ASSESSING SPATIAL AND TEMPORAL NUTRIENT DYNAMICS WITH A PROPOSED NUTRIENT BUFFERING INDEX

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Abstract

Continued adoption of precision agriculture will lead to the accumulation of spatially and temporally dense soil fertility and yield data. Current soil fertility recommendation strategies use regional estimates of soil buffering properties to adjust application rates. A site specific nutrient buffering index (BI) is presented that uses accumulated yield maps and soil test data to locally estimate soil buffering properties relative to fertilizer additions and crop removal. BI is a quantity-intensity relationship ($\Delta Q/\Delta I$) where ΔQ is the net balance of a nutrient, and ΔI is the change in soil test concentration. BI is interpreted as the quantity of nutrient balance change responsible for one unit of change in soil test value. The site-specific BI concept and calculation procedures are presented using an example dataset for P and K.

Introduction

Precision agriculture adoption has reached the point where farmers have collected multiple years of dense spatial data from fields. For example, because of the adoption and increased use of yield monitors since the mid 1990s, multiple years of yield maps are now available for some fields. Another common precision agriculture practice is grid soil sampling. Multi-year datasets of soil fertility maps are not as common as multi-year yield datasets, because of the labor and expense required for sampling and analysis prohibit annual testing. On-the-go soil fertility sensors offer the possibility that, in the near future, producers may obtain dense chemical property maps rapidly and with less expense (Adamchuck et al, 1999, Birrel and Hummel, 2001, Christy et al., 2003; Collings et al., 2003). Yet even if soil sampling occurs only every two to four years, a temporal picture of nutrient availability will eventually be available. Temporal soil test data makes it possible to track soil test change and relate that change to factors such as current and past management, soil genesis, and spatial patterns of crop nutrient removal. Temporal evaluation of soil test change information might be a useful estimate of a soil's nutrient buffering capacity, and could then be used for modifying site specific fertilizer recommendations.

Site specific management of soil fertility requires the same set of considerations that are necessary for traditional whole-field management. Foremost is the need for models that effectively predict plant response to nutrient management options. Secondly, an estimate of site yield potential can be used to adjust input requirements. Of necessity, a current measure of fertility is required to determine the initial conditions from which nutrient need is based. This is the function of the soil test. Finally, calculation of an amendment recommendation often requires an estimate of the soil's response to that amendment. This last concept refers to the soil buffering capacity, which indicates the soil's ability to adsorb and to release labile nutrients. In summary, a fertilizer recommendation strategy accounts for plant response, site yield potential, current fertility levels, and soil response to nutrient additions and removals.

The functional relationships used to apply these considerations are based on state-wide or region-wide experimentation, and as such, inherently lack the input of local variability in soil and crop response to fertilizer addition. Localized methods were obviously too cumbersome to implement before the advent of site-specific agriculture. However, software and hardware tools have improved the analysis and management of temporal and spatial datasets. Additionally, farmers have begun to pool data in warehousing operations that intend to mine spatial and temporal data for more specific relationships (e.g. SST Developer Group, Soilteq Professional Services)[1].

More On Buffering

In general, the buffering capacity of a system is defined as a ratio of change in quantity (ΔQ) to some change in intensity (ΔI), or $\Delta Q/\Delta I$ (Mengel and Kirkby, 1982). This relationship specifies that per some quantity added or subtracted (ΔQ), the system has changed in its ability to supply (ΔI). The pH buffering capacity of a solution, for instance, is the ratio of net balance in H+ (ΔQ_{H+}) to the change in H+ activity of the solution (ΔI_{pH}). In soils, pH buffering capacity is controlled by a number of factors including mineralogy, cation exchange capacity (CEC), exchangeable Al, Ca and Mg carbonates, and organic matter. The K buffering capacity of a soil would be characterized by the net balance of K added and removed (ΔQ_K) divided by the change in concentration of K (ΔI_K) in the soil as measured by soil tests. Buffering of cations in the soil is largely controlled by clay mineralogy, and is reflected by CEC. Phosphorous buffering capacity is controlled by clay mineralogy, Fe and Al oxides and hydroxides, Ca and Mg carbonates, and by organic matter (Pierzynski et al., 2000).

