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Modeling Within-field Soil Variability and Its Potential Use in the Variable-rate Treatment of Experimental Plots

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Abstract

This study described the soil variability in an experimental 10×10 m plot in Zanjan Province. The study was aimed at: (i) characterizing the short-range spatial variability of soil properties that control soil fertility and plant nutrition, (ii) delineating uniform areas within trial sites based on spatial dependence of soil properties, (iii) determining if this variation is large and can be managed at practical scales. Surface soil samples (0-30 cm) were analyzed for clay, silt and sand contents, calcium carbonate equivalent, pH, organic carbon, available phosphorus and available potassium. The spatial variability of soil properties was described using geostatistics. Sampling on a 1 m^2 grid, revealed a relatively large spatial variability of soil properties. Clay content exhibited no spatial dependence but other variables investigated were well-described with variogram models and significant short-range variations depicted. Based on the geostatistical analysis, a stratification of the field into potential management zones was possible.

Keywords: Trend analysis, Cross validation, Experimental plot, Variography, Kriging.

شبیه‌سازی تغییرات درون مزرعه‌ای خاک و قابلیت اعمال آن در تیمار کرت‌های آزمایشی با نرخ متغیر

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چکیده

در این تحقیق تغییرات خاک در یک کرت آزمایشی به ابعاد ۱۰ × ۱۰ متر در استان زنجان مورد بررسی قرار گرفت. اهداف تحقیق عبارت بودند از: (۱) تعیین تغییرات مکانی کوتاه-دامنه خصوصیات خاک کنترل کننده حاصلخیزی خاک و تغذیه گیاه، (۲) تعیین حدود مناطق دارای خصوصیات خاک همگن در داخل کرت‌های آزمایشی بر مبنای همبستگی مکانی خصوصیات خاک، (۳) تعیین اینکه آیا این تغییرات به اندازه‌ای بزرگ هستند که در مقیاس عملی قابل مدیریت باشند. نمونه‌های خاک سطحی (۳۰-۰ سانتی‌متر) در فواصل ۱ متر برای تعیین مقادیر رس، لای، شن، کربنات کلسیم معادل، اسیدیته، کربن آلی، فسفر قابل دسترس گیاه و پتاسیم قابل دسترس گیاه مورد تجزیه آزمایشگاهی قرار گرفت. تغییرات مکانی خواص خاک با اعمال تکنیک‌های زمین آماری تعیین شد. نمونه‌گیری خاک در یک شبکه ۱ متر مربعی، تغییرات نسبتا زیادی را در خواص خاک آشکار ساخت. مقدار رس ساختار مکانی مشخصی نشان نداد ولی سایر متغیرهای مورد بررسی به خوبی توسط مدل‌های نیم تغییرنما توصیف شدند و تغییرات کوتاه-دامنه بارزی نشان دادند. نتایج نشان داد که جداپش نواحی قابل مدیریت در داخل کرت آزمایشی مورد بررسی بر مبنای تجزیه و تحلیل‌های زمین آماری امکان پذیر است.

کلمات کلیدی: تجزیه و تحلیل روند، اعتبار سنجی متقاطع، کرت آزمایشی، پراش نگار، کریجینگ.

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Introduction

Among crop production factors, soil is obviously one of the most important. Therefore, within the context of precision farming, the knowledge of its physical and mechanical properties, as well as the spatial variability of these properties, is essential as decision support information for modifying cultural operations (Hanquet *et al.*, 2004). Both pedogenic and anthropogenic factors are responsible for within-field variations in soil properties, which in turn influence crop productivity and the risk of environmental losses. Many soil properties influence crop yield including soil water storage, thickness of the A horizon, organic matter content, pH and nutrient concentrations (Cambouris *et al.*, 2006). Yield ultimately integrates all variability factors and gives us a composite measurement of their impact (Reetz, 2008). Most often, removal of such variations is impractical, if not impossible. In trials sites that are established on heterogeneous areas, the potential of introducing variation into the plot increases and one or a few treatments received more or less fertilizer or a high or low rate of herbicide, etc., than adjacent treatments. Therefore, the amount of input applied may affect only one or a few treatments in a trial, leading to incorrect conclusions from the results. Where variation cannot be removed, we must seek new methods for it to occur equally across each treatment, aiming at suppressing the negative effects of variation on research results (Iqbal, *et al.*, 2005).

