



Spatial variability and geo-statistics application for mapping of soil properties and nutrients in semi arid district Kohat of Khyber Pakhtunkhwa (Pakistan)

Wasiullah^{1*}, A.U. Bhatti², F. Khan² and M. Akmal²

¹Project Director, Kohat University of Science & Technology, Kohat, Khyber Pakhtunkhwa

²Khyber Pakhtunkhwa Agriculture University, Peshawar

Abstract

Spatial variability and its importance was kept in view and this project was designed to model spatial variability of soil properties and their mapping in semi arid district Kohat of Khyber Pakhtunkhwa (KP) province of Pakistan. Soil sampling was done on a grid system using Global Positioning System (GPS) from two depths i.e. 0-15 and 15-45 cm during 2004 and were analyzed for soil physical properties (soil texture and bulk density), soil chemical properties (pH, ECe, SAR, lime and organic matter) and soil fertility status (Mineral N, AB-DTPA extractable P, K, Zn, Cu, Fe and Mn, and HCl extractable boron). Geostatistical techniques of semivariogram analysis and kriging were used to model the spatial variability and interpolation of data values at unsampled locations and mapping in the district. Semivariogram analysis showed that the soil separates viz. sand, silt and clay content in Kohat district showed spatial patterns in both surface as well as subsoil. In the surface soil, the data were described by linear models for all the three soil separates. However, in the subsoil, silt content was described by a spherical model with a range of 30.38 km. Semivariogram analysis of the data on soil pH was described by a spherical model in both the depths with a range of 12.55 km in the surface soil and 8.26 km in the subsoil. Lime content in the surface soil was described by a linear model while in the subsoil, it was described by a spherical model with a range of 5.50 km. Organic matter content in the surface soil was described by a linear model. Potash content of the surface and subsoil was described by linear models showing strong spatial patterns in surface and very poor structure in subsoil. Manganese content was described by a spherical model in the subsoil with a range of 20.19 km. Iron content was described by linear models with a poor structure in surface and strong spatial structure in subsoil. Boron content in both the depths was described by spherical models with a range of 15.70 km in surface soil and 4.32 km in the subsoil. The data on various measured soil properties and the semivariogram models developed were used to estimate the soil test values at unsampled locations using geostatistical technique of kriging. Maps were developed using Surfer 6.04 programme and the areas were delineated into low, medium and high levels of plant nutrients.

Key words: Spatial variability, Geo-statistics, Mapping, Kohat, Pakistan

Introduction

Knowledge about soil physical and chemical properties can save time and money in planning and management. Spatial variation of soil influences soil and crop management efficiency as well as the effectiveness of field research trials. Variability in soil properties causes uneven crop growth, confounds treatment effects in field experiments, and decreases the effectiveness of uniformly applied fertilizer on a field scale (Mulla *et al.*, 1990; 1992). Many research workers studied the spatial variability of soil properties and crop yields on small as well as large scale (Bhatti *et al.*, 1991; 1993; 1999). On the other hand, spatial variability of soil properties can be used for interpolation of soil test values at un-sampled locations using limited data

of sampled locations. Spatial variability of soil properties has been used for development of fertility management strategies as well as for reclamation of salt affected soils and mapping of field on small scale and districts on large scale (Bhatti and Bakhsh, 1995; Bhatti and Mulla, 1995; Wasiullah and Bhatti, 2005).

Foreseeing the importance of spatial variability, this project was carried out to model spatial variability of soil properties and their mapping in semi arid district Kohat of Khyber Pakhtunkhwa (KP) province of Pakistan with the objectives (1) to determine spatial variability in soil properties of Kohat district and their mapping (2) to delineate different areas into low, medium and high soil fertility areas for better management and (3) to delineate

*Email: wasiullahmalik_63@yahoo.com

problem soils of these districts for future planning. The information can be used for the best soil resources management, enhancement of agriculture production and for further research by the scientists.

Materials and methods

Soil sampling from district Kohat of KP province of Pakistan was done on a grid system using Global Positioning System (GPS) during 2004. From a total of 86 sites, soil samples from 0-15 cm and 15-45 cm depths were collected (Rashid *et al.*, 2008), covering Bannu road, Shakardara road, Rawalpindi road, Chorlaki Nizampur road, Hangu road and surroundings of Kohat city in Kohat district

Soil samples were collected from five cores randomly and composite sample was made. One core sample was also taken for bulk density. Soil samples collected were brought to the laboratory, dried, ground and sieved. Soil samples thus prepared were analyzed for texture (Gee and Boudier, 1986) and bulk density (Blake and Hartge, 1986), pH (McLean, 1982), electrical conductivity (Rhoades, 1982), organic matter (Nelson and Sommers, 1982), lime content (Cottenei, 1980), mineral N (Keeney and Nelson, 1982), AB-DTPA extractable phosphorus and potassium (Olsen and Sommers, 1982), micronutrients Zn, Cu, Fe and Mn (Soltanpour, 1985) and Boron (Bingham, 1982).

