Development of a Soil Quality Index

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Abstract

Soil quality can be defined for issues like productivity, environmental quality or human health. Good soil quality is a key to sustainable agriculture. If chemical, physical or biological components of soil degrade then soil quality declines and agricultural production cannot be maintained. Specific indicators of soil quality need to be identified and measured, and acceptable limits defined. Further, the data from several indicators must be combined meaningfully. We have developed a method to integrate multiple variables, such as those defining soil quality, into an index which can then be used to produce soil quality maps. This procedure requires the definition of critical values for each soil quality variable and a decision about which soil variables must be acceptable for a soil to be designated as having “good quality.” The method is flexible enough to compare soils of different regions or simply to evaluate different management practices or soil treatments.

Introduction

Recently there has been increasing interest in the concept of soil quality as related to agricultural productivity and sustainability. It is now becoming evident that the development of better yielding varieties and crop diversity for greater food production cannot overcome problems of poor soil quality. It is imperative that we develop methodologies that will enable us to monitor soil quality on a landscape basis in any area of the world.

Soil quality can be defined in terms of agricultural productivity, environmental quality or land use applications. For each of these definitions different soil parameters and criteria may be used to describe and quantify soil quality. For this analysis we are interested in soil quality as it pertains to agricultural production and/or management practices. Thus, the first step in evaluating soil quality is to identify those specific soil parameters that are desirable for sustained agricultural production. These include chemical, physical and biological properties (i.e., parameters) such as pH, soil organic matter, bulk density, microbial biomass, microbial respiration, water retention, soil depth and total nitrogen. However, no single parameter is likely to serve as a consistently reliable and ideal indicator of soil quality. Thus, for any given location, the information from measurements of several soil parameters must be combined in a meaningful way to provide an index of soil quality.

The identification of specific soil quality parameters does not address the complexity of integrating multiple variables into an overall soil quality index. The integration method must be applicable to large landscape areas while accounting for local soil variation, and it must provide estimates of soil quality from a few known values. We have developed an approach for integrating an unlimited number of soil quality parameters into a soil quality index. Our approach uses geostatistical analysis of measured parameters over a landscape to estimate values for locations that have not been sampled. Through an estimation procedure, termed multiple-variable indicator kriging (MVIK), maps are developed that model the probability of a soil meeting predetermined “good” soil quality criteria. The method is capable of defining soil parameter gradients, boundaries and interactive effects through integration of criteria developed by soil quality experts. This method is particularly useful in evaluating and monitoring long term changes in soil quality due to management practices or soil treatments. This paper presents a working example of this technique for a field site where several soil quality parameters were measured at 220 locations.

Field Sampling and Analysis

Soil samples were taken from an agricultural field in a winter wheat-green pea rotation. The soil is a deep loess mollisol classified as a Pachic Ultic Haploxeroll. The sampling scheme was designed to take advantage of geostatistical analysis methods. A total of 220 samples were taken over approximately 0.5 ha (50 x 110 m). The sampling was on a 10 x 10 m regular grid with random sampling throughout the larger grid. At each sampling location approximately 200 g of soil from the top 5 cm was placed in a plastic bag sealed and stored at 4^{o}C until analyzed. Several chemical and biological parameters were measured on each soil sample; however, for the working example presented in this paper only three parameters are considered to ensure simplicity, i.e., electrical conductivity, pH and inorganic nitrogen (NH_4^+ and NO_3^-).