Where variation in soil properties is large, and can be managed on practical scales, variable management within a field for agricultural inputs may be worthwhile. Geostatistical techniques help in mapping soil boundaries within a trial field before investing in more detailed studies. The conceptual frame and theoretical basis of geostatistics has been discussed by several authors (Krige, 1981; Trangmar *et al.*, 1985; Isaaks and Srivastava,1989; Oliver *et al.*, 1990; Pohlmann, 1993; Cressie, 1993; Webster, and Oliver, 2001; Webster, and Oliver, 2006), among others. Several studies have concentrated on the importance of soil sampling in the variability of spatial estimates (Anderson, *et al.*, 1992; Weitz *et al.*, 1993; Gascuel and Boivin, 1994; Dobermann, 1994). Studies were also designed to predict short-range variability of soil-related variables that control crop growth (Vauclin *et al.*, 1983; Davis *et al.*, 1995; Gupta *et al.*, 1997; Baxter *et al.*, 2003. These and other studies conducted over the last three decades, have proven that geostatistics is useful in predicting the spatial distribution of soil properties that are spatially dependent in fields. However, only a few applications have paid special attention to the pattern of soil micro variability in experimental plots.

This study was conducted to (i) characterize the short-range spatial variability of soil properties that control soil fertility and plant nutrition in a selected experimental plot, (ii) delineate homogeneous areas within trial sites based on the spatial dependence of soil properties, and (iii) determine if this variation is high and can be managed on practical scales that allow for the proper layout of on-farm trials, and ensure that meaningful data can be collected, interpreted and reported.

Materials and Methods

The spatial variability of the selected inherent and management-dependent soil variables was studied in an experimental 10×10 m plot of a research farm located in Zanjan Agricultural Experimental Station in western Iran (48° 45' 15" E, 36° 31' 51" N), where on-farm fertilizer and irrigation trials are conducted each year. The selected site is characterized by a semi-arid climate with relatively hot summers and cold winters. A systematic approach was used to take sample the soils in the spring of 2005. The area was divided into regularly spaced squares of 1 by 1 m and the sampling points were located at grid node by pacing (Fig.1).

A total of 100 composite samples were taken from the topsoil (0-30 cm) to obtain average values and minimize the deviations due to factors such as sheet erosion, animal droppings and burning crop residues. These samples were air dried and passed through a 2 mm sieve.

The laboratory determinations of the soil samples were carried out at the Soil and Water Research Division of Agricultural Research Center of Zanjan Province, following standard laboratory methods. Soil samples were analyzed for clay, silt and sand contents (Bonyoucos method), calcium carbonate equivalent in terms of TNV (volumetric calcimetry; HCl titration), organic carbon (potassium dichromate method), pH (saturated paste), available phosphorus (Olsen extraction) and available potassium (1 N ammonium acetate extraction). Continuous maps representing the within-field variation of soil property values were produced using ordinary kriging.

Descriptive statistics were applied to check data trends. Geostatistical analysis was applied to variography, model fitting and contour mapping, using the algorithm available in an extension called *geostatistical analyst* in ArcGIS environment (ESRI, 2008). Sample variograms of the selected inherent and management-