The readings taken by GPS in degrees and minutes were changed to meters and kilometers using Arc view GIS 3.2 version. The far most western edge of Kohat district was taken as zero point on X axis, and the most southern end of the district map as zero on Y axis. Graphic lines were drawn at regular intervals on the map. Points were made on the map sheets from where the samples were collected and then x and y readings were noted from the map of the district for further analysis (Figure 1). Geostatistical technique of semivariogram analysis (Bhatti *et al.*, 1991) was used to determine spatial structure of various soil properties. Soil test values at un-sampled locations were interpolated using geostatistical technique of kriging and detailed isarithmic maps were prepared at smaller grid spacing (Rashid and Bhatti, 2005).

Semivariogram Analysis

Semivariograms are used to examine the mean square differences between measurements at pairs of locations as a function of distance of separation (lag, h) and relative orientation. If sample variation occurs randomly in space, the total sample variance will not depend upon the separation distance between the samples. Samples which are correlated in space, however, will have lower sample variance at smaller separation distances than at larger

separation distances. Therefore, one method for assessing the spatial correlation between samples is to compute sample variance as a function of sample separation distance. It is useful to compute a quantity known as semivariance, $\gamma(h)$, instead of variance for interpolation at unsampled locations.

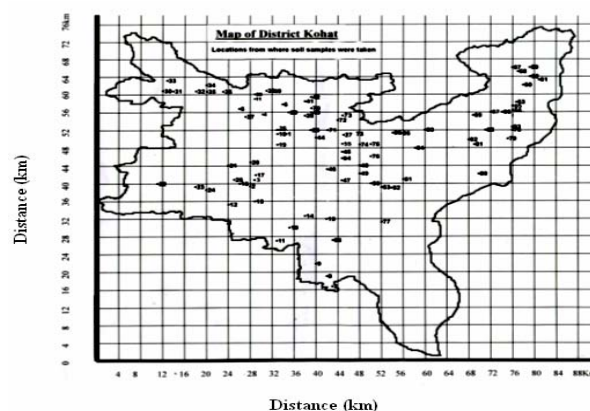


Figure 1: Soil sampling locations in Kohat District

To develop semivariograms for different soil properties, the following procedures were used. First, the distance (h) between any two samples is calculated along a specified relative orientation. Second, the mean-squared difference, $\gamma(h)$, between samples is calculated using one-half of the expected value, E:

$$\gamma(h) = (1/2) E [Z(x_i) - Z(x_{i+h})]^2 \quad (1)$$

Where Z is a regionalized variable representing a soil property, x_i is the position of the first sample, and x_{i+h} is the position of the second sample. In practice, the expectation is estimated using the following expression for semivariance:

$$\gamma(h) = [1/(2n(h))] \sum_{i=1}^{n(h)} [z(x_i) - z(x_{i+h})]^2 \quad (2)$$

Where $n(h)$ is the number of samples separated by a distance h, and z represents the measured value for a soil property.

Ideally, the semivariance equals zero at $h = 0$ since no variation in sample values is expected for measurements made at a given location. As separation distance increases, the semivariance function will typically increase because samples become more poorly correlated (the variance increases). At a critical distance known as the range, the sample pairs will cease to be correlated and values for the semivariance remain constant at a value known as the "sill" as separation distance continues to increase. Samples separated by distances greater than the range exhibit random variation.