Single Parameter Analysis

Individual parameters; such as pH, can be analyzed using geostatistics to produce single parameter landscape maps. In this procedure a number of locations are sampled and specific parameters are measured. Table 1 shows 3 of our 220 sample locations where soil samples were analyzed for electrical conductivity (Cond), pH, and inorganic nitrogen (In-N). The differences between the individual raw data values were calculated as a function of the distance between samples. A plot of average variance function vs. separation distance (or lag) is called a variogram. In this analysis we used a related measure that accounts for changing sample means and variances; this is called a correlogram (Rossi et al., 1991) and is illustrated in Figure 1a for pH. The plot indicates that sample values separated by distances less than 30 to 40 m are correlated with each other. This relationship can be modeled (dotted line) and used to estimate values at unsampled locations using a procedure called kriging. Kriging produces a map of pH values over the entire landscape (Figure 1b). This pH map is in the same units as the original data and can be used to identify localized areas of high or low pH. This procedure can be repeated for any biological, chemical or physical measurement resulting in a series of contour maps representing different variables.

Table 1. Example Data Set from Three Field Locations Using Measured Variables Electrical Conductivity (COND), pH and Inorganic Nitrogen (In-N).

Location (meters)	COND (DS/m)	pH	In-N (mg/kg)
5,5	1.73	4.93	20.7
20,10	2.16	5.32	16.0
95,5	2.69	5.37	27.3

Field size was 110 x 50 meters.

Indicator Transform

When data are not distributed normally, or are to be evaluated against some critical threshold, the indicator transform is a useful procedure (Journel, 1983, 1988; Isaaks and Srivastava, 1989). The indicator transformation is a simple binary transformation whereby each datum is compared to some cutoff value and coded as either 0 or 1 before valioglaphy or kriging. The threshold value is arbitrary and will depend upon the objective of the study. For example, a pH threshold of 4.0 might be selected as the minimum requirement for successful crop production. Untransformed pH data for each sampled location would then be evaluated against the value 4.0 and coded accordingly, resulting in a new data set comprised of 0s and 1s. For this work each datum was coded as 0 if it was below the chosen criteria or critical value, or 1 if it exceeded the predetermined threshold.

Like untransformed data (e.g., Figure 1) the indicator coded data can be analyzed with variography, modeled, and used to estimate values at other locations (via kriging), which will range from 0 to 1. These numbers correspond to the probability that the unknown values are greater or less than the specified threshold value. Table 2 shows an example of the indicator transformations for 3 variables measured at 3 locations. The transformed data for pH was modeled through variography and unknown locations estimated by kriging. Figure 2 shows the kriged map of the transformed pH data, which is a probability map (0 to 1) that pH is above 5.12 (Table 2). The lighter shades represent areas of low probability that pH was above 5.12 while the darker shades are areas of higher probability that pH was above 5.12. For this example a single number (the median) was chosen to evaluate the data, however, in reality soil variables might require that a critical range be designated as the threshold rather than a single value. Use of a critical range would cause data that was too high as well as data that was too low to be coded as 0.