Soils vary widely in their buffering properties depending on their mineralogical, chemical, and biological properties. Where information is not available about a soil's buffering capacity, assumptions are made. University of Missouri recommendations for fertilizer additions use variables, such as CEC, OM, and soil texture, to adjust for a site's buffering capacity (Buchholz et al., 1983). Information about a site's buffering properties is useful in fertility recommendation models, and information obtained from actual measurement of site buffering is an improvement on general state-wide or regional relationships. Still, techniques are needed for bringing this information to site-specific fertility recommendations.

We propose a site specific implementation of a Buffering Index (BI) that uses site specific data to calculate $\Delta Q/\Delta I$ for soil nutrients. Net nutrient balance (ΔQ_n) is the sum of nutrient change for nutrient n within a time interval t. Net nutrient balance can be calculated from maps or records of fertilizer application (F), and crop removal data (C) (Eq. 1).

$$\Delta Q_n = F_n - C_n \qquad [1]$$

1. Mention of trade names or commercial products is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the United States Department of Agriculture.

Soil test change (ΔI_n) is the estimated change in nutrient concentration over a time interval Δt. ΔI_n can be estimated by simple subtraction between two soil test dates. Alternatively, when more than two soil test dates are available, the rate of soil test change (βSt_n) can be estimated by statistical methods. βSt_n, multiplied by Δt, calculates the total soil test change (ΔI_n) (Eq. 2).

$$\Delta I_n = \beta St_n \times \Delta t \qquad [2]$$

The ratio of net nutrient balance (ΔQ_n) to measured or estimated soil test change (ΔI_n) provides a nutrient buffering index (BI) (Eq. 3).

$$BI = \frac{\Delta Q_n}{\Delta I_n} \qquad [3]$$

Objectives

The objective of this investigation is to present and illustrate the concept of using temporal, site-specific yield and soil-test data to calculate a nutrient buffering index that can be used to improve soil fertility management.

Materials and Methods

Spatial and Temporal Data

Data used for this analysis were gathered from an 88-acre field in the Central Claypan Region (MLRA 113) near Centralia, Missouri. Soils at the site are generally classified as fine, smectitic, vertic epiaqualfs and are characterized by a well-developed argillic horizon, or claypan. The surface of the field is gently sloping (1-3%). Sideslopes are eroded, and depositional areas are present along the central drainage channel of the field. Surface textures are silty clay to silty clay loam. Since 1993, grain has been harvested using a Gleaner R46 combine outfitted with an AgLeader YM2000 yield monitor (Kitchen et al., 1999). Soil samples were taken on a 30-meter grid each spring of odd years before fertilizer application, according to an established sampling protocol (Drummond et al., 2003) (Table 1). Amendments were applied uniformly to the field.

Table 1. Schedule of harvest operations, soil sampling campaigns, and fertilizer applications.

Year	1995	1996	1997	1998	1999	2000	2001	2002	2003
Yield Map	Grain Sorghum	Soybean	Corn	Soybean	Corn	Soybean	Corn	Soybean	-
Soil Test	X	-	X	-	X	-	X	-	X
P_2O_5 (lb/acre)	50	-	-	-	-	-	80	-	-
K_2O (lb/acre)	50	-	-	-	-	-	80	-	-

Yield data and soil test results were interpolated following generally accepted geostatistical procedures using ArcGIS Geospatial Analyst. Data were investigated for trend and anisotropy. In datasets where underlying trends existed, universal kriging was used, otherwise, simple kriging was chosen. Anisotropic models were selected when non-stationarity was detected by rotating the lag azimuth. Measurement error and spatial microstructure were modeled in the nugget to increase stability of the prediction estimates. Best performing semivariogram models were identified by eye. Point estimates were extracted from the resulting geostatistical models on a 10-meter grid.

Buffer Index Calculation Procedures

For each year, we calculated total removal (C in Eq. 1) as the product of yield and a generalized nutrient concentration (Buchholz et al., 1983). The values we used are given in Table 2. ΔQ_n was then calculated by subtracting total crop removal (C) from fertilizer additions (F) (Eq. 1).

Table 2. Concentration coefficients used to calculate nutrient content in removed grain (Buchholz et al., 1983).