For a quantitative description of these features, it is useful to fit standard models to the semivariance functions. Typical standard semivariograms include linear, spherical, and exponential models. Model selection is usually based on a criterion of goodness of fit, which involves fitting the model to data using non-linear least-squares methods. Expressions for each of the above models are given below:

$$\text{Linear model} : \gamma(h) = C_0 + Bh \quad (3)$$

$$\begin{aligned} \text{Spherical model} : \\ \gamma(h) = C_0 + C_1 [1.5(h/a) - 0.5(h/a)^3] \quad (4) \\ 0 < h < a \end{aligned}$$

$$\begin{aligned} \gamma(h) = C_0 + C_1 \quad h > a \\ \text{Exponential model} : \gamma(h) = C_0 + C_1 [1 - \exp(-h/a_0)] \quad (5) \end{aligned}$$

In these expressions, h is the separation distance between observations, ' a ' is a model parameter known as the range, C_1 is a model parameter which equals the sill minus the nugget, and C_0 is a model parameter known as the nugget. For the linear model, B is simply the slope of the line for a plot of semivariance versus separation distance. For the exponential model, a_0 is approximately equal to $a/3$. Physically, the sill is approximately equal to the total sample variance and is the maximum value of variance, which the model attains at large separation distances. Physically, sample observations separated by distances smaller than the range are statistically correlated to one another, while measurements separated by distances greater than the range are not correlated. Classical statistical methods can be applied to the data only if the range has a value, which is smaller than the closest sampling distance.

Ideally, the experimental variance should pass through the origin when the distance of sample separation is zero. However, many soil properties have non-zero semivariances as ' h ' tends to zero. This non-zero variance is called the "nugget variance" or "nugget effect" (Journel and Huijbregts, 1978). It represents unexplained or "random variance" often caused by measurement errors or variability in the measured property, which is not detected at the scale of sampling.

In this study the linear and spherical models were the best fit to the data on different soil physical and chemical properties.

Kriging

Kriging is a method for making optimal, unbiased estimates of regionalized variables at unsampled locations using the structural properties of the semivariogram and the initial set of measured data. A useful feature of kriging is that an error term expressing the estimation variance or uncertainty in estimation is calculated for each interpolated value. Kriging differs greatly from linear regression

methods for estimation at unsampled locations. Whereas a regression line never passes through all of the measured data points, kriging always produces an estimate equal to the measured value if it is interpolating at a location where a measurement is obtained. The basic equation for interpolation by kriging at an unsampled location x_0 is given by:

$$z_k(x_0) = \sum_{i=1}^{n(h)} \lambda_i z(x_i) \quad (6)$$

Where n is the number of neighboring samples and λ_i are weighting factors for each of the $z(x_i)$. The weighting factors for neighboring measured points are constrained to sum to unity, i.e.

$$\sum_{i=1}^n \lambda_i = 1 \quad (7)$$

This ensures that the estimate $z_k(x_0)$ is unbiased, i.e.

$$E[z(x_0) - z_k(x_0)] = 0 \quad (8)$$

The theory of kriging ensures that the kriging estimation variance, σ_k^2 is minimized.

Results and Discussion

Spatial variability of soil properties in Kohat district

Soil physical properties

Semivariogram analyses of some of the soil physical properties (Table 1) showed that the soil separates viz. sand, silt and clay content had spatial patterns in both the surface as well as subsoil. In surface soil, the data were described by linear models for all the three soil separates (Table 1, Figure 2-4). However, in the subsoil, silt content was described by a spherical model with a range of 30.38 km. The r^2 -values for these models were highest for the sand content in both the depths. It showed that there was a spatial continuity in the distribution of the three soil separates, which might be due to the parent material spatial distribution. As regards the bulk density in the surface soil, the data were described by a linear model with a negative slope. Thus the distribution of bulk density in Kohat district was random.

Soil chemical properties

Semivariogram analysis of the data on some soil chemical properties (Table 2) showed that soil pH was described by a spherical model in both the depths. The range for the spherical model of soil pH in the surface soil

was 12.55 km (Figure 5), while in the subsoil it was 8.26 km. This shows that soil pH is spatially distributed in Kohat district.

subsoil was described by a spherical model with a range of 5.50 km. It is clear that the lime content has spatial continuity in both the soil depths in Kohat district. Organic

Table 1: Parameters of semivariogram model for physical properties in Kohat district

Property	Nugget	Slope	Sill	Range (km)	r^2	Model
(0-15 cm depth)						
Sand (%)	136.07	11.22	-	-	0.94	Linear
Silt (%)	106.56	2.97	-	-	0.84	Linear
Clay (%)	86.63	3.71	-	-	0.82	Linear
Bulk density (g cm^{-3})	63.80	-3148.7	-	-	0.48	Linear
(15-45 cm depth)						
Sand (%)	104.97	14.19	-	-	0.94	Linear
Silt (%)	102.52	-	183.51	30.38	0.66	Spherical
Clay (%)	87.61	5.21	-	-	0.88	Linear

