

AN APPROACH TO SELECTION OF SOIL WATER CONTENT MONITORING LOCATIONS WITHIN FIELDS

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ABSTRACT

In an agricultural field, monitoring both spatial and temporal variability of soil conditions are important to determine the variable rate application of agricultural inputs. As an example, by monitoring soil water content, this information may be used to determine the amount and timing of irrigation. On-the-go soil sensing technology rapidly provides high-resolution, multiple data layers of soil spatial variability at a relatively low cost. Proper locations and the optimal number of soil monitoring sites need to be identified. In this paper, seven agricultural fields in Nebraska were mapped using on-the-go soil sensing technology. Apparent soil electrical conductivity (EC_a) and field elevation were used to estimate crop water supply potential. In a 37-ha agricultural field in Nebraska, nine locations were selected for monitoring soil matric potential and temperature using wireless technology. The Water Stress Index (WSI) used for indicating the soil water condition was determined in this particular field. The regression model was generated and applied to six other fields to simulate WSI surfaces. In these six fields, monitoring sites were chosen by two different methods: randomly chosen and manually chosen, using optimal criteria. The MSE of an estimated WSI surface based on monitoring locations chosen by these two methods and a “real” one was used to determine the integrity of the methods.

Keywords: on-the-go soil sensing, targeted sampling, electrical conductivity, irrigation

INTRODUCTION

In an agricultural field, both spatial and temporal variability of soil conditions are critical to determine variable rate application of agricultural inputs. As an example, to achieve precision irrigation, it is important to monitor soil water content to determine the amount and timing of irrigation. Conventional, on-the-spot evaluation of soil conditions is somewhat subjective and labor-intensive. In

addition, soil variability within a field can be extensive, which means that defining representative locations to make irrigation management decisions is challenging.

By contrast, on-the-go soil sensing technology provides an opportunity to rapidly obtain high-resolution multiple data layers of soil spatial variability at a relatively low cost (Adamchuk et al., 2004). Unfortunately, the relationships between data detected on-the-go and agronomic soil parameters, such as water content, are frequently site-specific. Therefore, sensor-based maps have been used to define the spatial variability of soil properties that influence water movement across a landscape (Hedley, 2009).

Furthermore, the amount of water stored in the soil profile changes both spatially and temporally. Wireless technology has been used increasingly to monitor soil conditions. Such systems allow the producer to obtain information about soil water conditions, temperature, and other properties in real time from a remote location (Kim et al., 2009). Irrigation systems managers have used the data to optimize the use of resources in response to dynamic changes in soil conditions and to reduce the risk of crop water stress (Han et al., 2009; Omary et al., 1997; Rodrigues et al., 2003).

As a precondition to apply wireless technology, the number of locations within the field needs to be selected. This is not trivial and is mostly subjective. Practitioners who use high-resolution data layers from the field to determine monitoring locations rely on the following general rules: 1) cover the entire range of data from each source, 2) avoid field boundaries and other transition zones, and 3) spread locations over the entire field. While these criteria are useful, they do not translate into an operational algorithm and, therefore, can produce numerous outcomes with different degrees of satisfaction. In principle, this process is similar to prescribing targeted sampling locations needed to either calibrate high-resolution data, or to quantify agronomic soil attributes of established management zones (Lesch, 2005; Minasny and McBratney, 2006; Brus and Heuvelink, 2007; de Gruijter et al., 2008).

The objective of this research was to provide an analytical methodology for optimally locating a set of strategic locations for soil moisture monitoring with optimized performance-to-cost ratios in an agricultural field.

MATERIALS AND METHODS

Seven agricultural fields in Nebraska were chosen and mapped using on-the-go sensing technology with a Veris® 3150 unit (Mobile Sensor Platform, Veris Technologies, Inc., Salina, Kansas)¹ equipped with an RTK-level AgGPS® 442 GNSS receiver (Trimble Navigation Ltd., Sunnyvale, California). Soil apparent electrical conductivity (EC_a) and elevation were used to estimate crop water supply potential. In one of these fields (a 37-ha field (Field 1.14) at the Agricultural Research and Development Center near Mead, Nebraska), nine