Crop	P	K
	- % -	- % -
Corn	0.8	0.53
Soybean	1.4	2.4
Grain Sorghum	0.93	0.6

Ordinary linear least squares regression was used to estimate βSt_n. The data used for calculating P buffering was from 1995-2003, while the data for K was from 1997-2003 due to a laboratory bias discovered in the 1995 K data. The soil test at each grid site was regressed against the time points, four dates for K, five dates for P. The slope of the regression was interpreted as the rate of soil test change (in units of the soil test measurement) per unit of time. A confidence level was then calculated for the slope estimates. The slope confidence level can be interpreted as the percentage chance that the estimate is a type I error, due to high variability in the soil test measurements, or no soil test change over time.

ΔI_n was calculated by multiplying the slope estimate by the time interval (Eq. 2). In the last step net nutrient balance (ΔQ_n) was divided by the soil test change (ΔI_n) to get BI (Eq. 3).

Results and Discussion

Current recommendations estimate crop removal as a crop removal maintenance component, separate from soil buffering. Furthermore, generalized regional estimates are used for buffering capacity. In contrast, the site-specific BI we propose here integrates crop removal and buffer capacity, and characterizes the interaction between them using local data.

Use of ΔI_n in place of generalized buffering relationships in recommendation calculations would be an improvement. However, ΔI_n alone is insufficient for empirically estimating soil buffering potential. Crop removal may be responsible for substantial soil test change and may vary independently from chemical and physical soil buffering properties. A fertilizer rate based on ΔI_n or on a generalized buffering relationship could result in an over- or under–application since neither includes the soil response to local net nutrient balance. The net nutrient balance component is necessary to fully characterize a site's capacity for buffering.

Figure 1 and 2, a, b, c, and d show the resulting ΔQ_n, ΔI_n, βSt_n confidence level, and BI of the case study field, for P and K, respectively. The interpretation of these maps is included as a part of the following discussion.

Nutrient Removal (ΔQ_n)

Nutrient removal with grain is controlled by complex relationships that are not well characterized, and that vary site to site. Frequently, interactions between yield, fertility levels, and climate affect grain nutrient concentration. With this dataset we are limited to using average grain concentration values. Current recommendations at the University of Missouri use these same values along with yield goal to calculate maintenance fertilizer additions (Buchholz et al., 1983).

ΔQ_P and ΔQ_K maps (Fig. 1a and 2a) are effectively weighted averages of each year's yield data where the weight is the appropriate nutrient concentration for the crop. As such, nutrient removal follows patterns in the field that are seen in the yield maps. Much of the spatial structure in these maps is due to spatial patterns in topsoil depth, soil texture, water redistribution, and field edge effects. Additionally, ΔQ_P and ΔQ_K maps are entirely negative. This experimental field has been managed uniformly with minimal fertilizer additions, in part for the purpose of exposing spatial variability in yield due to nutrient deficit.

Soil Test Change (ΔI_n)

Several methods are apparent for calculating ΔI_n. The simplest case of subtraction between two time points is problematic since measurement error associated with sampling and analysis may exceed differences. ΔI_n can also be determined by estimating βSt_n with linear regression on a series of soil tests, as performed in this example, or by using sophisticated time-series and spatiotemporal modeling techniques (Bennet, 1979; Ripley, 1981).

The regression, temporal, and spatiotemporal methods for estimating βSt_n are preferable because of their statistical robustness, and because they provide measures of certainty in their results. Sufficient soil sampling dates are necessary (>2).

ΔI_P and ΔI_K maps are presented in Figs 1b and 2b. ΔI_K is negative throughout the field while ΔI_P is largely negative except for locations corresponding to old homestead sites, field entrances, and depositional areas (Fig 1b, i, ii, and iii). Even in the case where no significant relationship in soil test change can be detected, spatial structure in maps of the confidence was apparent (Fig. 1c. and 2c.)

Interpreting the Nutrient Buffering Index

Meaningful interpretation of BI involves first examining the sign and value of the numerator and the denominator independently, and then looking at the resulting sign and value of BI. The processes represented by ΔQ_n and ΔI_n can concurrently work in the same or opposite directions, thus, reasons why ΔQ_n and ΔI_n are positive or negative must be considered to interpret the sign of BI. For ΔQ_n and ΔI_n, areas where change is positive or negative represent areas where nutrient supply is greater than or less than nutrient demand, respectively. The sign of ΔQ_n is dependent only on nutrient removals and additions. The sign of the ΔI_n component is dependent on the equilibrium kinetics of the soil buffering reactions, and all changes in ΔI_n due to removals and additions are considered to have occurred through these equilibrium reactions. Some potential conditions that may control sign of ΔQ_n and ΔI_n are presented in Table 3.

