Evaluating Spatial Variability of Soil Parameters for Input Management

By Sylvie Brouder, Brenda Hofmann, and Harold F. Reetz, Jr.

Agronomic recommendations are usually designed to provide good results under average conditions over a relatively large geographic area. Nutrient recommendations, for example, are commonly targeted for an average soil and management system and are applied for general soil types across a whole state, or even across multiple states. Variety recommendations are usually made for average conditions over a large area and multiple years. Pesticide recommendations likewise are usually the same for large areas.

Site-specific management, on the other hand, should focus on the unique characteristics of the field, the soil types, and the management system. It is through managing specifically for those unique characteristics that the value of site-specific systems can be realized. In changing one component, we affect the optimums for others. In understanding those interactions and how to manage them we find the real value of site-specific management. Responding to those interactions, paying attention to details of the system, is the key to profitable implementation of site-specific management. Successful action begins with field assessment that focuses on the spatial and temporal differences in manageable production components instead of on the production uniformities.

Crop production is affected by factors that vary both in space (spatial variability) and time (temporal variability). Site-specific crop and soil management systems apply agronomic science to manage production practices and inputs to address spatial and temporal variability on the farm.

When studying and managing several varying factors, as is usually the situation in crop and soil management, it is important to look not only at which factors vary, but also at whether their variability is independent or linked to another factor. If the variabilities of certain factors are linked, then their measurement and management may be more efficiently handled by using one as a predictor, or surrogate, for the variability in the other. If there is no relationship between the variances of two factors, then they should be assessed separately and may require independent management.

Studies at the Purdue University Davis

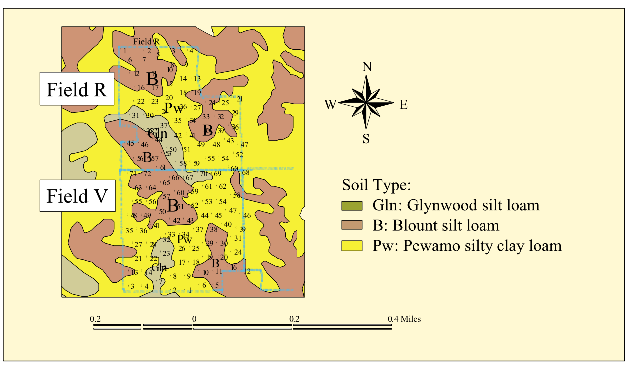

Figure 1. Two adjacent 35-acre fields are being intensively sampled to characterize soil and plant variability. Numbered points mark locations of soil samples collected on a 0.5-acre grid intensity.

Research Center in east central Indiana are focusing on analysis of the spatial structure of soil nutrient availability and its relationship to plant nutrient status, nutrient export, and on the spatial and temporal stability of yield and yield variability.

In order to study spatial variation in soil test values a stratified, systematic, unaligned pattern imposed on a 0.5-acre grid was used to select the point sample locations, and multiple core composites were collected (**Figure 1**). Several approaches are being used to analyze these data. Common interpolation techniques such as kriging are being used to characterize the sampling intensity needed to adequately describe expected soil test values at unsampled locations. Moving window analysis, a very simple statistical technique, is being used to explore whether manageable soil properties such as phosphorus (P), potassium (K), and pH vary spatially in such a way as to permit their joint management.

For this analysis, fields were divided into 32 overlapping five-acre local neighborhoods, each containing nine to 13 soil-sampling points (**Figure 2**). The analysis in the variability of ***means*** of the sampling points as you move across the landscape identifies the spatial variability of the individual factors. The analysis of variability in the ***standard deviations***, on the other hand, helps determine whether these variations are related or are independent.

