 cm; and the 2000XA which has employs a single, adjustable array to investigate soil depths up to 80 cm.

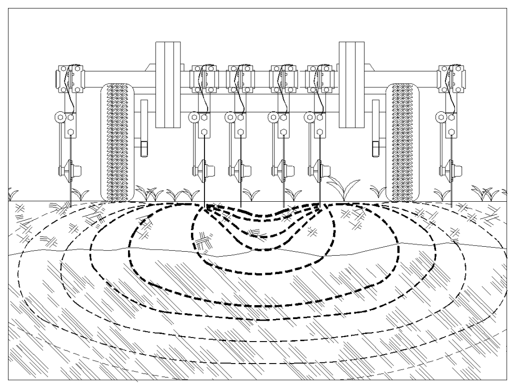



Figure 1. Veris Technologies 3100 soil EC mapping systems; signal array shown at right.

The relationship between soil EC and yield

Because soil serves as the primary growth medium for crops, it is not surprising that maps of soil physical properties and yield maps show visible correlation. Soil EC can serve as a proxy for soil physical properties such as organic matter (Jaynes, et al., 1994), clay content (Williams and Hoey, 1987), and cation exchange capacity (McBride, et al., 1990). These properties have a significant effect on water and nutrient-holding capacity, which are major drivers of yield (Jaynes, 1995). The relationship between soil EC and yield has been reported and quantified by others (Kitchen and Sudduth, 1996; Fleming, et al., 1998;). The soil EC and yield maps shown in Figure 2 are examples of fields where these two layers of information exhibit similar spatial patterns.

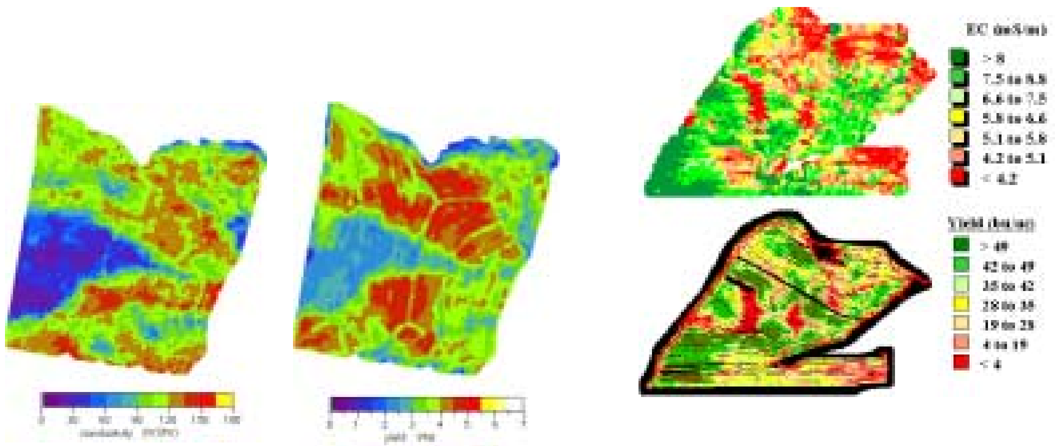


Figure 2. Examples of EC and yield maps: durum yield in Australia (left) and soybean yield in Alabama (right).

RESULTS AND DISCUSSION

Correlation statistics

It is becoming increasingly common for precision agriculture service providers to create scatter plots and calculate bi-variate regression correlation co-efficients for paired data. When this is applied to EC and yield data sets, as shown in Figure 3, the results typically show statistically significant correlation. The yield and soil EC from this Michigan soybean field has a statistically significant (at the 1% significance level) correlation co-efficient of .63. Much of this is due to the underlying soil property relationships that both data sets have in common, as described above. However, another factor is the density at which both data sets are collected. The virtually continuous-sensed, dense data collected with the mobilized EC mapping system and from the yield monitor provides measured data from similar locations in the field, reducing the errors induced by interpolating sparser data.

