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Research Article

Field Scale Studies on the Spatial Variability of Soil Quality Indicators in Washington State, USA

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Arable lands are needed for sustainable agricultural systems to support an ever-growing human population. Soil quality needs to be defined to assure that new land brought into crop production is sustainable. To evaluate soil quality, a number of soil attributes will need to be measured, evaluated, and integrated into a soil-quality index using the multivariable indicator kriging (MVIK) procedure. This study was conducted to determine the spatial variability and correlation of indicator parameters on a field scale with respect to soil quality and suitability for use with MVIK. The variability of the biological parameters decreased in the order of respiration > enzyme assays and qCO_2 > microbial biomass C. The distribution frequency of all parameters except respiration were normal although the spatial distribution across the landscape was highly variable. The biological parameters showed little correlation with each other when all data points were considered; however, when grouped in smaller sections, the correlations were more consistent with observed patterns across the field. To accurately assess soil quality, and arable land use, consideration of spatial and temporal variability, soil conditions, and other controlling factors must be taken into account.

1. Introduction

The challenge of feeding 9 billion people by the year 2050 is intimidating. Multiple strategies are needed to meet this challenge. Strategies include reducing human population growth, decreasing protein consumption, increasing crop and animal production, and increasing the agricultural land base for production. While some food staples (crops and livestock) are increasing, others are static or decreasing [1]. Currently food production for 6 billion people occurs on 13% of the global land surface [2].

The current strategical focus has been on increasing yields and increasing the agricultural land base [3, 4]. The challenge to moving these strategies forward is to evaluate (1) new land for the ability to produce crops and (2) the soil's resilience and resistance to degrade over time from agriculture management. Thus, the concept of soil quality needs to be developed to evaluate and manage land developed for increased crop production [5, 6]. In a global context, soil quality affects not only soil productivity but is also a significant factor governing environmental quality, human and animal health, and food safety and quality [7]. Soil quality of current and future agricultural land is of similar importance to humankind as air and water quality; thus, it is apparent that simply protecting soil quality by slowing soil degradation or maintaining the current level of soil health will not provide the soil quality that will be needed for future generations. Soil quality must be improved as well.

To properly assess soil quality, appropriate soil indicators or properties must be identified. These indicators must be quantified on a local and landscape basis as a means for making small-scale and regional management decisions. Indicators proposed to asses soil quality are diverse and include chemical, physical, and biological variables as well as descriptive terms [8]. Once the indicators are identified, methods need to be developed to integrate the indicators into a soil quality index. This integration procedure will require the use of information from all indicators as well as their interactions [9]. Several years ago, a procedure was developed to spatially evaluate soil quality. The procedure, multiple

variable indicator kriging (MVIK), categorizes numerous variables based on specific criteria producing a probability that an "area" or "soil" meets qualified standards [9]. For example, criteria can be developed and parameters measured and integrated to evaluate if a land area is suitable for development of irrigated agriculture. The MVIK method has been used to map the distribution of soil nutrients [10], define zones of soil pollutants [11], evaluate chemical health risks of groundwater [12], evaluate soil quality indices [6, 13], classify soil degradation in agricultural lands [14], and assess groundwater quality for irrigated agriculture [15].

The underlying principle of MVIK is the spatial variability of indicator parameters across the landscape. In this study, we have chosen several chemical and microbiological parameters that have been shown to be important in agriculture and are considered good indicators of soil quality [8, 9]. These indicators, not meant to be inclusive, include microbial biomass, respiration, metabolic quotient (qCO_2), dehydrogenase, and phosphatase enzyme activity as well as pH, organic carbon (%C), and electrical conductivity (EC). We explore the spatial variability and relationships of indicators across a small landscape that was intensively sampled. Knowing the range and spatial variability criteria for MVIK, we can develop a system for the evaluation of suitable land for crop production.

2. Materials and Methods

2.1. Soil Collection. Soil samples were taken from a slightly north-sloping agricultural field in Southeastern Washington State, USA. The field had previously been cropped to winter wheat (*Triticum aestivum L.*). The soil is a Palouse silt loam classified as a fine-silty mixed, superactive, Pachic Ultic Haploxeroll having an average organic C content of 1.5% and a total N content of 0.15%.