¹ Mention of a trade name, proprietary product, or company name is for presentation clarity and does not imply endorsement by the authors, McGill University, or the University of Nebraska-Lincoln, nor does it imply exclusion of other products that may also be suitable.

locations were selected for monitoring soil matric potential and temperature using wireless technology (Pan et al., 2011). The WSI used for indicating soil water supply was determined in this field. A regression model was generated and applied to six other fields to generate field surfaces of WSI. In these six fields, monitoring sites were chosen by two different methods: randomly chosen and manually chosen using optimization criteria. Based on the chosen monitoring sites, new regression models could be generated and applied to predict WSI surfaces. The MSE of the predicted surface and of the “real” one was used to determine the reliability of the methods for selecting the monitoring sites.

Optimization Criteria

The definition of the optimum guided sampling scheme is quite vague. There are many parameters that can quantify 1) spatial separation, 2) spread across sets of measurements and 3) local homogeneity within each set of measurements. Furthermore, there are several alternatives to derive the overall objective function as a combination of these parameters. In this study, to define soil water content monitoring sites, EC_a and field elevation maps shown in Fig. 1 were analyzed using three combined optimization criteria (Adamchuk et al., 2011). These criteria included: (1) complete spatial field coverage using the S-optimality criterion (SAS, 2008); (2) even distributions throughout both data layers using the D-optimality criterion (SAS, 2008); and (3) the relative homogeneity of the selected sites using a criterion developed based on the sum of squared differences between the measurements obtained in each location and its immediate neighbors. The overall objective function was the geometric mean of these criteria normalized against the median of a large number of random selections. The same optimization criteria were used to determine monitoring sites for six other fields in this study.

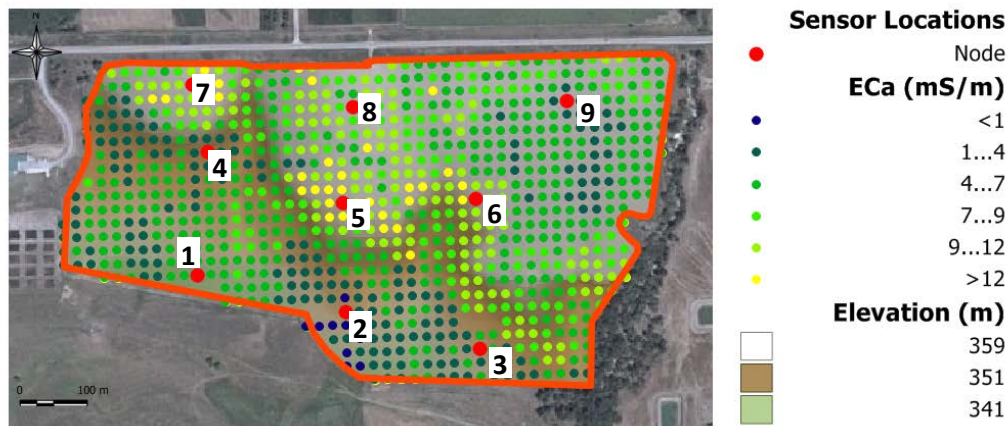


Fig. 1. Maps of topsoil EC_a and field elevation with sensor installation locations (Field 1.14 at the University of Nebraska-Lincoln Agricultural Research and Development Center (Meade, Nebraska)).

WSI Regression Model

In this study, measurements collected during the growing season (99 days from late June to early October) at the nine sensor installation locations were used

to calculate WSI values. The daily average WSI for each node was used to establish the regression model with EC_a and field elevation value collected at each location. The model was as following:

$$WSI = \beta_0 + \beta_1 \cdot EC_a + \beta_2 \cdot Elev + \beta_3 \cdot EC_a \cdot Elev \quad (1)$$

where EC_a is apparent electrical conductivity, mS/m; $Elev$ is relative field elevation (subscribed from the median value), m; $\beta_0, \beta_1, \beta_2, \beta_3$ are model coefficients.

For each of the 99 days when data was collected in 2009, the WSI regression model was generated. The coefficients of the model which represent the major condition and can be generated in the day with the highest average number of WSI values thus indicating the driest soil status; this was applied to the six other experimental agricultural fields to calculate WSI values for the entire field based on the known EC_a and field elevation. The field elevation for generating the model was adjusted by subscribing the mean value for each field in order to compensate for the effect of variable field elevation.