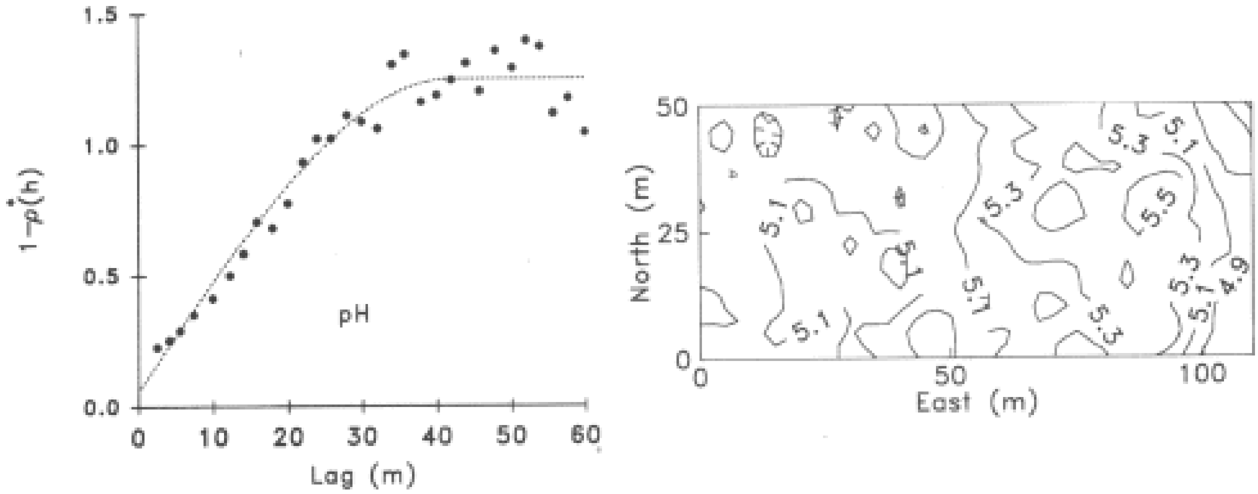

Figure 1. (a) Correlogram (lag Variance Plot) of pH and a Model (Dashed Line) Describing the Relationship between Samples; (b) A Contour Plot of pH Developed from Estimating Unsampled Locations through the Kriging Procedure

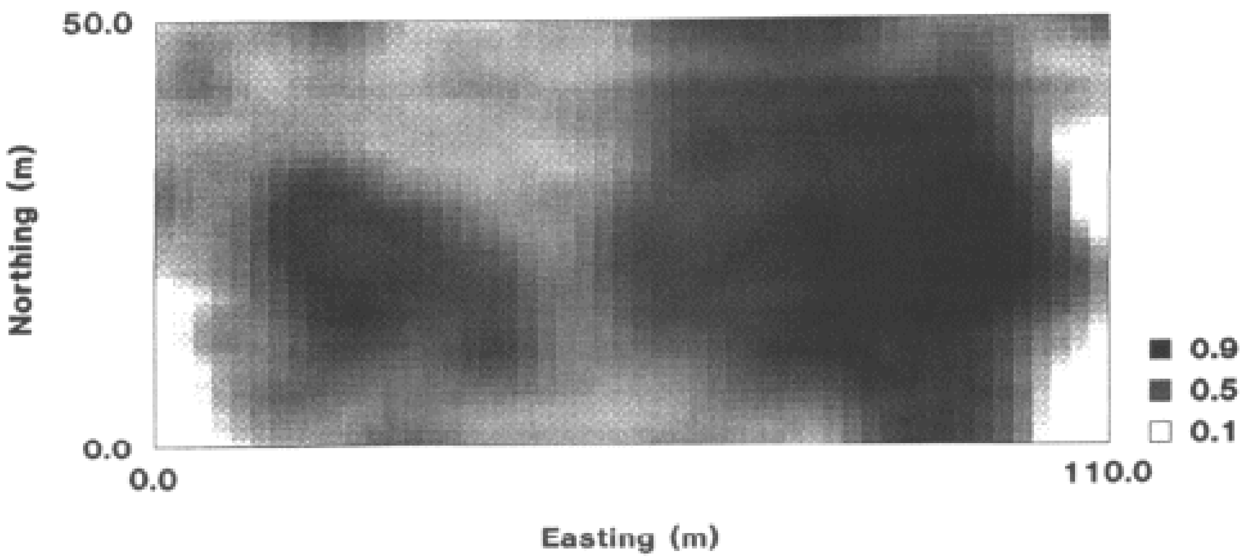

Figure 2. Grey Scale Plot of Indicator Transformed pH Data. The Scale is from 0.1 (White, to 0.9 (BlacK) ProDablllty ofMectiilg the Critical Thrcshold Valuc for pH, which for This Example is 5.12.

Table 2. Indicator Transformation of Raw Data into 0s and 1s Based on Being Below or Above the Median Value, Respectively.