Conclusions from the preliminary analysis of the soils data underscore the need to be able to integrate information from other data layers such as crop performance into smarter sampling strategies. Specifically:

1. Descriptive univariate statistics indicate substantial within-field variability in input needs that would be overlooked in a whole field approach to management. For example, the mean soil pH across the field is 6.5, requiring no lime additions. However, point soil test values range from 5.0 to 7.9.
2. Results of kriging and cross validation show that the 0.5-acre sampling grid may be too sparse to adequately characterize the structure of spatial variability of selected soil parameters. **Table 1** gives the results the semivariance analysis used to find the best models to describe the spatial structure of selected soil properties. Our results show that, while models can be fit to our data, the models' abilities to predict the soil test values at untested locations within the field are not very good. For example, sample locations for P must be closer together than 130 ft. (range = 130 ft.) in order to be dependent (to be able to predict something about the soil test value at one location simply by knowing the soil test value at the neighboring location). The model cross validation shows how well we can predict the soil test value at any sample point from all the other sample points. A model that predicts the right value at every single location would have a regression coefficient (slope) of 1.0, an r^2 of 1.0 and a Y-intercept of 0. Y intercepts greater than 0 and regression coefficients less than 1 indicate that the model tends to over predict lower soil test values and under predict higher ones.
3. The spatial analysis of the five-acre moving window means and standard deviations for various parameters shows that P and K

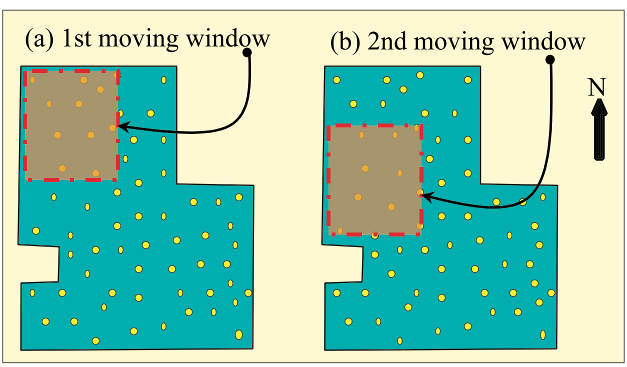

Figure 2. Overlapping moving windows were used to calculate moving average statistics (means and standard deviations) for five-acre regions of the field. Each moving window contained 9 to 13 soil sample grid points (yellow dots).

TABLE 1. Semivariance analysis of selected soil properties.

		Isotropic model				Cross validation of model			
Parameter	Model	Range A_0, ft.	Effective range, ft.	Proportion $C/C_0 + C$[1]	r^2	Regression coeff. (S.E.)	r^2	Y intercept	S.E. of produc-tion
Bray P-1, ppm[2]	Exponential	130	394	0.94	0.88	0.82 (0.19)	0.13	10.3	18.0
K, ppm	Spherical	269	269	0.999	0.78	0.67 (0.60)	0.10	47.5	29.3
OM, %	Exponential	194	577	0.999	0.95	0.79 (0.12)	0.25	0.77	0.69
pH	Spherical	148	148	1.0	0.45	0.78 (0.20)	0.10	1.4	0.55

[1]C_0, nugget; C, sill; [2]ppm = parts per million.

change together in space, and that regions of high variability in soil test P are also highly variable in soil test K (**Tables 2** and **3**). Regions of greatest and least variability in organic matter (OM), cation exchange capacity (CEC), calcium (Ca), and magnesium (Mg) were different from the regions of extreme P and K variability. Therefore, in this field, there is the potential to monitor and manage P and K together, but their spatial variability does not match that of OM, CEC, Ca or Mg. Thus, P and K should be considered independent of those parameters. A smart sampling strategy that minimizes the total number of soil samples collected while still successfully characterizing zones of uniformity in P and K availability and fertilizer need would not necessarily be optimal for the identification of the spatial variability in OM, a soil property that may be required for the development of optimal variable rate (VR) nitrogen (N) recommendations.