Simulation Analysis

In order to verify the necessity of optimal criteria to determine strategic sampling locations, the error surface with different spatial distribution patterns were generated and applied on the calculated WSI surface to simulate the “real” WSI data layer. All three error surfaces have the same sill values, which was determined using the MSE of the generated WSI regression model with data from the ARDC field. Different values of nugget and range were applied in order to generate three error surfaces with different levels of smoothness. The variogram for these three error surfaces are shown in Fig. 2.

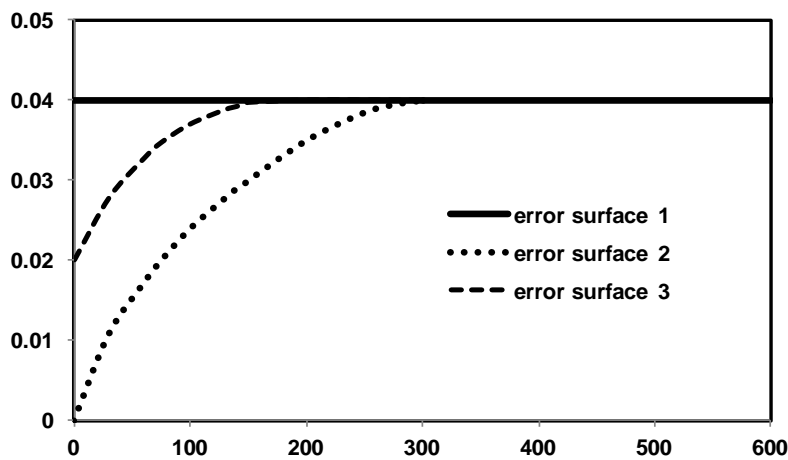


Fig. 2. Variogram for three error surfaces (error surface 1: completely random with sill of 0.04; error surface 2: sill=0.04, nugget=0, range=300 m; error surface 3: sill=0.04, nugget=0.02, range=150 m).

For all six fields (BR, HS, HU, KR, LU, and RU) used for assessment in this study, EC_a and field elevation (Fig. 3 shows the maps for Field HS as an example) data layers were divided with a 10 by 10 m grid. For each grid, the WSI value was calculated with the regression model mentioned above using EC_a and field

elevation values. Adding the calculated WSI surface with the generated error surface, the surface of WSI was simulated and regarded as the “real” WSI surface used for validation.

The quality of the selection of monitoring sites with the given number of them (5 and 10) was assessed. Both random selection and manual selection based on the optimization criteria were used to determine the set of strategic sampling locations, and the MSE of the “real” WSI surface and the estimated WSI surfaces using the chosen sites was used as the parameter to determine the quality of selection.

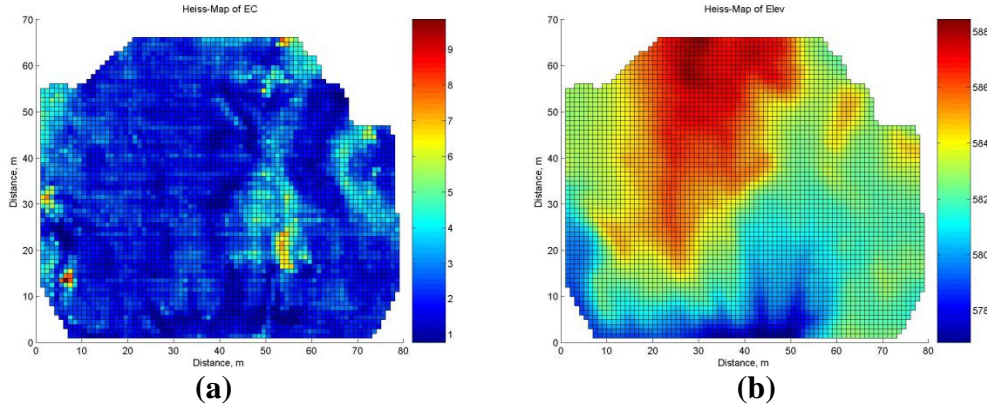


Fig. 3. Maps of a) EC_a , b) field elevation (Field HS as an example).