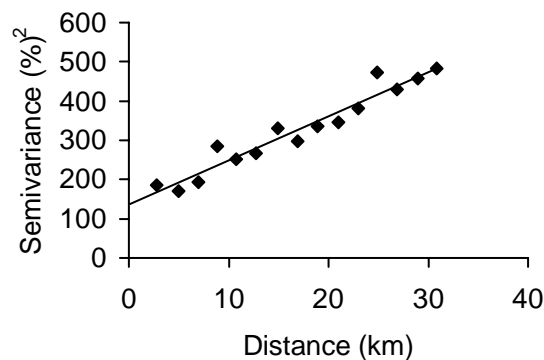


Figure 2: Semivariance and the best fitting model for surface sand content in Kohat district

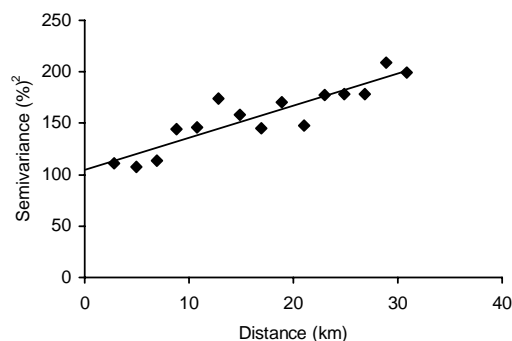


Figure 3: Semivariance and the best fitting model for surface silt content in Kohat district

Electrical conductivity (ECe) in both the depths showed random variability. Similarly, sodium adsorption ratio (SAR) in surface soil as well as subsoil had random distribution. Lime content in the surface soil was described by a linear model with an r^2 -value of 0.63 showing spatial distribution of lime content (Figure 6). Lime content in the

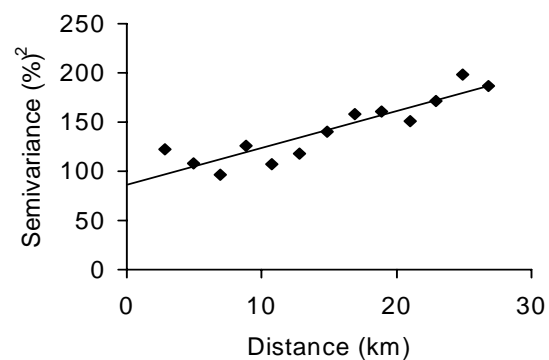


Figure 4: Semivariance and the best fitting model for surface clay content in Kohat district

matter content in the surface soil was described by a linear model (Figure 7). However, the slope of the linear model for the data in subsoil was negative. Thus the organic matter content in the surface soil was spatially distributed while in the subsoil it was randomly distributed.

Soil fertility status

Semivariogram analysis of the data on plant nutrients in the surface as well as subsoil of Kohat district soils (Table 3) showed that mineral N content and phosphorus content of the soils in both the depths showed random distribution. Potash content of the surface soil was described by a linear model (Figure 8) with a high r^2 -value of 0.76 showing strong spatial patterns.

Zinc content of both the depths was described by linear models but the surface soil had a very poor structure while it had a moderate spatial structure in the subsoil with an r^2 -value of 0.40. Copper content in both the depths had random variation. Manganese content of the surface soil had no spatial structure while it was described by a

spherical model in the subsoil with a range of 20.19 km. Iron content of the sub soil was described by a linear model with r^2 -value of 0.67 showing strong spatial structure. Boron content in both the depths was described by spherical models with a range of 15.70 km in surface soil (Figure 9), and range of 4.32 km in the subsoil.

Interpolation and mapping of soil properties

Soil physical properties

Map of sand content of the surface soils of Kohat district (Figure 10) shows that the western part is low in sand content while soils of the central and eastern parts of

Table 2: Parameters of semivariogram models for soil chemical properties of Kohat district

Property	Nugget	Slope	Sill	Range (km)	r^2	Model
(0-15 cm depth)						
PH	0.125	-	0.3214	12.55	0.45	Spherical
ECe (dS m ⁻¹)	11.15	2.15	-	-	0.02	Linear
SAR (mmol L ⁻¹)	1.82	0.008	-	-	0.06	Linear
Lime (%)	32.072	0.62	-	-	0.63	Linear
Organic matter (%)	0.124	0.002	-	-	0.33	Linear
(15-45 cm depth)						
PH	0.01	-	0.021	8.26	0.14	Spherical
ECe (dS m ⁻¹)	38.14	-4.21	-	-	0.51	Linear
SAR (mmol L ⁻¹)	21.77	-0.003	-	-	0.01	Linear
Lime (%)	2.89	-	49.61	5.50	0.31	Spherical
Organic matter (%)	60.38	-456.12	-	-	0.16	Linear