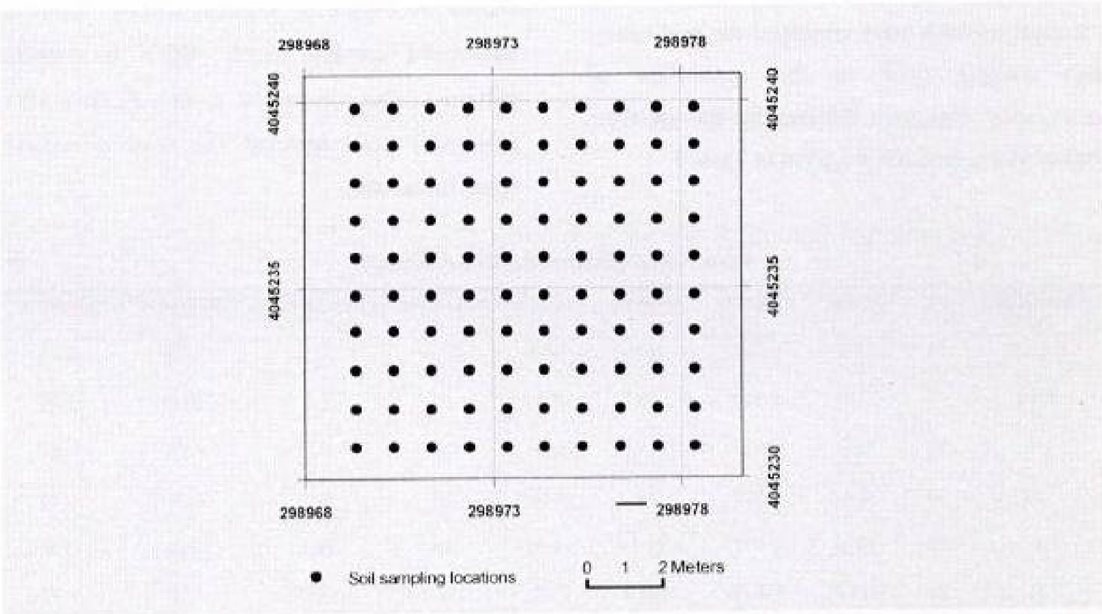

Figure 1: Map of the study site showing 100 soil sampling locations.

dependent soil variables were computed to characterize their spatial structure. In each case, an appropriate variogram model, closest to the spatial dependence presented by the data, was superimposed on the variogram and the contour maps were produced using deterministic and geostatistical interpolation techniques.

Results

Classical Statistics

The application of statistical methods to sample data requires consideration of the assumptions on which the statistical methods are based. In assessing soil spatial variability, assumptions of normality are of particular concern (Young *et al.*, 1998). In variogram analysis, it is desirable that the underlying data distribution meet Gaussian (normal) assumptions, where departure from normal is minimal, or normality is approximated after appropriate mathematical transformation. Another recommendation is that the intrinsic hypothesis (stationarity of the mean) should be met (Cambardella and Meek, 2006). Conventional statistical methods were employed for exploratory data analysis prior to the application of variography. Summary statistics for the variables studied in this research are given in Table 1.

The values for skewness and kurtosis are low and the mean and median values fairly coincide for all variables. These, together with the normal probability plots of the variables (Fig. 2), on which the variables data points roughly follow the straight normal distribution line, indicate that the distribution of the soil properties studied approximate normal distribution. The coefficient of variation (CV) was calculated for all variables. Values of CV were lowest for pH and highest for TNV. The coefficient of variation for TNV (about 20%) and for available phosphorus (about 11%) was high, suggesting a relatively high variation in soil data.

Geostatistical Analysis

Trend Analysis

Prior to conducting variography, a trend analysis procedure (ESRI, 2008) was used to identify and remove trends in the input datasets to satisfy stationarity assumptions (Cressie, 1993). As shown in Figure 3, organic carbon shows a downward curving trend, which is definite pattern to the polynomial model. A zero-order (constant) trend removal was used to remove trend in the data.

Table 1: Descriptive statistics for soil properties.