RESULTS AND DISCUSSION

The WSI maps shown in Fig. 4(a) were generated based on the regression model obtained using the ARDC field data layers. The coefficients for intercept, EC_a , field elevation and the interaction were fixed for all six fields. These four coefficients were obtained from the regression model for July 30, 2009 (the driest day of the season):

$$WSI = -0.26 - 0.13 \cdot EC_a - 0.40 \cdot Elev + 0.08 \cdot EC_a \cdot Elev \quad (2)$$

To simulate the “real” field surface of WSI, the error surface was generated with three different spatial distribution patterns as summarized in Fig.2. Error surface 1 which was randomly distributed had a completely random spatial pattern. By contrast, error surfaces 2 and 3 had smoother patterns. Error surface 2 had the highest level of geo-correlation patterns among these three. The three generated “real” WSI surfaces according to three simulated error surfaces were shown in Fig. 4(b-d) using Field HS as an example.

Both the random selection and the manual selection methods were based on the optimization criteria method used for selecting monitoring sites. Fig. 5 shows the manually chosen monitoring sites with a given number (5 and 10) while showing the relationship between EC_a and the field elevation. For the randomly selected locations, 20 sets of selection were used to calculate MSE values between the “real” WSI surface and the one predicted based on the selection of locations.

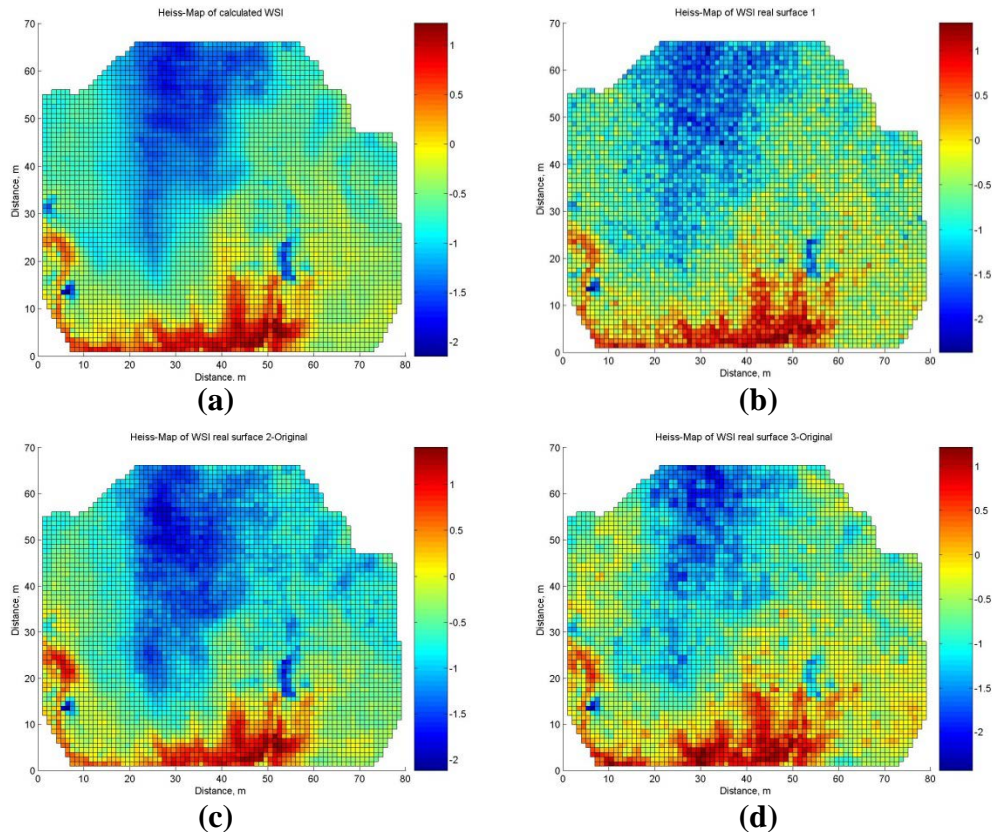


Fig. 4. Maps of a) calculated WSI surfaces, b) “real” WSI surface 1, c) “real” WSI surface 2, and d) “real” WSI surface 3 (Field HS as an example).