The relationships among different soil test parameters, like those determined in this study, will likely vary geographically due to differences in soil physical properties, management history, climate, and other factors. The spatial variability of common soil test factors measured in this study shows that current sampling patterns do not provide sufficient information to accurately draw soil test variability maps. Because sampling densities needed to provide such accuracy are impractical and cost-prohibitive, other tools are needed to refine soil-sampling procedures for accurate representation and management decisions on VR nutrient application. More intense data sets are needed from remote sensing, soil electrical conductivity, yield monitors, and other more data-intense, lower-cost measurements of within-field variability. These measurements can help define management zones, which can be combined with less-dense soil samples to provide a more accurate prediction of spatial variability of soil nutrient levels.

To date, much of the effort in site-specific management has been focused on P and K

TABLE 2. Spearman Rank correlation (p-value) for selected soil properties. Comparisons are between area means of "moving windows."

	OM	Bray P-1	K	Mg	Ca	pH
Bray P-1	0.41(*)					
K	0.39(*)	0.90(***)				
Mg	0.46(*)	0.02(n.s.)	-0.03(n.s.)			
Ca	0.62(***)	0.17(n.s.)	0.29(n.s.)	0.77(***)		
pH	0.81(***)	0.05(n.s.)	-0.02(n.s.)	0.71(***)	0.55(**)	
CEC	0.81(***)	0.29(n.s.)	0.41(*)	0.60(***)	0.90(***)	0.25(n.s.)

*, **, *** = significant at the 0.05, 0.01, and 0.001 levels, respectively.

TABLE 3. Spearman Rank correlation (p-value) for the standard deviations of selected soil properties. Comparisons are between standard deviation of area means of "moving windows."

	StdD-OM	StdD-Bray P1	StdD-K	StdD-Mg	StdD-Ca	StdD-pH
StdD-Bray P-1	0.13(n.s.)					
StdD-K	-0.08(n.s.)	0.51(**)				
StdD-Mg	0.34(n.s.)	-0.07(n.s.)	0.05(n.s.)			
StdD-Ca	0.44(*)	0.12(n.s.)	0.35(n.s.)	0.71(***)		
StdD-pH	-0.11(n.s.)	0.55(**)	0.40(*)	0.10(n.s.)	0.11(n.s.)	
StdD-CEC	0.66(***)	0.04(n.s.)	0.22(n.s.)	0.66(***)	0.86(***)	-0.10(n.s.)

*, **, *** = significant at the 0.05, 0.01, and 0.001 levels, respectively.

management and on liming, because variability in those components was measurable and technology for VR application was available.

The most cost-effective approach for inputs such as P, K and lime is still to build them to a level where they are not limiting. But with site-specific systems, that level can be determined for each management zone (or grid cell) within each field, based on the characteristics and productive potential of that individual zone. If the field has been well-managed under conventional systems, shifting to site-specific management will likely reduce the fertilizer application for parts of the field and increase it for others, but will usually increase the total fertilizer application and should generate an increase in yield potential. BC

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In-season Fertilization... *(continued from page 7)*

TABLE 3. Effect of late-season N rate and source on irrigated soybean yield.

N rate, lb/A	N source	JO94	JO95	SN94	SN95	RN94	RN95	SF94	SF95	Avg.
		Grain yield, bu/A								
0	–	64	58	72	57	56	58	35	43	55
20	UAN	70	62	76	62	75	66	39	47	62
40	UAN	65	56	73	60	59	73	37	41	58
20	AN	64	66	78	64	61	71	38	47	61
40	AN	69	66	76	69	61	66	35	44	61
20	Urea	67	63	76	65	69	76	37	48	63
40	Urea	70	69	74	68	67	68	43	51	64
20	Urea + NBPT	64	63	79	65	82	72	41	46	64
40	Urea + NBPT	70	70	83	70	67	67	42	48	65
LSD(0.10)		5	5	7	4	11	9	NS	NS	6

Assuming soybean prices of $5.00/bu and $0.30/lb N, these results would show a return of $35.00 per acre for a $6.00 per acre investment in 20 lb N. BC

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