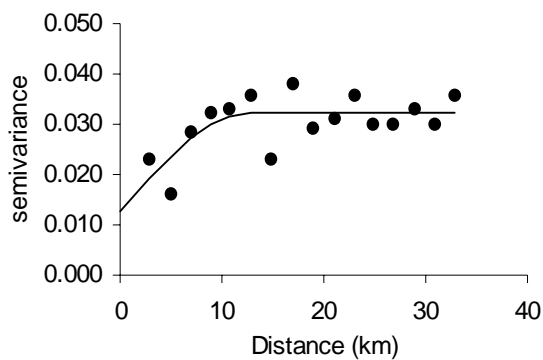


Figure 5: Semivariance and the best fitting model for surface pH in Kohat district

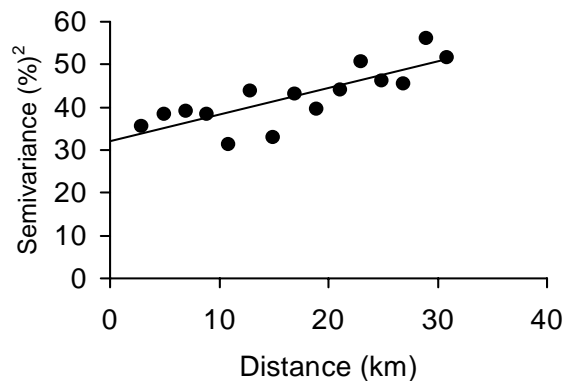


Figure 6: Semivariance and the best fitting model for surface lime (%) content in Kohat district

the district have higher sand content ($\geq 40\%$). Silt content of the surface soils of Kohat district varied considerably being higher in the western and central part ($> 40\%$) (Figure 11). In contrast to sand, the soils were low in silt content ($< 30\%$) in the eastern part. Clay content of the surface soils (Figure 12) show similar trend as that of the silt content, it was higher in the central and western-north part ($\geq 35\%$) i.e. the soils of these areas are fine-textured. The clay content of the surface soils in the east was low in clay content ($\leq 30\%$).

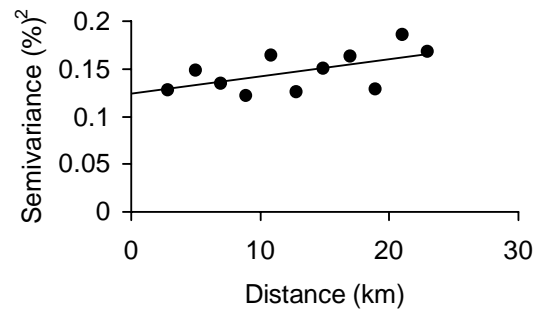


Figure 7: Semivariance and the best fitting model for surface organic matter (%) in Kohat district

Soil chemical properties

Map of pH of the surface soils of Kohat district (Figure 13) shows that there was no considerable variation in the pH values of different parts of Kohat district. However, the pH was alkaline (≥ 7.5). Map of lime content of surface soils of Kohat district (Figure 14) shows that the lime content

is higher in the central and western parts ($\geq 13\%$) being highly calcareous. The eastern soils are moderately calcareous (3-13%). Map of organic matter content of the surface soils of Kohat district (Figure15) shows that all the soils are low in organic matter ($<1\%$).

reaction and calcareous of different degree. Salinity problem existed in various areas of Kohat district ranging from 14 to 17% area. No sodicity problem was observed. Organic matter of all the soils was low. Phosphorus, potassium, zinc, copper, iron and Boron were found

Table 3: Parameters of semivariogram models for nutrients in Kohat district

Nutrients (mg kg ⁻¹)	Nugget	Slope	Sill	Range (km)	r ²	Model
(0-15 cm depth)						
N	46.68	-0.13	-	-	0.32	Linear
P	21.98	-2.90	-	-	0.002	Linear
K	8263.5	328.28	-	-	0.760	Linear
Cu	27.62	-0.30	-	-	0.180	Linear
Zn	15.71	3.58	-	-	0.004	Linear
Mn	31.29	-2.68	-	-	0.080	Linear
Fe	26.71	-0.27	-	-	0.080	Linear
B	0.084	-	0.11	15.70	0.230	Spherical
(15-45 cm depth)						
N	63.07	-1.07	-	-	0.28	Linear
P	4.89	22.27	-	-	0.04	Linear
K	3991.3	45.42	-	-	0.03	Linear
Cu	0.072	-	2.09	4.89	0.08	Spherical
Zn	0.136	0.01	-	-	0.40	Linear
Mn	0.804	-	1.258	20.19	0.50	Spherical
Fe	1.49	0.08	-	-	0.67	Linear
B	0.038	-	0.12	4.33	0.02	Spherical