Table 3. Table of conditions that contribute to the sign of net nutrient balance (ΔQ_n) and soil test change (ΔI_n).

	Negative	Positive
ΔQ_n	Yield limited by nutrient supply. Insufficient fertilizer was added. Reduced subsoil fertility.	Yield limited by factors other than fertility. Excess fertilizer was added. Crop accessed elevated subsoil fertility.
ΔI_n	Soil buffer sites are relatively available. Buffering reactions favor adsorption. Labile nutrient forms converting to resistant forms. Nutrient is lost from the soil-plant system (e.g. erosion and leaching)	Soil buffer sites are saturated. Buffering reactions favor desorption. Resistant nutrient forms converting to labile forms Nutrient is added to the soil-plant system (e.g. run-on and deposition)

The sign of BI results from the combination of signs in the numerator and the denominator according to the rules of division. Magnitude of the BI quotient results from the magnitudes present in the numerator and denominator, and is interpreted as *the quantity of nutrient balance responsible for one unit of change in soil test value.* The following table reflects the four possible combinations of sign and some statements of interpretation (Table 4).

Table 4. Interpretation of sign in the buffering index (BI) calculation.

	$-\Delta Q_n$	$+\Delta Q_n$
$+\Delta I_n$	**-BI** Nutrient supply is less than demand. Soil test is increasing. For the calculated amount of removal, soil test increases one unit. Buffered nutrient supply is sustainable with reduced additions.	**+BI** Nutrient supply is greater than demand. Soil test is increasing. For the calculated amount of over-supply, soil test increases one unit. Buffered nutrient supply is sustainable with reduced additions.
$-\Delta I_n$	**+BI** Nutrient supply is less than demand. Soil test is decreasing. For the calculated amount of nutrient removal, soil test decreases one unit. Buffered nutrient supply is not sustainable without increased additions.	**-BI** Nutrient supply is greater than demand. Soil test is decreasing. For the calculated amount of nutrient over-supply, soil test decreases one unit. Buffered nutrient supply is not sustainable without saturating the equilibrium with resistant forms.

The two possibilities resulting in positive BI correspond to soils with relatively simple buffering systems. They estimate the buffering capacity of a soil from opposite directions, one via addition and one via removal. Thus, given two field locations with similar buffering equilibrium kinetics, where both ΔQ_n, and ΔI_n are positive for one location, and negative for the other, BI will be similar. For each of these conditions, some quantity of nutrient balance change results in one unit of soil test change, in the same direction.

The two possibilities resulting in negative BI correspond to soils with more complex buffering systems. They estimate the buffering capacity of two different situations. In the first case, $+\Delta Q_n$ /$-\Delta I_n$, either labile nutrients are converting to resistant forms, or the nutrient n is being lost from the soil-plant system. In the former, regardless of the excess supply, the soil is strongly or specifically binding the nutrient in such a way that the soil test cannot extract it. For the second case, $-\Delta Q_n/+\Delta I_n$, soil buffering capacity for n is low, and/or the adsorption sites for n are relatively saturated. In this case, nutrient drawdown is compensated for by desorption of n, and extractable nutrient forms are favored.

Interpreting Buffering Index for the Example Dataset

Maps of BI_P and BI_K are shown in Fig. 1d and 2d. BI_P for the example field expresses both positive and negative conditions, while BI_K is positive throughout the field. At all of the locations where BI_P is negative, soil test is increasing ($+\Delta I_P$) indicating the condition in the upper left quadrant of Table 4. These are the locations corresponding to homestead sites, field entrances, and depositional areas (i, ii, and iii, Fig 1b). Homesteads and field entrances may show increasing P due to the influence of animal manures from when these areas served as feedlots, or from the spilling of feed, forage, and fertilizers. High soil-test P exists at these locations indicating that P adsorption sites are relatively more saturated, leaving little room for additional P buffering. Because of this, equilibrium reactions of P additions favored extractable forms and soil test increased. Buffered nutrient supply at these locations is sustainable with reduced P applications.