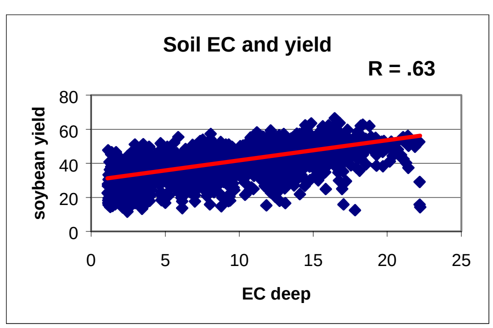


Figure 3. Scatter plot of yield and soil EC with R of .63.

The correlation analysis is an important first step in investigating the causes of yield variability. The visual similarities of the maps and the statistical correlation of the data indicate that the patterns are not random. One can observe trends in the field, begin to ascertain which yield variances are caused by soil properties versus other causes, and learn to what degree soil variability affects yield. However, the relationship between soil EC and yield is more complex than typically can be explained with bi-variate linear regression. For example, the relationship is rarely linear. A model of EC-yield where yield peaks at the mid-EC range due to an optimal balance of soil EC and hydraulic conductivity has been proposed (Kitchen, et al., 1996). Figure 4 shows data from a Michigan corn field exhibiting this EC-yield relationship.

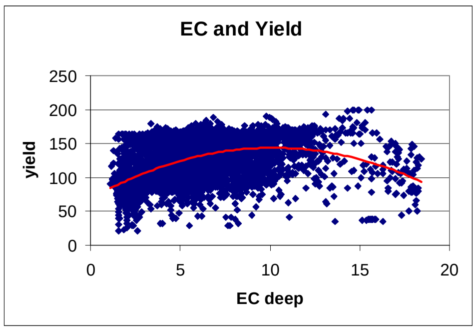
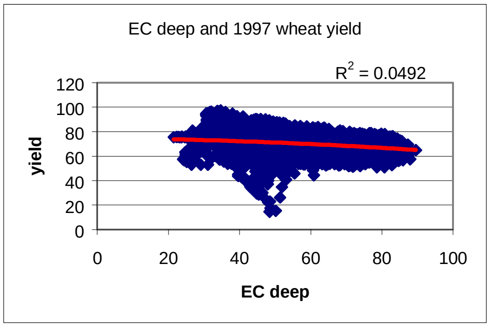


Figure 4. Non-linear relationship between EC and corn yield in Michigan.

Another factor that must be considered is that EC-yield relationships may invert from year to year, depending on rainfall (Jaynes, et al., 1995). This same phenomenon is one that must be dealt with when normalizing and averaging multiple years of yield data (Kitchen, et al., 1999).

Boundary Line Analysis Method results

An advanced method of analyzing yield with soils data is the boundary line analysis (McBratney and Pringle, 1997; Kitchen et al., 1999). This method isolates the top yielding points for each soil EC range and fits a non-linear line or equation to represent the top-performing yields within each soil EC range. This method knifes through the cloud of EC/yield data and describes their relationship when other factors are removed or reduced. Figure 5(a) is a scatter plot of a Kansas wheat field which does not show a statistically significant relationship when both data sets are correlated in their entirety. It would seem that EC explains less than 5% of the yield variability on this field. Yet a relationship does appear to exist at the upper yield limits. This relationship is clarified using the boundary line method which shows that EC explains over 50% of the yield-limiting factors on this field Figure 5(b). The upper boundary represents the maximum yield for each soil EC range. While there may be a number of factors causing yields to be lower than the boundary, the maximum yield for each soil EC type has been established, for the crop year being considered. This can be useful in deriving yield goals as will be discussed later in this paper.



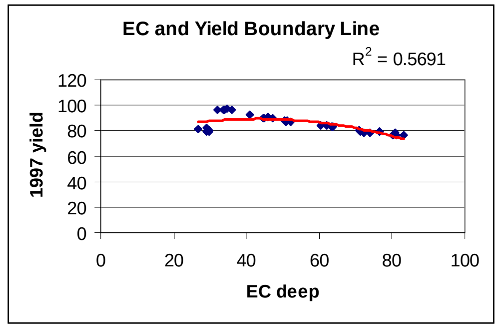


Figure 5. Scatter plot of EC and yield data from a Kansas field for (a) all EC and yield data and (b) upper boundary line.