Variable	N	Mean	Variance	Median	CV	Minimum	Maximum	Skewness	Kurtosis
CLAY	98	25.9	4.361	26.0	8.03	22.0	32.0	0.04	-0.23
TNV	94	7.0	1.954	6.8	19.79	4.9	9.1	0.06	-1.49
OC	98	0.7	0.003	0.7	8.04	0.6	0.8	-0.01	-0.84
pH	99	7.8	0.012	7.8	1.42	7.7	8.0	0.41	-1.27
P	95	12.9	2.097	13.1	11.16	9.8	16.1	-0.04	-0.68
K	93	514.0	834.30	518.0	5.62	452.0	570.0	0.01	-0.87

This helps more accurately modeling the random short-range variation and eliminating the influence of global trend in spatial analysis. For the rest of the variables, the curve through the projected points is flat, indicating no definite trend in data sets and hence no justification for trend removal (ESRI, 2008).

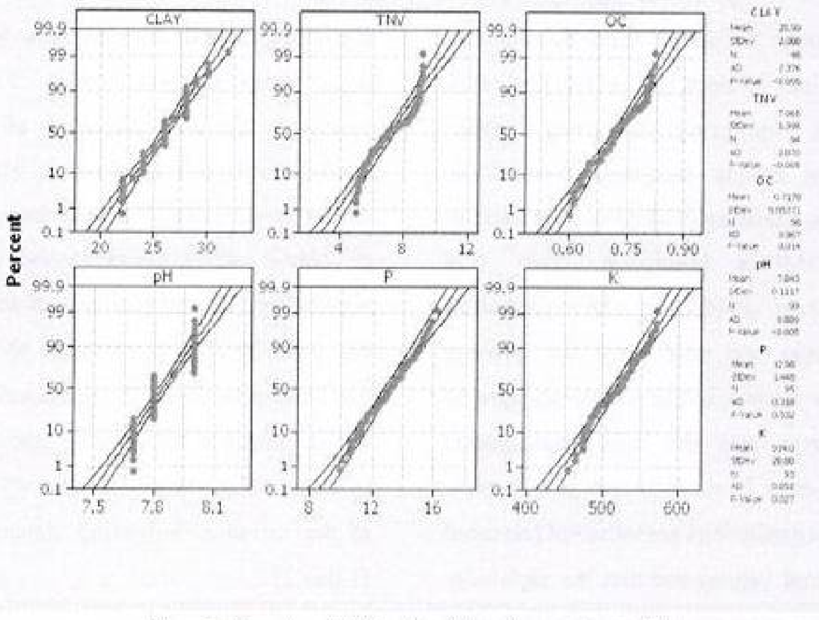

Figure 2: Normal probability plot of the soil properties studied.

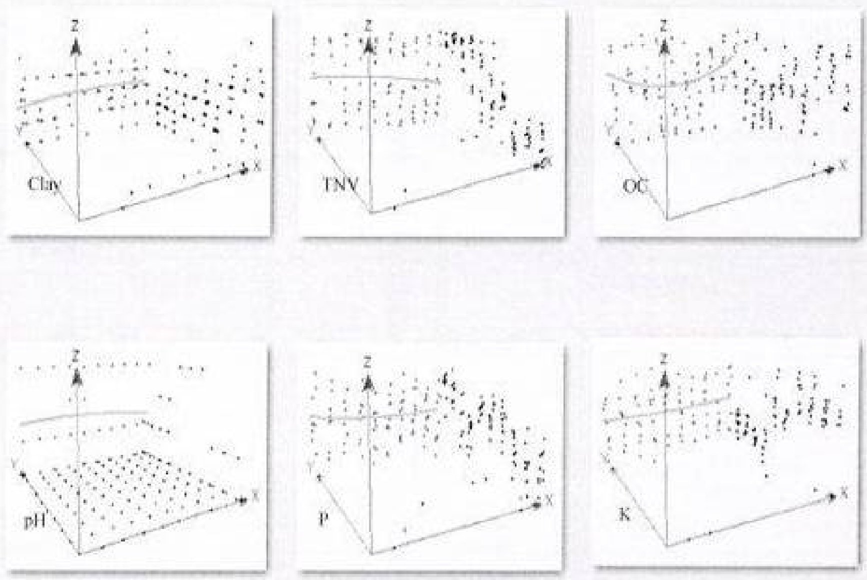

Figure 3: Three-dimensional perspective of the trends in the input datasets.