The climate of this region is characterized by cold wet winters and hot dry summers with 80% of the annual 500 mm of precipitation being received between October and March. Soil samples (220) were collected in October (Fall) from an area of approximately 0.5 ha (50 × 110 m). The sampling design was a regular 10 × 10 m grid with smaller sampling distances randomly placed throughout the larger grid. At each sampling location, approximately 200 g of soil was collected from the top 10 cm, placed in a plastic bag and stored at 4°C until analyzed.

The 220 soil samples were analyzed for total organic C, pH, electrical conductivity (EC), microbial biomass C (SIRC), basal respiration, phosphatase (PNP), dehydrogenase (TPF), and calculated metabolic quotient (qCO_2). Analyses were done in triplicate.

2.2. Biological Assays. Microbial biomass was assayed using the substrate induced respiration (SIR) method developed by Anderson and Domsch [16]. Triplicate 10 g (dry weight) samples of soil were weighed into 40 ml glass vials, brought to 20% moisture (w/w), covered and kept in the dark for 7 days at 23.5 ± 0.5°C. After the preincubation, each sample was amended with a saturating level of 600 ug glucose (240 mg C) g^{-1} soil, bringing the soil moisture content to 25% (w/w) (−30 kPa). Water only was added to each control sample also bringing the soil to 25% (w/w) (−30 kPa). All tubes were flushed with hydrated air and capped with a septum. Headspace CO_2 was measured from each vial at 3 and 24 h by injecting 0.2 ml of headspace in to a gas chromatograph. Microbial biomass carbon (SIRC) was calculated using the equation published by Anderson and Domsch [16]. Soil respiration (RESP) rate was calculated as the average rate of CO_2 production per hour from the control samples (only water added).

Soil dehydrogenase and phosphatase activity was measured using the modified technique of Bolton et al. [17]. The substrate for dehydrogenase activity was 2,3,5-triphenyltetrazolium (3% w/v) and p-nitrophenol phosphate for phosphatase activity. Enzyme assays were made in triplicate on moist soil (10 g dry weight) and reported for dehydrogenase as 10^{-5} μmol triphenylformazan g^{-1} min^{-1} (TPF) and for phosphatase as 10^{-2} μmol p-nitrophenol g^{-1} min^{-1} (PNP).

Metabolic quotient (qCO_2) is defined as the basal respiration per unit of microbial biomass in units of μg CO_2-C μg^{-1} biomass-C h^{-1} and was calculated from the control sample respiration rate at the end of the incubation period divided by the SIRC biomass [18].

2.3. Chemical Analysis. Total organic C was measured in triplicate on each of the 220 soil samples by a wet oxidation method [19]. The pH and electrical conductivity (EC) measurements were made on saturated pastes of soil (1 : 1 w/w, soil : water).

2.4. Statistical Methods. Summary statistics were calculated for the 220 samples including mean, median, and standard deviation (SD), coefficient of variation (%CV), and skewness. In addition, Pearson correlation coefficients were calculated for untransformed data. We also constructed maps of the spatial distributions for each individual variable over the 0.5 ha area from untransformed data using a weighted least squares algorithm. Every point at an unsampled location is calculated by a weighted quadratic multiple regression on all the points [20].

3. Results

3.1. Chemical and Biological Indicators. Univariate statistics for measured soil properties are shown in Table 1. For the chemical properties the mean and median values were similar and the skewness values were low to moderate (EC). The relatively high variability of total C (%CV = 39.6) on this landscape was related to spatial patterns. We observed lower values on the eastern 25% of the field (see Figure 2). However, in general, the %CVs for chemical properties on a landscape area are typical [21].

All biological variables, except microbial respiration, also showed similar mean and median values with low to moderate skewness (Table 1). The sample distribution for respiration exhibited significant skewness (4.35) due to a few

Table 1: Univariate statistics for measured soil properties ($n = 220$). Total C, pH, EC: electrical conductivity; SIRC: microbial biomass C by substrate-induced respiration; RESP: nonamended soil respiration; PNP: phosphatase activity; TPF, dehydrogenase activity and qCO_2, metabolic quotient.