Median Analysis Method results

This approach is similar to the boundary line analysis, except that it uses the median yield for each soil EC range, rather than the upper boundary. Yield data can include anomalies caused by erroneous swath widths, uneven flow, and poor yield monitor calibration. These errors result in noise in the yield data, often at the higher yield levels. When the median, the 75th percentile, and the 95th percentile are plotted for the same data, the noise at the upper yield levels is evident (Figure 6).

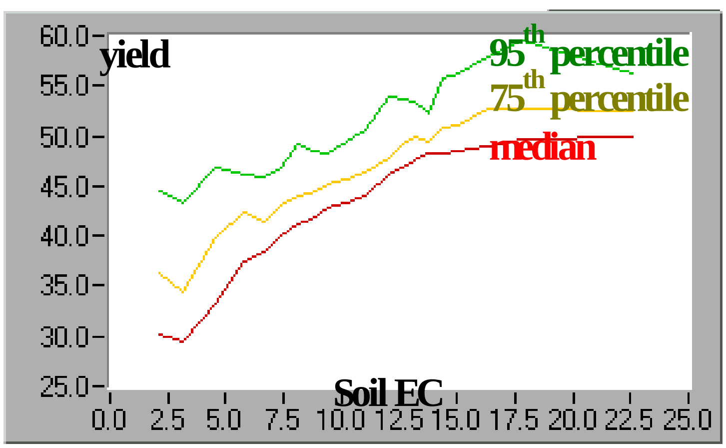


Figure 6. Comparison of 95th, 75th, and median EC/yield lines from an Indiana soybean field.

Analyzing crop performance using the median as a benchmark

The analysis methods described above identify yield differences across soil EC ranges. Yet within each soil EC type, there is important yield variability. Not all the top producing soils yield up to their potential, and some areas of the poorer producing soils yield better than other areas. This phenomenon isn't readily apparent because the dominant relationship between yield and soil type often masks the subtle variations within soil types.

The median yield for each soil EC range can serve as a benchmark yield for that soil EC type, and yields from the same EC range can be compared to it. Figure 7 shows the median benchmark method applied to a 1997 Kansas wheat yield also shown above. The value for each pixel is derived by dividing its actual yield by the median yield for each soil EC range. In effect, this removes soil EC from the equation and displays yield performance based on factors other than soil EC and the soil properties it relates to. The areas yielding significantly below the benchmark represent areas to target for further investigation and action. High yielding areas relative to the benchmark can be investigated to gain a better understanding of the nature of ideal producing soils. Among the possible causes for under-performance are compaction, nutrient deficiency, weed pressure or drainage.

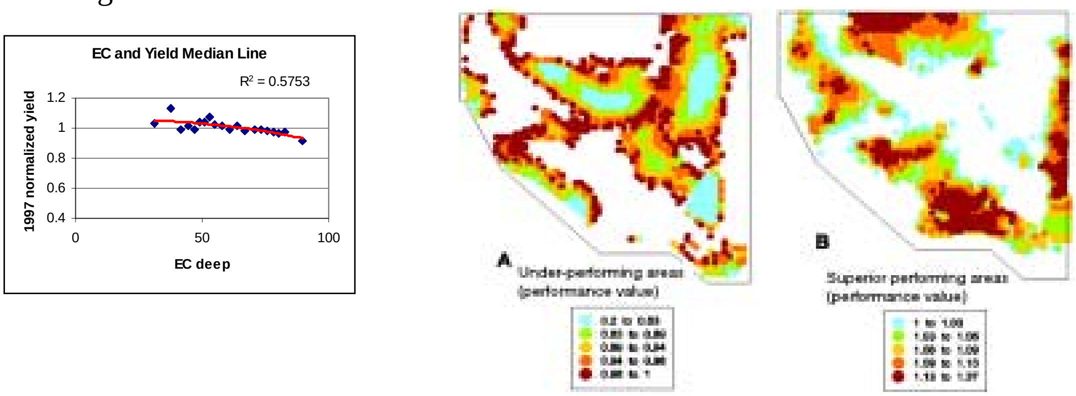


Figure 7. Median benchmark line plot and (a) areas of field yielding below median benchmark and (b) areas yielding above median benchmark.