Cross Validation

Cross validation was used as a measure of the uncertainty of the prediction to give an indication of how good the predictions made were. A scatter plot of predicted values versus measured values is given in Figure 4. Excepting clay, the fitted line through the scatter of predicted points (thick solid line) is close to the 1:1 line (thin dashed line), indicating a strong spatial autocorrelation among measured points. For most variables, the mean prediction error and the mean standardized prediction error (the prediction errors divided by their prediction standard errors) are near zero, the average standard error is close to the root-mean-squared prediction error and the root-mean-squared standardized error is close to one (not shown), indicating that predictions are unbiased (centered on the measured values) and that the variability in predictions is correctly assessed (ESRI, 2008).

Semivariogram Modelling

Sample variograms of the selected inherent and management-dependent soil properties and fitted models are displayed in Figure 5. The variability of TNV, organic carbon, pH, available phosphorus and available potassium exhibited spatial dependence that could be well-described using semivariogram models. The estimated variogram for the percentage of clay content exhibited a large nugget effect, which reveals a strong assumption of independence. In the case of organic carbon, the pentaspherical model fits reasonably well the positions of the nugget and sill. For TNV, pH, available phosphorus and available potassium, the spherical model most closely matches the sample variograms. For most variables, the sill is a satisfactory estimate of the variance, indicating stationarity in data (Table 2).

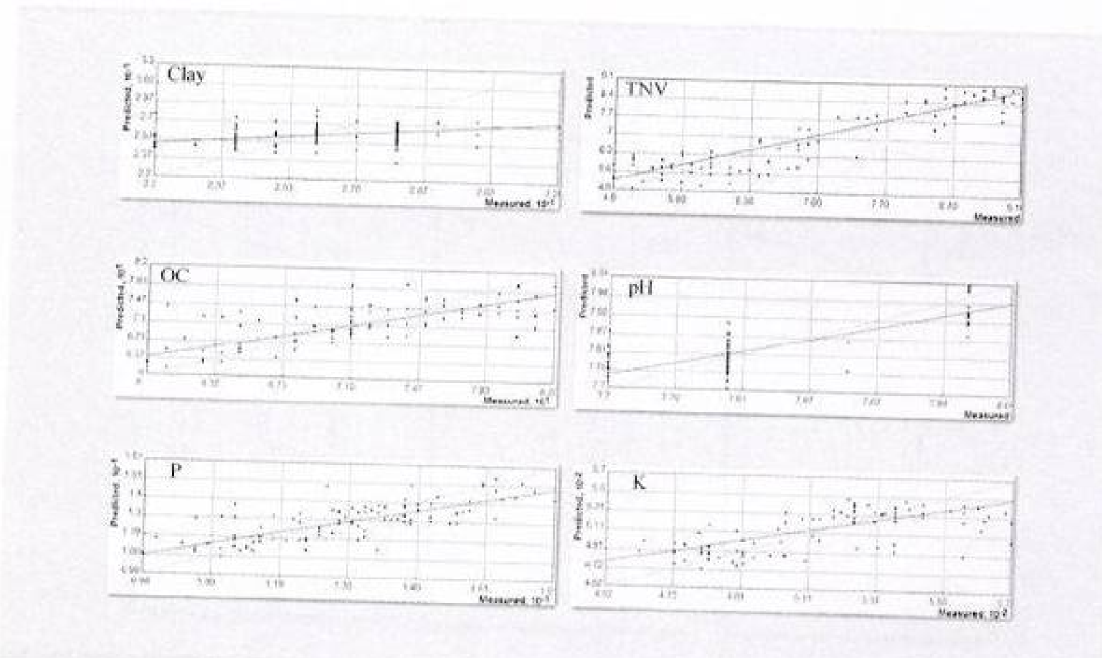

Figure 4: Cross validation plot of soil properties.