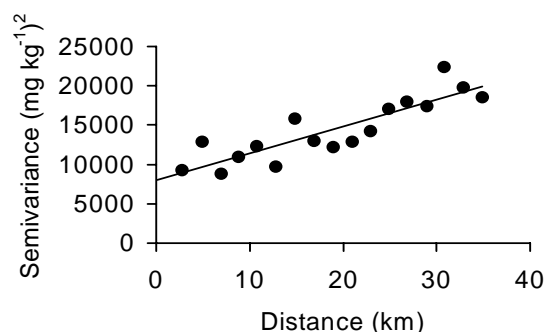


Figure 8: Semivariance and the best fitting model for surface K in Kohat district

Soil fertility status

Potassium content of the surface soils of Kohat district (Figure16) is adequate in all the soils ($> 20 \text{ mg kg}^{-1}$). However, it is relatively low in the east and south. Boron content of the surface soils of Kohat district (figure17) shows that central and northern parts of the district are marginal in B content ($0.45\text{-}1.0 \text{ mg kg}^{-1}$).

Conclusions

Soil texture in Kohat district ranged from clay to sandy loam. All the soils of Kohat district were alkaline in

deficient in different areas in different degrees. Sand, silt and clay content, soil pH, organic matter, potassium, zinc and iron either in the surface soil, subsoil or both have spatial patterns. Maps of various soil properties showed variation in different parts and can be managed accordingly.

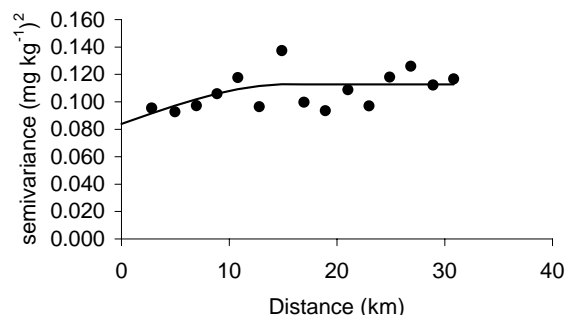


Figure 9: Semivariance and the best fitting model for surface soil B content in Kohat district

Recommendations

Based on the results of this study, researchers can develop variable rate fertilizer technology for wheat and other crops. Comparison of variable vs. uniform rates of fertilizer can be studied and recommendations can be drawn for site specific fertilizer management.