	Chemical Properties			Biological Properties				
	C (%)	PH	EC (dS m^{-1})	SIRC (mg C kg^{-1})	RESP (mg C kg^{-1} h^{-1})	PNP (μmol g^{-1} $min^{-1}\times 10^{-2}$)	TPF (μmol g^{-1} $min^{-1}\times 10^{-5}$)	qCO_2[a] ($\times 10^{-3}$)
Mean	1.70	5.14	2.13	642	1.65	3.91	4.33	1.04
Median	1.76	5.12	2.00	620	1.41	3.85	4.36	1.04
SD	0.67	0.24	0.68	198	1.17	1.30	1.57	0.44
% CV	39.6	4.70	32.0	31	71.0	33.2	36.1	42.4
Skewness	−0.22	0.12	1.81	1.5	4.35	0.53	0.12	0.62
Minimum	0.35	4.56	0.95	227	0.53	1.13	0.75	0.12
Maximum	2.97	5.74	5.79	1694	9.44	9.21	7.96	2.61

[a] μg CO_2-C g^{-1} h^{-1}/ μg biomass C g^{-1} soil.

high outlier values. This outlier effect is confirmed by the 75th percentile value (1.76 mg kg^{-1}) being close to the mean value of 1.65 mg kg^{-1} (data not shown) and also reflected in the CV of 71%. Microbial biomass C ranged from 227 to 1694 mg C kg^{-1} soil with a CV of 31%, typical for this biological parameter [22]. Values for metabolic quotient (qCO_2) ranged over an order of magnitude, from 0.12 to 2.61 $\times$ 10^{-3} μg CO_2-C μg^{-1} biomass-C h^{-1}, with a CV of 42%. The enzyme assays, phosphatase and dehydrogenase, showed similar variation among samples with CVs of 33 and 36%, respectively.

3.2. Spatial Mapping and Correlation. The distribution of electrical conductivity (EC), dehyrogenase (TPF), and respiration (RESP) over the 0.5 ha sampling area are depicted in Figure 1. Most sample respiration rates were near the overall mean of 1.65 mg-C kg^{-1} h^{-1} (Figure 1, RESP). However, we also observed a zone of higher values in the 60–70 m Easting area and a few other elevated values at about 85–100 m Easting. In contrast, dehyrogenase activity was distributed throughout the field in zones of high and low activity (Figure 1, TPF), much different than what might have been predicted from the univariate statistics (Table 1) [23, 24]. Highest TPF activity was observed from the 0 m to 20 m Easting, the portion of the field that also had the lowest respiration values. Dehyrogenase activity was lower than the mean at random locations mostly in the north half of the field between 30 and 100 m Easting. Values of EC, an important soil variable since soluble salts may affect microbial and enzyme activity [25, 26] were generally similar to the overall field mean except in the 110 m easting area and in a few locations randomly distributed across the field (Figure 1, EC). The trend in EC was generally opposite of TPF and, in some areas, seemed to be similar in pattern to RESP.

Figure 2 shows the spatial distribution of total C (%C), pH, and microbial biomass (SIRC). Microbial biomass was characterized by a fairly uniform spatial distribution with many values close to the field mean (Figure 2 SIRC). However, we also observed a significant area of the field