Location (meters)	COND (dS/m)	pH	In-N (mg/kg)	Indicator Values		
				COND	pH	In-N
	(2.00)*	(5.12)*	(18.3)*			
5,5	1.73	4.93	20.7	0	0	1
20,20	2.16	5.32	16.0	1	1	0
95,5	2.69	5.37	27.3	1	1	1

* Critical threshold value or median

Multiple Variable Indicator Transform

Integration of several soil variables to evaluate soil quality is intuitive (Smith et al., 1993). It also seems likely that using the probability of locations meeting specified soil quality criteria is more useful than raw data maps or a synthetic (e.g., multiplicative) index. Integration of multiple variables can be accomplished following the indicator transformation of each single soil quality variable. This requires that a critical threshold value be identified for each variable. Table 3 shows the individual indicator transformations for three example variables using the median as the critical value. The pattern of 0s and 1s for each location are then used collectively to evaluate soil quality.

Table 3. Multiple Variable Indicator Transform of Indicator Values into Combined Indicator Values Based on at Least I Indicator Value Per Location Being Acceptable (COMB1); at Least 2 Indicator Values Being Acceptable (COMB2); or Requiring That All Indicator Values Be Coded Acceptable (COMB3) for the Location to Have a Combined Acceptable Value (1).

Location	Indicator Values			Combined Indicator Values		
	COND	pH	In-N	COMB1	COMB2	COMB3
5,5	0	0	1	1	0	0
20,10	1	1	0	1	1	0
95,5	1	1	1	1	1	1

To integrate the individual indicators a second decision needs to be made about how many and which variables at any location must be coded as acceptable (i.e., coded 1) in order for that location to be deemed acceptable. For example, Table 3 presents 3 alternative scenarios. In the first, COMB1, only one soil variable needs be coded acceptable for the integrated indicator value to be coded acceptable. The second, COMB2, requires at least 2 variables at any location be coded acceptable for the integrated value to be 1. And finally, COMB3 requires that all three variables meet the specified criteria for the location to be considered acceptable.

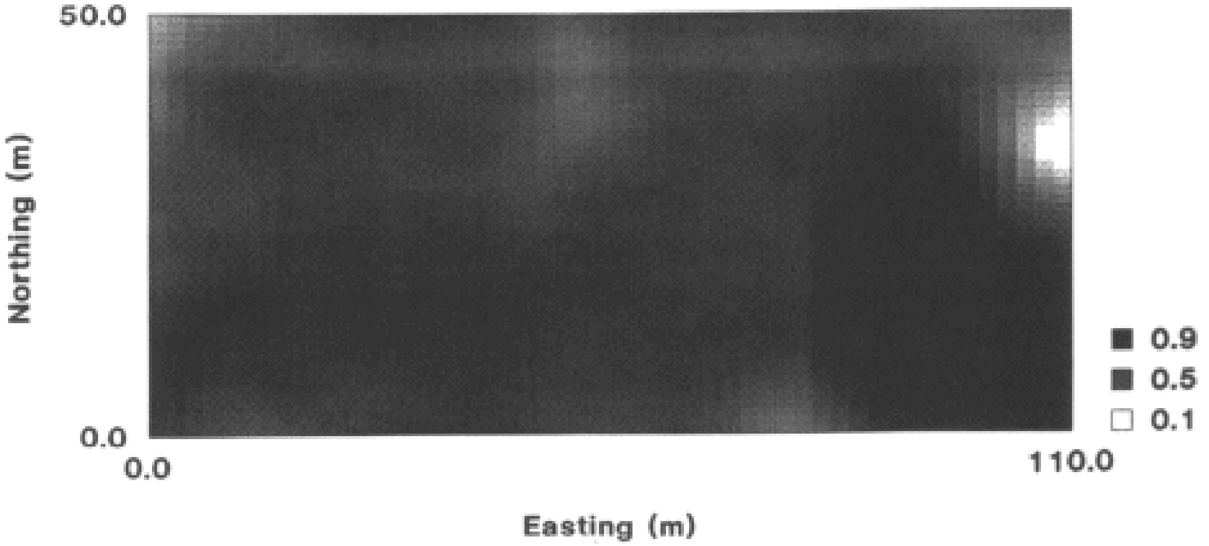

Figure 3. Grey Scale Plot of COMBI Where at Each Location Only One Variable is Required to Meet the Critical Value.