The field drainage outlet and a former pond site (iii, Fig. 1b) are zones of deposition from surrounding locations. $+\Delta I_P$ may be due to P-saturated hill-slope sediments, P dissolved in runoff water, and from crop residue rich in P settling in these areas, saturating adsorption reactions. Remaining buffer capacity for P additions is reduced as above. Positive BI_P across the majority of the field is due to the double negative condition (lower left quadrant, Table 4) and indicates the general mining of P via crop removals. For most of this field, buffered P supply is not sustainable without increased additions.

ΔI_K and ΔQ_K are both negative across the field, therefore positive BI_K indicates the condition in the lower left quadrant of Table 4. The areas corresponding to homestead sites and field entrances (i, ii, Fig. 2b) have a higher capacity to supply K relative to removal, but due either to the simpler buffering kinetics of K, or leaching of accumulated K, resistant forms are not likely to be present. Drawdown is mainly from cation exchange sites, which are assumed to be completely extracted in the soil analysis. K applications were insufficient to prevent soil test K drawdown everywhere in the field.

While buffered P (for most of the field) and K supply are not sustainable without increased additions, not every location in the field needs to receive the same amount to sustain P and K supply. Sites with a positive BI nearing zero are the least buffered. At these locations, small amounts of removal cause large reductions in soil test, therefore, they should receive lower rates of P and K more frequently to maintain supply. Fertilizer additions, whether maintenance or buildup applications, could be modified by the locally derived BI to provide an application rate that more efficiently meets the crop's need, with potentially less environmental damage.

Conclusions

A comparison of these BI results to a generalized estimate of buffering capacity is needed to determine the expected value of applying the proposed method to fields. And better techniques are needed to accurately estimate ΔQ_n and ΔI_n to carry this idea forth on a wider scale. In the future, on-the-go grain quality sensors may be developed to estimate spatial grain nutrient concentration. Though grid soil sampling currently requires too much labor and expense to sample as intensively and regularly as would be desired, technological advances in on-the-go soil fertility sensors will improve the temporal and spatial resolution.

Continued adoption of precision agriculture will lead to the accumulation of spatially and temporally dense soil fertility and yield data. Through the BI presented here, these data have the potential to move soil fertilizer recommendations from the paradigm of minimalist representation of soils as regional features with regional properties, to a more realistic and efficient site specific representation from local soil data.

References

Adamchuck, V.I., M.T. Morgan, D.R. Ess. 1999. An automated sampling system for measuring soil pH. Transactions of the ASAE 42(4), 885-891.

Bennet, R.J. 1979. Spatial Time Series, Analysis – Forecasting – Control. Pion Ltd., London.

Birrel, S.J., J.W. Hummel. 2001. Real-time multi-ISFET/FIA soil analysis system with automatic sample extraction. Computers and Electronics in Agriculture 32(1), 45-67

Buchholz, D.D., R.R. Brown, J.D. Garret, R.G. Hanson, and H.N. Wheaton. 1983. Soil Test Interpretations and Recommendations Handbook. Revised 12/92 ed. University of Missouri - College of Agriculture, Department of Agronomy, Columbia, Missouri.

Christy, C., P. Drummond, D. Laird. 2003. On-the-Go Optical Reflectance of Soil. Paper Number: MC03-204. 2003 Mid-Central ASAE Meeting. St. Joseph, Missouri. April 04-05. ASAE.

Collings, K., C. Christy, E. Lund, P. Drummond. 2003. Developing an Automated Soil pH Mapping System. Paper Number: MC03-205. 2003 Mid-Central ASAE Meeting. St. Joseph, Missouri. April 04-05. ASAE.

Drummond, S.T., K.A. Sudduth, A. Joshi, S.J. Birrell, and N.R. Kitchen. 2003. Statistical and neural methods for site-specific yield prediction. Transactions of the American Society of Agricultural Engineers 46: 5-14. ASAE.