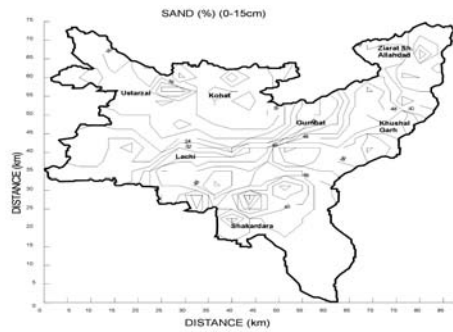


Figure 10: Map of surface sand (%) by kriging, Kohat district

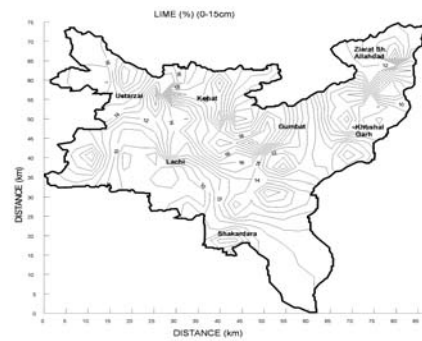


Figure 14: Map of Surface Lime (%) by kriging, Kohat district

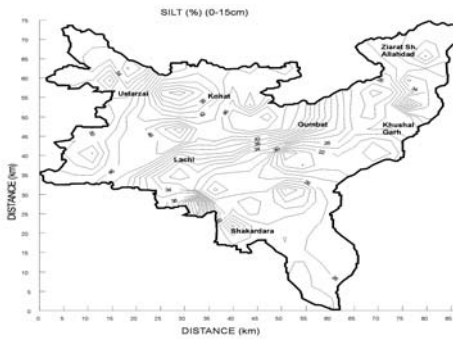


Figure 11: Map of surface silt (%) by kriging, Kohat district

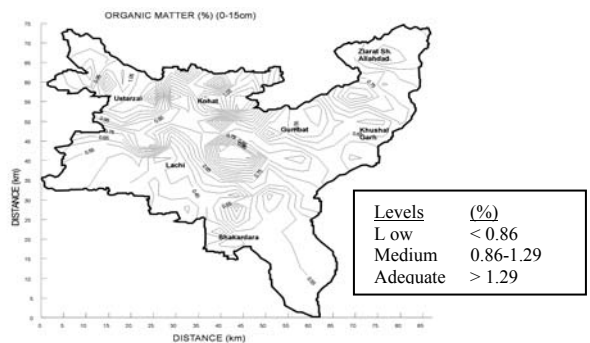


Figure 15: Map of Surface Organic Matter (%) by kriging, Kohat district

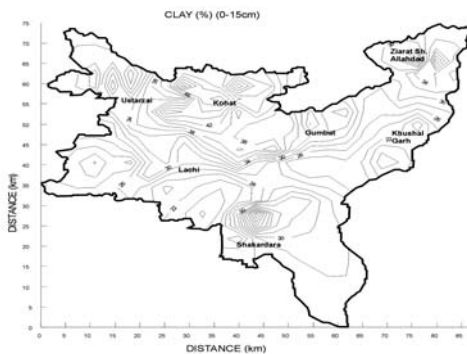


Figure 12: Map of Surface Clay (%) by kriging, Kohat district

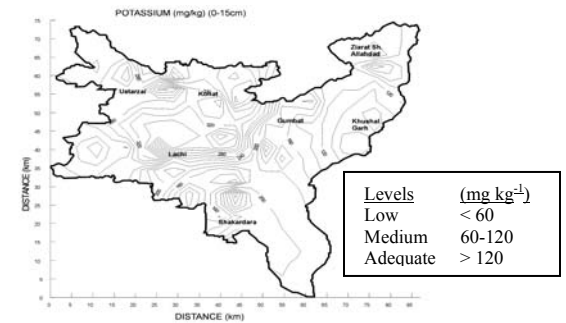
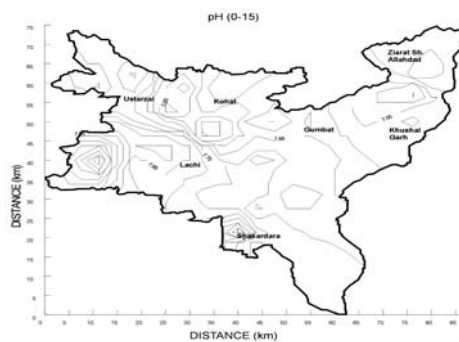
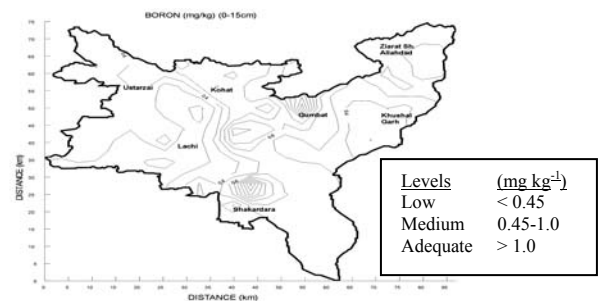
Figure 16: Map of Surface Potassium (mg kg⁻¹) by kriging, Kohat district

Figure 13: Map of Surface pH by kriging, Kohat district

Figure 17: Map of Surface Boron (mg kg⁻¹) by kriging, Kohat district

Acknowledgment

The authors are thankful to Higher Education Commission of Pakistan for financial support.