If we compare COMBI to COMB2 to COMB3, it is obvious that we are progressively restricting the areas of acceptability by requiring more stringent compliance with the chosen criteria. The combined indicator values, 0s and 1s for each location, are again modeled through variography and unknown locations estimated by kriging. Figure 3 is a map of COMB1, where only 1 variable is needed to meet the chosen criteria for a location to be acceptable. This figure shows large areas of the landscape that have a high probability of having acceptable soil quality. Figure 4 shows a more restricted case where at least 2 variables at each location had to meet their criteria (i.e., COMB2). This map shows more than half the area having an intermediate probability of being acceptable. Figure 5 is the most restrictive case where all parameters were required to meet the chosen criteria before a location could be designated as having acceptable soil quality (i.e., COMB3). It shows that only a few locations in the study field have a high probability for each of the 3 soil variables, i.e., electrical conductivity, pH, and inorganic-N, being above the median.

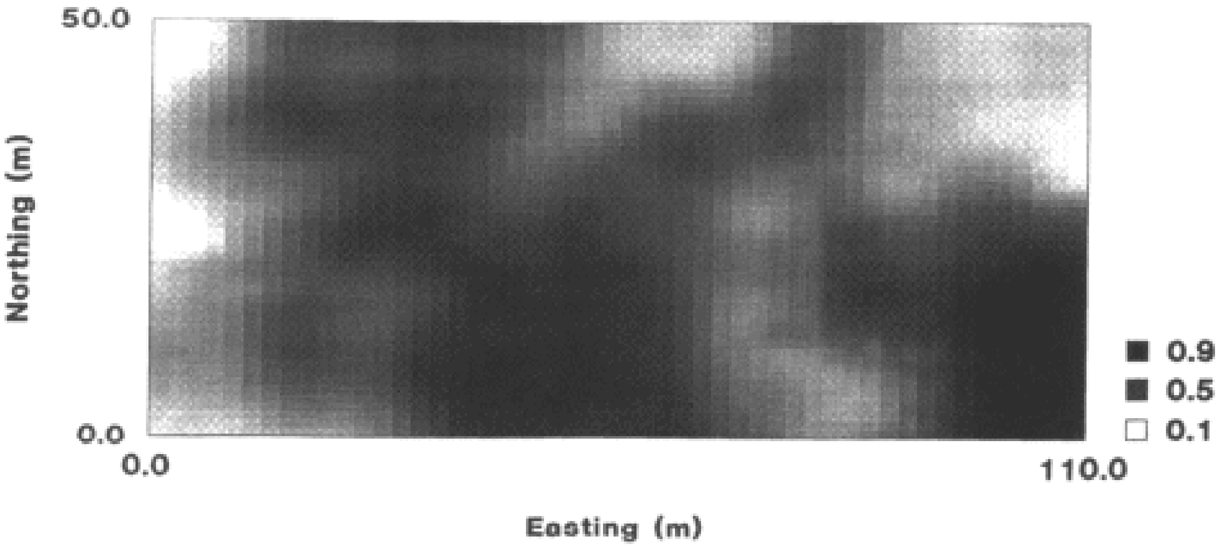

Figure 4. Grey Scale Plot of COMB2 Where Two Variables are Required to Meet Their Critical Values for Each Location to Be Acceptable. The Scale is the Probability of Meeting the Chosen Criteria.