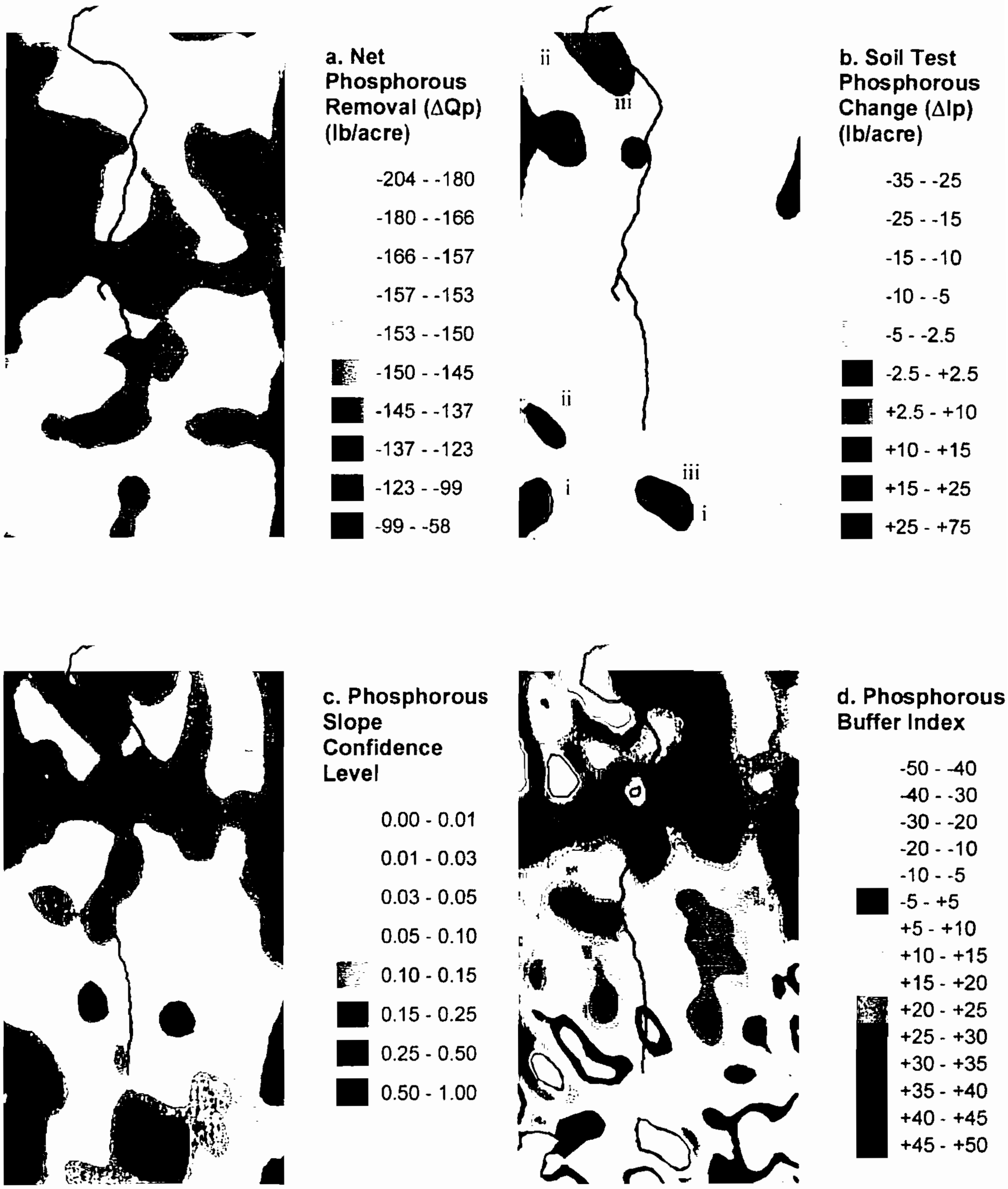
Kitchen, N.R., K.A. Suddduth, and S.T. Drummond. 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. J. of Prod. Agric. 12:607-617.

Mengel, K., and E.A. Kirkby. 1982. Principles of Plant Nutrition. 3rd ed. International Potash Institute, Bern.

Pierzynski, G.M., J.T. Sims, and G.F. Vance. 2000. Soils and Environmental Quality. 2nd ed. CRC Press, Boca Raton.