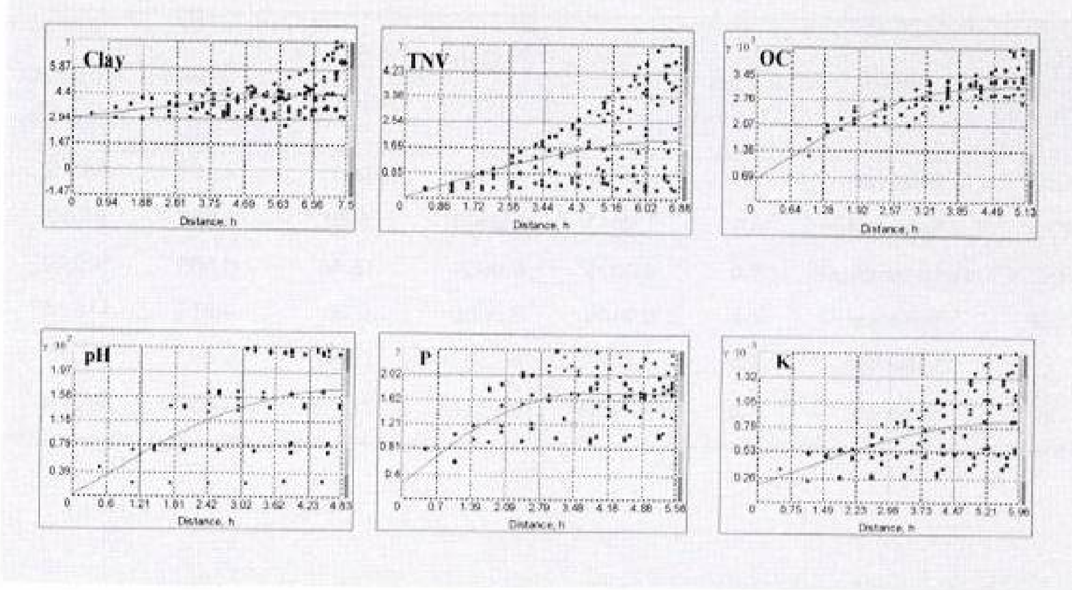

Figure 5: Experimental variogram of soil properties and the best-fitting geostatistical model.

Autocorrelation of the soil data is obvious up to a range of 6.7 m. If the variogram models which are fitted in Figure 5 are valid, the nugget variance has a proportion of nugget variance/sill variance of less than 16.6 percent of the process variance for organic carbon, TNV, pH and available phosphorus and 21 for available potassium. This indicates a good representatively for soil properties examined (Webster and Oliver, 2006).

The range of the properties is relatively small, varying between 3.6 m for available phosphorus and 6.7 m for the TNV. pH, organic carbon, available potassium and clay show intermediate range values, varying from 4.8 to 5.9 m.

Map Generation using Kriging

Kriged maps for TNV, organic carbon, pH, available phosphorus and available potassium are given in Figure 6. For clay, the nugget variance is close to the sill variance (Nugget/sill ratio =88.33%), indicating a weak autocorrelation between nearby points (Cambardella, *et al.*, 1994). In other words, there is much random noise and less local representatively in the data. This has implications for kriging because the larger the nugget effect is, the greater the smoothing of the predicted values (Grunwald, 2006). In the case of week spatial dependence, the construction of contour maps by geostatistical interpolation techniques will not give any reliable results, because geostatistical techniques, such as kriging, quantify the spatial autocorrelation among measured points and account for the spatial configuration of the sample points around the prediction location. Therefore, the inverse distance weighted interpolator which is an exact deterministic interpolation technique that can force the resulting surface to pass through the data values and predicts a value that is identical to the measured value at a sampled location (ESRI, 2008), was used to produce a contour map of the soil clay content (Fig. 6).