References

- Bhatti, A.U., D.J. Mulla and B.E. Frazier. 1991. Estimation of soil properties and wheat yields on complex eroded hills using geostatistics and thematic mapper images. *Remote Sensing of Environment* 37: 181-191.
- Bhatti, A.U., A. Wadud, R.A. Khattak and Farmanullah. 1993. Spatial variability of some soil properties of Malakandher Farm. *Sarhad Journal of Agriculture* IX(6): 619-632.
- Bhatti, A.U. and A. Bakhsh. 1995. Management strategy of using gypsum for reclamation of salt affected soils. *Journal of the Indian Society of Soil Science* 43(4): 657-659.
- Bhatti, A.U. and D.J. Mulla, 1995. Spatial variability of soil properties and wheat yields on complex hills and their fertility management. *Journal of the Indian Society of Soil Science* 43(1): 53-58.
- Bhatti, A.U., A. Bakhsh, M. Afzal and A.H. Gurmani. 1999. Mapping of major plant nutrients and crop productivity using geostatistical techniques for fertilizer management. *Pakistan Journal of Soil Science* 16: 129-136
- Bingham, F.T. 1982. Boron. p. 431– 448. *In: Methods of Soil Analysis, Part 2: Chemical and mineralogical properties.* A.L. page (ed.). American Society of Agronomy, Madison, WI, USA.
- Blake, G.R. and K.H. Hartge. 1986. Bulk density and Particle density. *In: Methods of Soil Analysis, Part 1, 2nd Ed.* A. Klute (ed). Agronomy 9: 363 – 381.
- Bohn, H.L., B.L. McNeal and G.A. O'Connor. 1985. Soil Chemistry, 2nd Ed. John Wiley and Sons, New York.
- Bremner, J.M. and C.S. Mulvaney. 1982. Nitrogen-total. *In: Methods of Soil Analysis. Part 2, 2nd Ed.* A.L. page (ed.). Agronomy 9: 595-621.
- Cottenie, A. 1980. Soil and plant testing as a basis of fertilizer recommendations, Food and Agriculture Organization of United Nations. *FAO Soils Bulletin* 38: 64.
- Gee, G.W. and J.W. Bauder. 1986. Particle Size Analysis, Hydrometer Method. p. 383-411. *In: Methods of Soil Analysis, Part 1. 2nd Ed.* A. Klute (ed.). American Society of Agronomy, Madison, W.I.
- Journel, A.G. and C.H. Huijbregts. 1978. Mining Geostatistics. Acadmics Press, New York.
- Keeney, D.R. and D.W. Nelson. 1982. Nitrogen-inorganic forms. p. 643 – 698. *In: Methods of Soil Analysis, Part 2. 2nd Ed.* A.L. Page, M.H. Miller and D.R. Keeny, (eds.). American Society of Agronomy, Madison. WI, USA.
- McLean E.O. 1982. Soil pH and lime requirements. p. 209-223. *In: Methods of Soil Analysis, Part 2. 2nd Ed.* A.L. Page. M.H. Miller and D.R. Keeny (eds.). American Society of Agronomy, Madison. W.I.
- Mulla, D.J., A.U. Bhatti and R. Kunkel. 1990. Methods for removing spatial variability from field research trials. *Advances in Soil Science* 13: 201-213.
- Mulla, D.J., A.U. Bhatti, M.W. Hammond and J.A. Benson. 1992. A comparison of winter wheat yield and quality under uniform versus spatially variable fertilizer management. *Agriculture Ecosystem and Environment* 38: 301-311.
- Nelson, D.W. and L.E. Sommers. 1982. Total carbon, organic carbon and organic matter. p. 539-577. *In: Methods of Soil Analysis, Part 2, 2nd Ed.* A.L. Page, M.H. Miller and D.R. Keeny (eds.). American Society of Agronomy, Madison W.I.
- Olsen, S.R. and C.E. Sommers. 1982. Phosphorus in Soil Analysis. p. 403-430. *In: Methods of Soil Analysis, Part 2, 2nd ed.* A.L. Page, R.H. Miller and D.R. Keeny (eds.). American Society of Agronomy, Madison WI, USA.
- Rashid, M. and A.U. Bhatti. 2005. Mapping of spatial variability of macro and micro nutrients for site specific management. *Soil and Environment* 24(1): 34-52.
- Rashid, M., A.U. Bhatti, F. Khan and Wasiullah. 2008. Physico-chemical properties and fertility status of soils of districts Peshawar and Charsadda. *Soil and Environment* 27(2): 228-235.
- Rhoades, J.D. 1982. Soluble salts. p. 167-179. *In: Methods of Soil Analysis, Part 2, 2nd Ed.* A.L. Page, M.H. Miller and D.R. Keeny (eds.). American Society of Agronomy, Madison WI, USA.
- Richards, L.A. 1954. Diagnosis and Improvement of Saline and Alkali Soils. USDA Agriculture Handbook 60. Washington, D.C., USA.
- Soltanpour, P.N. 1985. Use of AB-DTPA soil test to evaluate elemental availability and toxicity. *Communication in Soil Science and Plant Analysis*. 16: 323-338
- Wasiullah and A.U. Bhatti. 2005. Mapping of soil properties and nutrients using spatial variability and geostatistical techniques. *Soil and Environment* 24(2): 88-97.