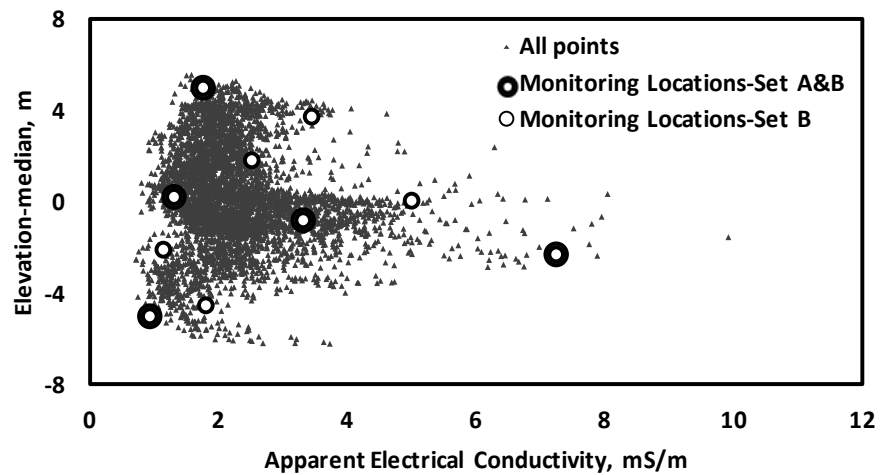


Fig. 5. Relationship between EC_a and field elevation (Field HS as an example).

Fig. 6 provides the summary of MSE values for both selection methods. It is obvious that with a larger number (10) of monitoring locations, even when a random selection set was used, the prediction of WSI surface was accurate. When the number was 5, due to the small amount of monitoring locations, there was a greater risk of obtaining a large MSE value, which indicates a large variance between predicted WSI surface and the “real” one. With the same preset number

of monitoring locations, the manual selection of monitoring locations generated smaller MSE values compared to the median MSE values using the random selected locations, eliminating the probability of predicting the WSI surface which has considerable difference between the predicted and the “real” one.

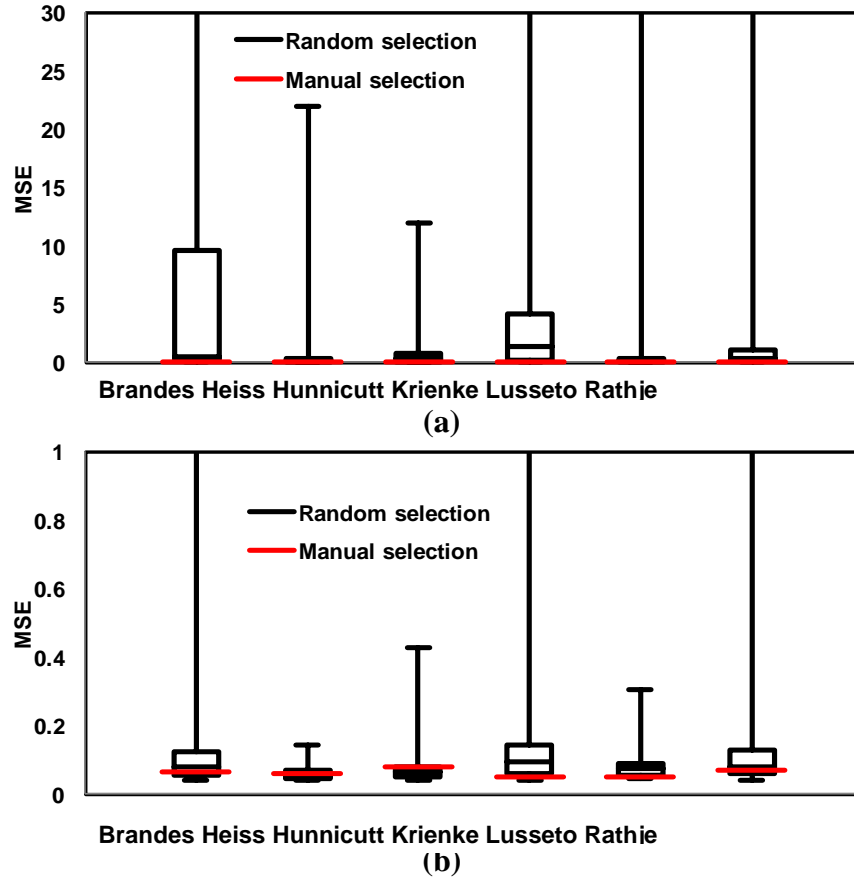


Fig. 6. Summary of MSE values for the predicted WSI surface and the “real” one: a) 5 monitoring locations, b) 10 monitoring locations.