By delineating the specific area where yield has been affected, and quantifying the amount of loss, performance benchmark maps can be used to aid in management decision regarding remediation. A similar approach can be applied to remote sensed crop images whereby crop scouting efforts can focus on areas that show poor vigor relative to their soil EC type.

Using EC/yield data to derive yield goals

Many growers are hesitant to establish site-specific yield goals using yield data alone, even with multiple years of data, because of a concern that historical yields aren't strong enough proof of productivity. Because of the severe economic penalty for under-applying inputs such as nitrogen, they are unwilling to reduce inputs on low-yielding areas until they have some confirmation that the low yielding areas truly have lower yield potential, and are not being limited by a factor which can be easily remedied. It has been shown that 7 to 10 years of yield data may be needed in order to establish yield goals effectively based solely on yield maps (Lutticken, 1998), and other research has found that yields are not stable after six years of monitoring (Colvin, et al., 1997). Research into variable rate application of nitrogen shows that including information about soil physical properties, along with yield data improves economic returns to the practice (Lutticken, 1998; Moulin, et al., 1998).

The relationship between soil EC and yield can be used to help derive site-specific yield goals. The yield map in Figure 8 comprises 3 years of normalized yield data from one year each of wheat, grain sorghum and soybean production. The soil EC map (Figure 8a) shows visual correlation to the yield map (Figure 8b), and statistically significant correlation as well (Figure 9a). The upper yield boundary line explains more than 96% of the yield limiting factors on this field (Figure 9b). Coupled with the grower's knowledge of the eroded clay bank represented by the higher EC values, this provides strong evidence of lower yield potential in the higher EC soils on this field. These data suggest that the yield potential in the low EC soils is 25% higher than in the high EC soils, and a variable rate nitrogen program could easily incorporate this in a recipe.

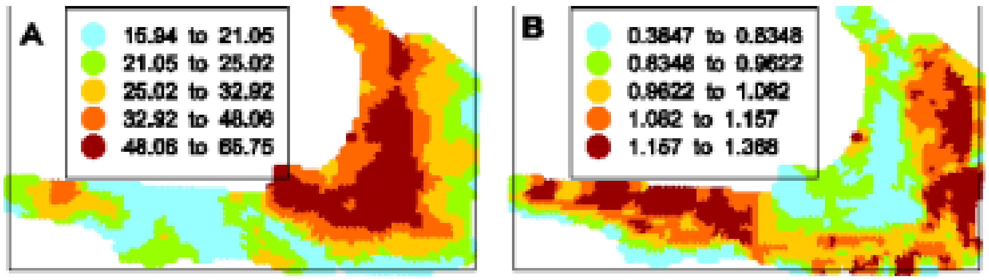


Figure 8. (a) soil EC and (b) 3 years of normalized yield

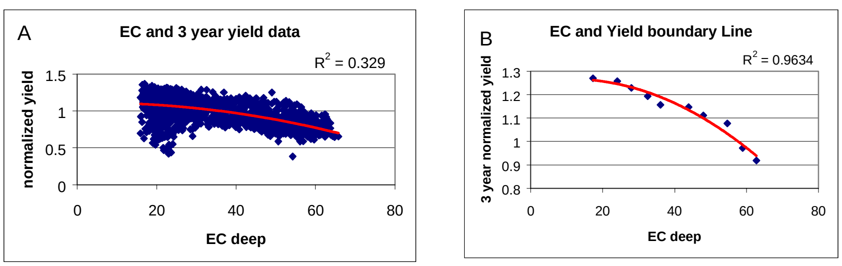


Figure 9. (a) correlation of EC and 3 years of normalized yields, and (b) upper boundary limits on yield based on soil EC ranges

Economic returns are higher for those initiating variable rate nitrogen, as opposed to continuing with a uniform rate (Hopkins, et al., 1998). Yet before varying inputs based on site-specific yield goals it is important to investigate the relationship between the soil type and the input to be varied. For example, in the field (Figure 8) above, one should be certain that the lower yields in the higher EC soils were not the result of de-nitrification or a shallow soil which could actually benefit from increased nitrogen (Barraclough and Weir, 1988).