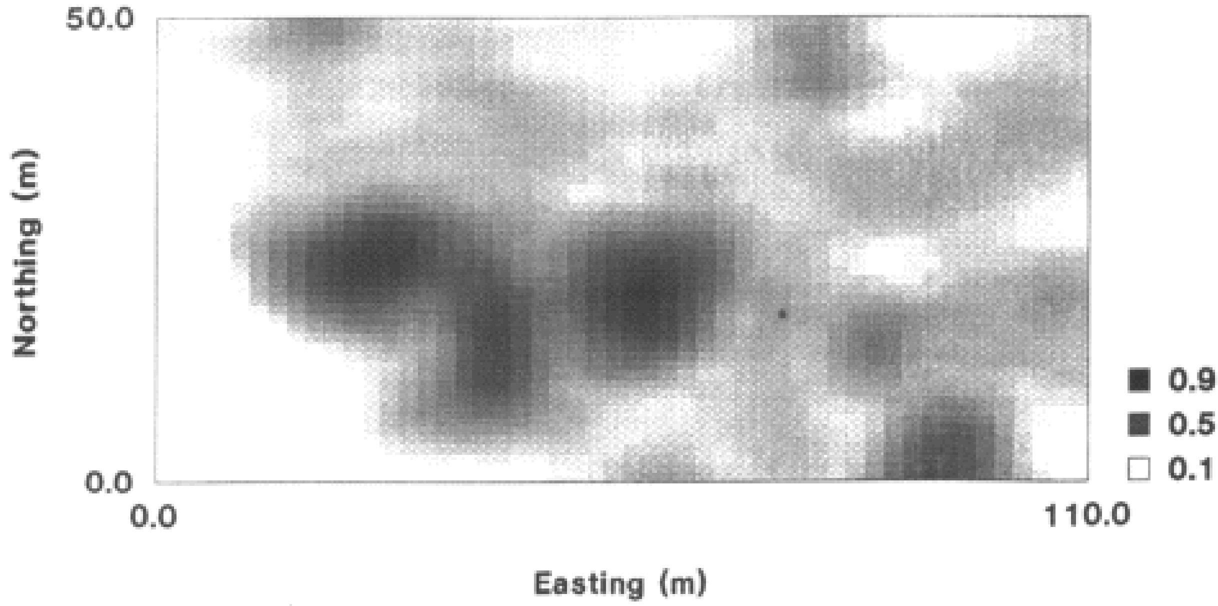

Figure 5. Grey Scale Plot of COMB3 Which Shows the Areas of Probability That All Variables Meet the Specified Criteria for Each Location.

As previously mentioned, the number of sampling point locations can be infinite as well as the variables measured. Therefore, the final integration of variables by this method can be quite flexible depending upon the purpose of the study. For example, if 50 variables are measured and indicator transformed, the final integration may require that 8 of 10 critical parameters meet the criteria for a location and any 15 of the remaining 40 also meet the chosen criteria. For environmental risk assessment of chemical contamination many critical thresholds may be envisioned. Thus, alternative scenarios can be tested, say for example where 8 out of 15 parameters meet specified values, then 12 out of 15 and so on. This flexibility gives the procedure a wide range of applications and enhances its usefulness.

Conclusions

Soil quality for agricultural production can be defined by measuring specific soil indicators spatially over landscapes. Several soil indicators have been proposed to monitor soil quality, however, indicators may change depending upon the soil quality monitoring objective.

Because soil quality is comprised of many variables an integration procedure is needed to establish a soil quality index. We have developed an integrative procedure [multiple variable indicator kriging (MVIK)] that provides a means of integrating soil quality parameters into an index to produce soil quality maps on a landscape basis. These maps indicate areas with a high probability of having good soil quality according to predetermined criteria. This procedure and the resultant maps can be produced at various time intervals to monitor changes in soil quality due to management practices or treatments. Moreover, by evaluating individual indicators over time, it is possible to identify specific soil properties that are affected by management practices. The probability maps produced from MVIK are more useful than rating soil quality on a scale of 1 to 10, and provide more flexibility to incorporate management decisions and environmental constraints into the soil quality profile.

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