CONCLUSIONS

In this research, apparent soil electrical conductivity and field elevation data layers were mapped using on-the-go soil sensing technology; they were used to estimate crop water supply potential. WSI values for sites with sensors installed were calculated and used to generate the regression model depending on apparent soil electrical conductivity and field elevation data in one field. To assess the effect of monitoring sites selection, the “real” WSI surfaces were obtained by adding the calculated WSI surface and the simulated error surfaces with different spatial distribution patterns. A random selection method and a manual selection method based on optimization criteria were applied and compared by checking the MSE of the predicted WSI surfaces and the “real” one. The optimized selection of monitoring locations was helpful to eliminate the chance of choosing locations unrepresentative in both the small (5) and the large (10) number of locations. When the smaller number of monitoring sites was used, the optimized selection was more critical for a reliable prediction. This study provides the

methodology for optimizing the selection of monitoring sites as well as optimizing the number of sites to maximize the performance-to-price ratio.

REFERENCES

- Adamchuk, V.I., Viscarra Rossel, R.A., Marx, D.B., and Samal, A.K. 2011. Using targeted sampling to process multivariate soil sensing data. *Geoderma* **163**: 63-73.
- Adamchuk, V.I., Jummel, J.W., Morgan, M.T., Upadhyaya, S.K. 2004. On-the-go soil sensors for precision agriculture. *Computers and Electronics in Agriculture* **44**(1): 71-91.
- Brus D.J., Heuvelink GBM. 2007. Optimization of sample patterns for universal kriging of environmental variables. *Geoderma* **138**: 86-95.
- de Gruijter J.J, McBratney AB, Taylor J. 2008. Sampling for high resolution soil mapping. In: Proceedings of the First Global Workshop on High Resolution Digital Soil Sensing and Mapping (The University of Sydney: Australia, Sydney).
- Han, Y. J., Khalilian, A., Owino, T.O., Farahani, H.J., Moore, S. 2009. Development of Clemson Variable-Rate Lateral Irrigation System. *Computer and Electronics in Agriculture* **68**(1): 108-113.
- Hedley, C. 2009. A method for spatial prediction of daily soil water status for precise irrigation scheduling. *Agricultural Water Management* **96**(12): 1737-1745.
- Kim, Y., and Evans, R.G. 2009. Software design for wireless sensor-based site-specific irrigation. *Computer and Electronics in Agriculture* **66**(2): 159-165.
- Lesch S.M. 2005. Sensor-directed spatial response surface sampling designs for characterizing spatial variation in soil properties. *Computers and Electronics in Agriculture* **46**: 153-180.
- Minasny B, McBratney A.B. 2006. A conditioned Latin hypercube method for sampling in the presence of ancillary information. *Computers and Geosciences* **32**, 1378-1388.
- Omary, M., Camp, C.R., Sadler, E.J. 1997. Center pivot irrigation system modification to provide variable water application depth. *Applied Engineering in Agriculture* **13**(2): 235-239.
- Pan L., Adamchuk, V.I., Martin, D.L., Schroeder, M.A., Ferguson, R.B. 2011. Combining on-the-go soil sensing and a wireless sensor network to increase irrigation water use efficiency. In: *Precision Agriculture: Papers from the 8th European Conference on Precision Agriculture*, Prague, Czech Republic, 11-14 July 2011, ed. J. Stafford, Czech Centre for Science and Society, Prague, Czech Republic, pp. 459-468.
- Rodrigues, F., Yoder, R., Wilkerson, J. B. 2003. A site-specific irrigation control system. Paper No. 031129. ASABE, St. Joseph, MI.
- SAS (2008) Optimality criteria. In 'SAS/QC User's Guide' (SAS Institute, Inc: Cary, North Carolina).