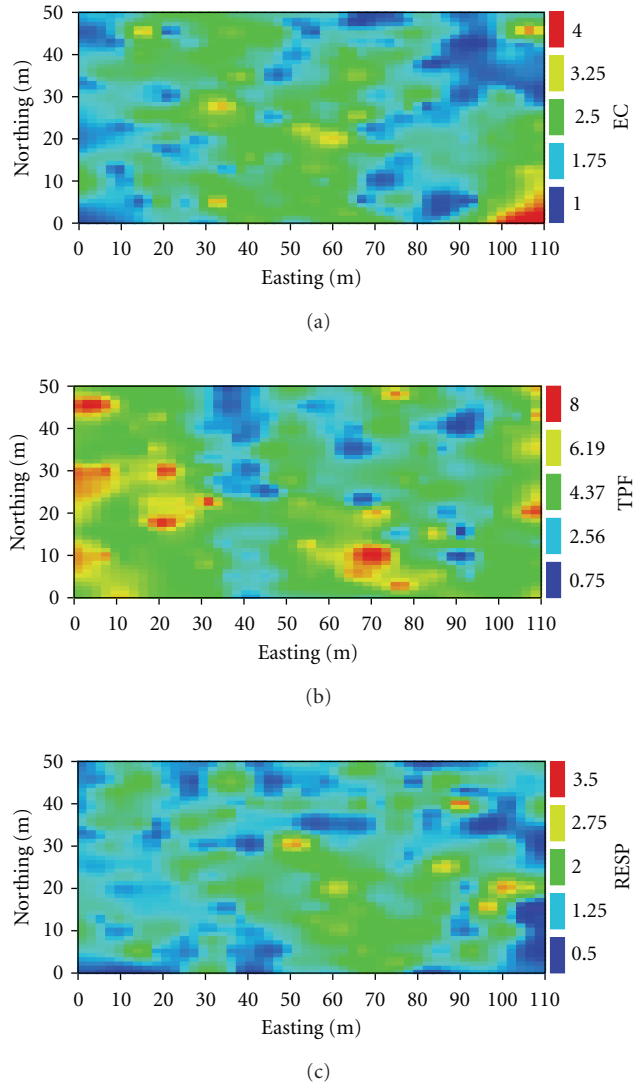

Figure 1: Interpolated spatial maps, over the 110 by 50 m field, of electrical conductivity (EC), dehydrogenase (TPF), and microbial respiration (RESP). Units are the same as Table 1.

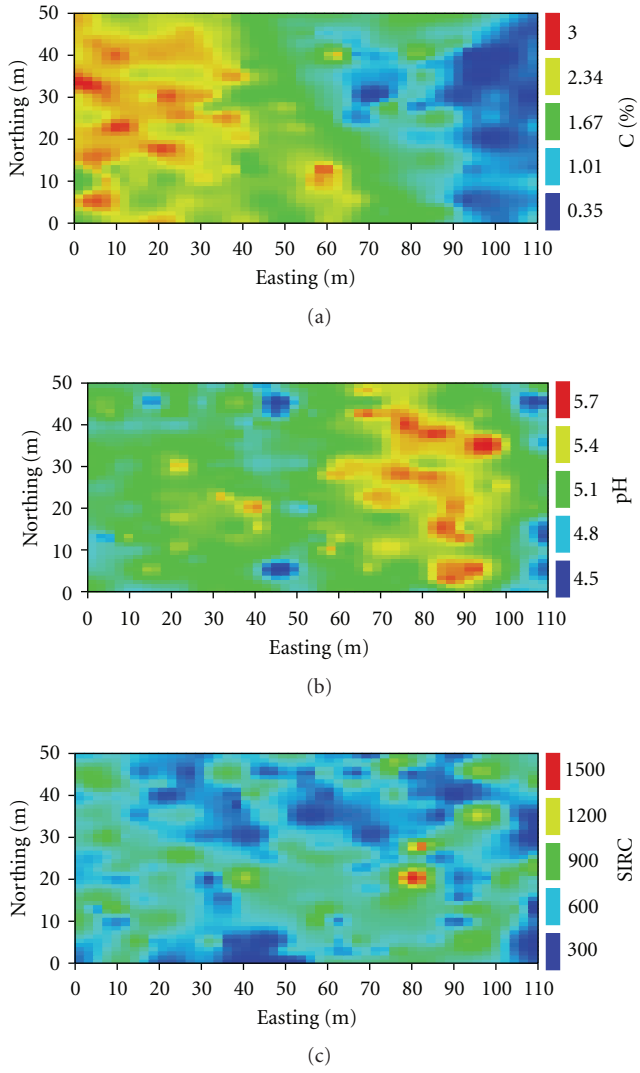

Figure 2: Interpolated spatial maps, over the 110 by 50 m field, of %C, pH and microbial biomass C (SIRC). Units are the same as Table 1.

with values 50% greater than the mean (green). Soil pH was less evenly spatially distributed across the field than SIRC (Figure 2 pH). We observed a zone with relatively high values of pH between 60 and 100 m Easting. Lower values of pH in the eastern edge of the field also coincided with a decrease in SIRC and %C (Figure 2 %C). Total C was distributed with highest concentrations in the west half of the field and lowest concentrations in the east. However, the grading from high to low concentration was not smooth, and the field appears to be divided into two patches. Values near the overall field average (green) occurred mostly in a relatively narrow band with a NW-SW orientation, near the center of the field.

Table 2 provides the Pearson correlation coefficients (r) for the measured soil properties. We calculated r for two spatial scales, full field or subfield. Full field calculations represent an overall r value based on all 220 data points. Subfield calculations were based on the data from each of four 27.5 m W to E subsections of the field from 0 to 110 m. Analyses of the entire field generally showed poor correlation's between variables except between RESP and qCO_2 and SIRC and TPF (Table 2). Transformation ($\log_{10}$) the data did not improve the overall correlation's with the only increase due to normalizing RESP.