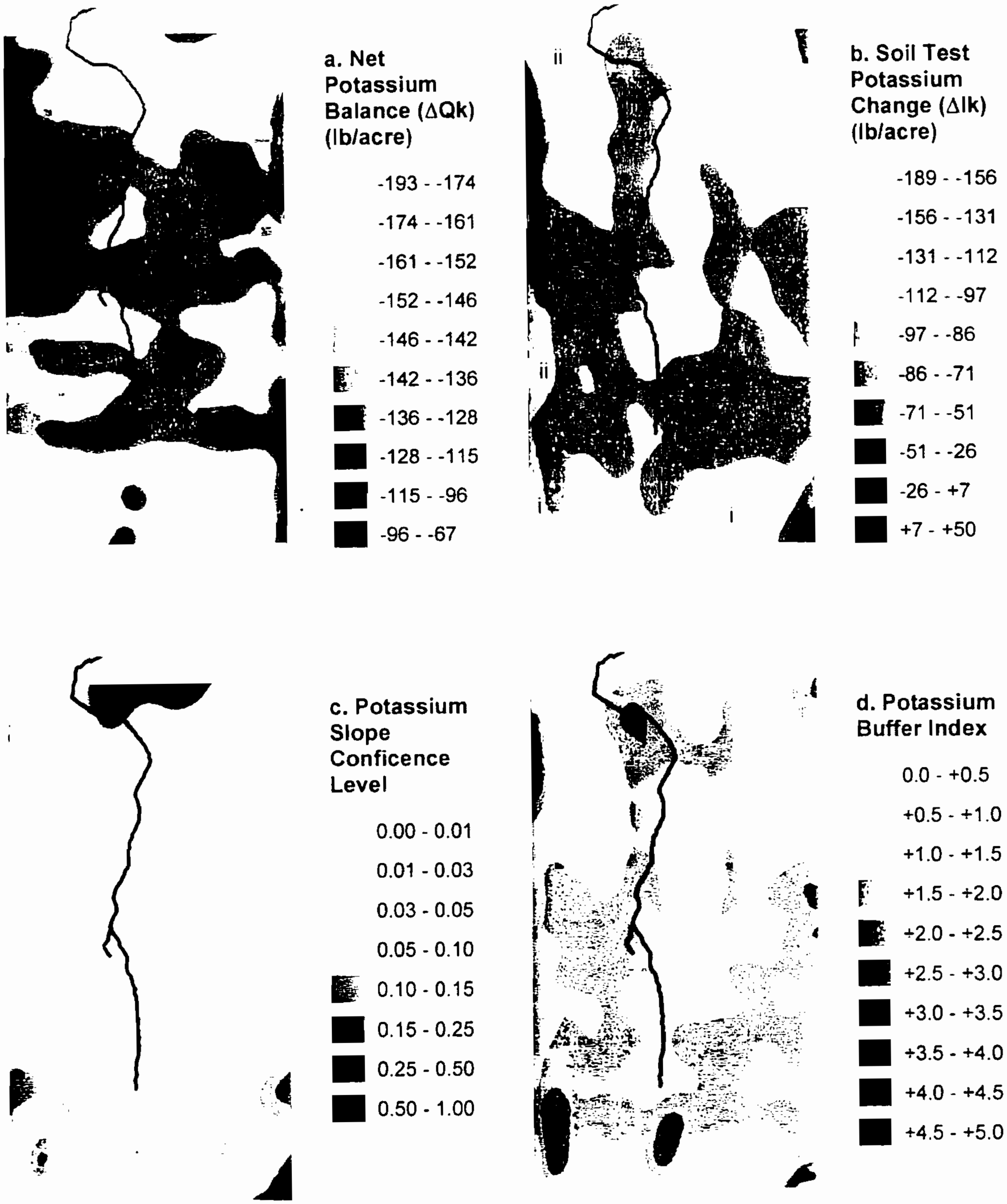
Ripley, B.D. 1981. Spatial Statistics. John Wiley & Sons, Inc., New York.

Figure 1. a. Net Phosphorous balance (ΔQp) (lb/acre). b. P soil test change (ΔIp) (lb/acre). c. Confidnece level of P slope estimate. d. P buffer index (BI).



i. homestead sites. ii. field entrances. iii. depositional areas

Figure 2. a. Net Potassium removal (ΔQk) (lb/acre). b. K soil test change (ΔIk) (lb/acre). c. Confidnece level of K slope estimate. d. K buffer index (BI).



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