Table 2: Parameters of models fitted to the experimental variograms of soil properties.

Soil property	Model	Range	Sill	Nugget Effect	Nugget/sill ratio (%)	Variance	Sill /variance ratio (%)
Clay	Spherical	5.9	0.7591	3.1005	88.33	4.361	88.50
TNV	Spherical	6.7	1.9052	0.0000	0.00	1.954	97.50
OC	Pentaspherical	5.0	0.0025	0.0005	16.66	0.003	100.00
pH	Spherical	4.8	0.0140	0.0000	0.00	0.012	116.66
P	Spherical	3.6	1.4785	0.2383	13.88	2.097	81.86
K	Spherical	5.8	663.9500	176.5814	21.00	834.300	100.74

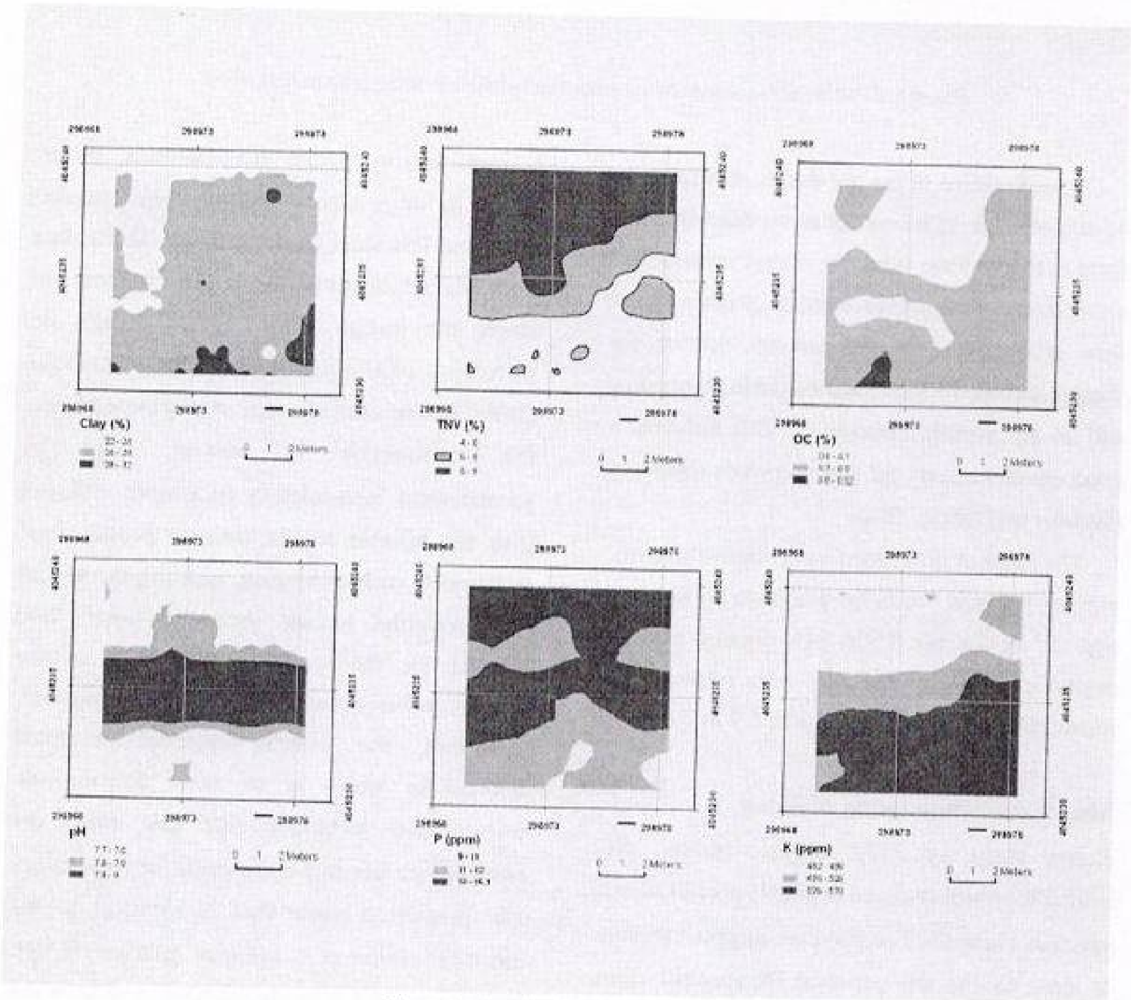

Figure 6: Contour map of soil properties.

Discussion

Keeping other factors unrestricted, in soil-plant relationships assessment studies in experimental plots, important questions to be answered are: what is the magnitude of the soil variation and what is the geographical distribution of this variation? Spatial interpolation techniques, such as kriging which gives an optimal estimate in the sense of minimized estimation variance (Krige, 1981; Isaaks and Srivastava,1989; Trangmar *et al.*, 1985; Pohlmann, 1993), allowed mapping the extent and spatial variability of the soil-related factors in the selected experimental plot. From a land management point of view, this not only provides information about the geographical distribution of the problem-areas, but also gives necessary clues to the magnitude of the efforts and investments needed to solve the problem.

The geostatistical analysis indicated significant short-range variations in spatial structure of all soil property values investigated, which could be partly attributed to the inherent characteristics of the soils and partly to build up plus maintenance fertilizer recommendations on the basis of the whole-field average soil-test and other mitigation activities. The high and low values of the selected soil properties within the selected experimental plot that were identified via kriging analysis can be regarded as an indication that application of agricultural inputs based on whole-field approach has randomized rather than homogenized fine-scale spatial structure in soil properties. This may affect the overall growth and yield of agricultural crops.

The contour maps produced in this research, reflect the status of inherent and management-dependent soil properties at the selected experimental plot. The contour maps of soil property values depict large heterogeneous areas of low and high values. The values of some soil properties fall into the high and very high interpretation classes (Clay content, TNV, available potassium) while others tend to be limiting for most crops (organic carbon, pH, available phosphorus). It