Separate analyses of the 27.5 m subfields revealed areas of relatively high and low correlation obscured at the scale of the entire field. For example, the full field correlation coefficient of SIRC and RESP was 0.15 ($n = 220$, $P < .05$); however, these two variables were significantly and positively correlated in two subfields lying between 0 and 55 m Easting, section of the field, (0.48, $n = 55$, $P < .05$ and .54, $n = 55$, $P < .05$), respectively. In a more extreme example, the overall field correlation of SIRC and PNP was 0.02 ($n = 220$, $P < .05$), while correlation coefficients in the subfields varied: near 0 in the 0 to 27.5 m section of the field, slightly positive in the 27.5 to 55 m subfield, slightly negative in the 55.0 to 82.5 m subfield, and significantly positive in the 82.5 to 110 m subfield.

By accounting for this intrafield heterogeneity, the correlations between variables were more similar to the qualitative, visual analysis of Figures 1 and 2. For example, RESP and EC exhibited some positive correlation (0.29, $n = 55$, $P < .05$), in the 0 to 27.5 m Easting subfield (Table 2, Figure 1). However, in the subfield located from 27.5 to 55.0 m, where EC was increasing, the correlation coefficient decreased to 0.10 ($n = 51$, $P \leq .05$) (Figure 1). In the east half of the field (55+ m Easting), correlation between RESP and EC became increasingly negative (-0.14, $n = 55$, $P < .05$ and -0.18, $n = 53$, $P < .05$) due to opposing spatial gradients shown in Figure 1. Soil microbial biomass was uncorrelated with %C over the entire field (Table 2, Figure 2); however, SIRC was significantly correlated with pH in all except in the 55.0 to 82.5 m subfield (Table 2) also suggested by Figure 2 which shows SIRC as constant over the landscape and pH as increasing.

4. Discussion

The objectives of developing a method to evaluate soil quality include (1) the ability to monitor changes in the soil over time and be able to quantify the direction and rate of change, (2) evaluation of the time rate of change in soil quality due to specific management in both the short and long term, and (3) the ability to detect patterns of soil quality at different spatial and temporal scales. To meet these objectives the evaluation methodology, such as MVIK, must be based on sensitive indicators of change in soil quality that are stable and predictable with respect to other soil properties such that comparisons between different locations and between different time periods can be made.

Several biological indicators of soil quality have been proposed because they are thought to be integrative variables, sensitive to changes in soil degradation or improvement [27–30]. However, we are interested in mapping soil quality on the landscape level to monitor change or implement remediation, and there are several problems associated with the use of only biological indicators over field to landscape scales.

First, biological indicators are likely to be more variable in time and space than chemical or physical parameters and

Table 2: Pearson correlation (r) matrix correlating chemical and biological soil parameters on a subfield and full field basis (whole field $n = 220$, subfield $n = 50$ to 55). Values in red are significant correlations where $.01 < P < .05\%$ probability level.

	%C		pH		EC		SIRC		RESP		PNP		TPF	
	Subfield	Full field												
pH	0.02	**−0.21**												
	0.21													
	−0.39													
	0.10													
EC	−0.18	−0.01	−0.29	**−0.35**										
	0.20		0.01											
	0.34		**−0.36**											
	0.07		−0.54											
SIRC	−0.01	−0.01	**0.39**	**0.31**	−0.04	−0.07								
	−0.02		**0.4**		0.27									
	0.02		0.09		−0.12									
	−0.04		**0.32**		−0.13									
RESP	−0.11	**−0.17**	0.14	**0.2**	0.29	−0.09	**0.48**	0.15						
	0.06		**0.37**		0.10		**0.54**							
	0.10		−0.21		−0.14		−0.05							
	−0.06		0.27		−0.18		0.17							
PNP	0.16	**0.32**	−0.01	0.14	0.15	0.08	−0.05	0.02	0.20	−0.01				
	0.23		**0.65**		0.27		0.28		0.30					
	0.01		0.04		0.17		−0.25		0.01					
	−0.16		0.3		−0.13		**0.33**		0.11					
TPF	0.14	**0.23**	**0.37**	−0.02	−0.16	0.02	**0.38**	0.22	0.03	0.04	−0.28	−0.05		
	0.07		0.3		0.32		**0.33**		0.26		0.13			
	0.31		−0.17		−0.06		0.18		0.28		0.15			
	0.08		−0.28		0.23		0.12		−0.05		0.07			
qCO_2	0.01	−0.01	**−0.43**	−0.11	0.01	0.04	−0.06	**−0.29**	**0.45**	**0.52**	0.16	0.13	−0.07	**−0.17**
	0.12		−0.07		−0.16		−0.21		**0.4**		−0.01		−0.08	
	0.09		−0.12		−0.04		−0.3		**0.73**		0.14		0.09	
	0.03		0.06		−0.03		0.12		**0.68**		−0.17		−0.03	

may also be influenced by these parameters [21]. Second, univariate statistics of biological indicators may be of limited use in the context of evaluating soil quality, because they only characterize a system at the overall scale and do not account for spatial patterns [23]. Finally, even if we account for the spatial and temporal variability of biological indicators, the precise relationship between the amount of a particular biological indicator and it's functional characteristics has yet to be determined [31].