CONCLUSIONS

Soil EC and yield measurements are both densely collected data sets that provide closely correlated information about crop production. Beginning with simple correlation statistics and proceeding to more advanced and rigorous analysis methods, this relationship can help explain yields, identify under-performing areas of the field, and help establish site-specific yield goals.

REFERENCES

Barraclough, P.B., and A.H. Weir. 1988. Effects of a compacted subsoil layer on root and shoot growth, water use and nutrient uptake of winter wheat. J. Agric. Sci., Cambridge 110:207-216

Colvin, T.S., D.B. Jaynes, D.L. Karlen, D.A. Laird, J.R. Ambuel. 1997. Yield variability within a central Iowa field. Trans. ASAE 40(4):883-889

Fleming, K.L., D.G. Westphall, D.W. Wiens, L.E. Rothe, J.E. Cipra, D.F. Heerman. 1998. Proceedings of 4th International Conference on Precision Agriculture. 335-343

Hopkins, J.W., G.S. Schnitkey, M.J. Miranda, L.G.Tweeten. 1998. Learning from yield monitors: a Bayesian approach. 1998 Proceedings of 4th International Conference on Precision Agriculture. 183-193

Jaynes, D.B. 1996. Improved Soil Mapping Using Electromagnetic Induction Surveys. Proceedings of the 3rd International Conference on Precision Agriculture. 169-179.

Jaynes, D.B., Colvin, T.S., Ambuel, J. 1995. Yield Mapping By Electromagnetic Induction. Proceedings of the 2nd International Conference on Site-Specific Management for Agricultural Systems. 383-394.

Jaynes, D.B., Novak, J.M., Moorman, T.B., Cambardella,C.A. 1994. Estimating Herbicide Partition Coefficients from Electromagnetic Induction Measurements. Journal of Environmental Quality. 24, 36-41.

Kitchen, N.R, and K.A. Sudduth. 1996. Predicting Crop Production Using Electromagnetic Induction. Information Agriculture Conference Proceedings, Urbana IL.

Kitchen, N.R., K.A. Sudduth, and S.T. Drummond. 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. J. Prod. Agric.12:607-617

Lund, E.D., C.D. Christy, P.E. Drummond. 1998. Applying Soil Electrical Conductivity Technology to Precision Agriculture. Proceedings of the 4th International Conference on Precision Agriculture, St. Paul MN. 1089-1100

Lutticken, R.E. 1998. Implementation of precision fertilizing concepts on practical farms in western Germany. Proceedings of the 4th International Conference on Precision Agriculture, St. Paul MN. 859-867

McBratney, A.B. and M.J. Pringle. 1997. Spatial variability in soil—implications for precision agriculture. Precision Agriculture 1997, 3-31

McBride, R.A., Gordon, A.M., Shrive, S.C. 1990. Estimating forest soil quality from terrain measurements of apparent electrical conductivity. Soil Science Society of America Journal, 54, 290-293.

Moulin, A.P., H.J. Beckie, D.J. Pennock. 1998. Strategies for variable rate nitrogen fertilization in hummocky terrain. Proceedings of 4th International Conference on Precision Agriculture. 839-846

Sudduth, K.A., N.R. Kitchen, S.T. Drummond. 1998. Soil conductivity sensing on claypan soils: comparison of electromagnetic induction and direct methods Proceedings of 4th International Conference on Precision Agriculture. 979-990

Williams, B., Hoey, D. 1987. The use of electromagnetic induction to detect the spatial variability of the salt and clay content of soils. Australian Journal Soil Research, 25, 21-27.