is expected that crop responses be high in the low-testing areas and small in areas testing within the optimum class. In all cases, the spatial variation is strongly fragmented. This indicates that such a high spatial variability in soil property values in the selected experimental plot is the norm rather than the exception. This could reflect local differences in management practices and will necessitate variable-rate application of agricultural inputs, as defining soil spatial variability is the first step for site specific crop management.

Short-range spatial randomness of soil-related factors is most likely to be a key factor in assessing the production capacity of the newly introduced crop varieties in experimental plots, as randomly distributed soil properties cannot be properly managed under whole-field management systems. Probably, high short-range spatial variability in soil could obscure experimentally measured estimates of crop production.

In the selected experimental plot, the variation in soil property values was large enough to be managed by variable-rate applications. Based on the geostatistical analysis, a stratification of the field into three potential management zones was possible. Each portion of the selected experimental plot can be managed separately because of relatively large areas covered by individual management zones. Sampling on a 1 m^2 grid, revealed relatively large spatial variability of soil properties, making the interpretation of soil property values highly site-specific.

The geostatistical analysis of soil data for the selected experimental plot indicated significant short-range variations in spatial structure of all soil property values investigated. The contour maps of soil property values produced in this research depict large heterogeneous areas of low and high values, reflecting the status of the inherent and management-dependent soil properties at the selected experimental plot. The values of some soil properties fall into the high and very high interpretation classes (Clay content, TNV, available potassium) while others tend to be limiting for most crops (organic carbon, pH, available phosphorus). Sampling on a 1 m^2 grid, revealed relatively large spatial variability of soil properties, making the interpretation of soil property values highly site-specific. Based on the geostatistical analysis, a stratification of the selected experimental plot into potential management zones was possible. Each management zone was large enough to allow for variable-rate application of agricultural inputs.

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