These problems can become critical when using the MVIK procedure to evaluate specific criteria. The MVIK procedure uses cutoff values to determine if a criteria has been met, thus if indicators vary greatly in time, the cutoff value may not be stable and land evaluation may change.

The coefficient of variation for the biological variables measured in this study ranged from 31% for microbial biomass-C and 30% to 40% for the enzyme assays to 71% for soil respiration. Rochette et al. [24] found respiration measurements in a 1 ha field (average 50 sampling points) to have a CV ranging from 25% to 69% over the growing season. Bonmati et al. [25] found the CV for enzymes ranged from 28 to 60% in a small field (<0.1 ha). This is in contrast to many chemical and physical parameters that typically have a CV in the range of 5% to 25% on a spatial basis. While mean values or the relative ranking of variability may not change, actual estimates of statistical dispersion (e.g., standard deviation) will be affected by the size of the sampling unit especially for soil properties with strongly skewed distributions [32].

Understanding the spatial distribution of chemical and physical indicators of soil quality is likely to be important for corroborating biological data and necessary to help to explain the spatial variability of biological parameters. For example, Figure 2 shows areas of high and low concentrations of three variables occurring simultaneously in a single field. These distinct areas maybe caused by secondary or

tertiary factors affecting the primary variable of interest. Greater correlation between soil quality indicators in some sections of the field (Table 2) suggests the factors controlling these variables change over the landscape. For example, unlike the rest of the field, SIRC and pH were uncorrelated in the 55 to 82 m Easting section of the field (Table 2). Since the values of SIRC were distributed, on the average, similarly across the entire field, the lower correlation is likely due to increasing pH values in this section of the field seen in Figure 2. The gradient of pH across the field may have been related to patterns of NO_3 and soil moisture content, which decrease from W to E across the field (data not presented). These two soil variables, individually or in combination, may have influenced the increase in pH, and thus its correlation with microbial biomass. Thus, successful use of biological indicators for soil quality analysis will require an understanding their spatial variability as well as that of any underlying factors that might affect this variability.

Our data further illustrate that while the overall univariate distribution of a biological parameter may be normal for a field-size sample unit (Table 1), the variable may be distributed in zones of high and low concentrations within the field (i.e., TPF, Figure 1). Thus the full field mean value may be of little value for guiding management decisions. It would be impossible to manage this field to increase its biological potential based on univariate statistics alone. In order to be useful, we are required to sample in a manner that will allow us to identify and delineate the significant spatial patterns within the field. Contour maps for each soil parameter of interest are desirable but require more sampling and analysis meaning greater expense.

Two other aspects of soil quality indicators can affect land evaluation even using the MVIK procedure. Firstly, evaluating soil quality based on the quantity of a biological indicator assumes that laboratory analyses accurately represent conditions in the field. Secondly, a critical assumption is that the relationship between the quantity of a biological indicator and its activity is well understood and predictable. Yet, little attempt has been made to distinguish between these two facets of soil quality.

Thus based on this study we suggest that soil sampling for soil quality analysis using biological indicators should be conducted when the soils are between 50 to 70% of field capacity (−30 kPa), during mild temperature regimes (Fall or late Spring) and that enough samples be taken that contour maps can be developed. Other chemical data should be collected at the same time, such as pH and electrical conductivity, to provide collaborative information for the soil quality assessment. Biological indicators of soil quality are spatially variable; however, they are also sensitive indicators, thus with proper analysis and interpretation they will enhance our development of a soil quality index.

That biological indicators of soil quality should vary across the landscape or during the course of a season is neither novel nor surprising. This is why we developed the MVIK procedure to smooth the variability into a probably that can be used to define good soil quality or good arable land. However, the more stable the data used in the MVIK procedure the better the prediction of arable land. With the spatial variability information on an area basis we can use procedures such as MVIK to evaluate the probably that a new land base will be sustainable for agricultural production.

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