



P-ISSN: 2349-8528

E-ISSN: 2321-4902

IJCS 2020; 8(1): 1014-1019

© 2020 IJCS

Received: 21-11-2019

Accepted: 25-12-2019

Rakesh Banwasi

Department of Soil Science and
Agriculture Chemistry, College of
Agriculture, IGKV, Raipur,
Chhattisgarh, India

SK Singh

Division of Remote Sensing
Applications, ICAR-National
Bureau of Soil Survey and Land
Use Planning, Nagpur,
Maharashtra, India

Nirmal Kumar

Division of Remote Sensing
Applications, ICAR-National
Bureau of Soil Survey and Land
Use Planning, Nagpur,
Maharashtra, India

KK Sahu

Department of Soil Science and
Agriculture Chemistry, College of
Agriculture, IGKV, Raipur,
Chhattisgarh, India

Assessing the accuracy of geostatistical techniques for mapping soil macronutrients on basaltic landscape of central India

Rakesh Banwasi, SK Singh, Nirmal Kumar and KK Sahu

DOI: <https://doi.org/10.22271/chemi.2020.v8.i1m.8379>

Abstract

A study was conducted to interpolate and to explore the analysis of spatial variability of major soil nutrients in Basaltic Terrain of Bemetara district, Chhattisgarh. A total of 182 soil samples (0-25 cm) were collected randomly using GPS. Soil chemical properties i.e. available nutrients (N, P and K) were measured in laboratory. Data were interpolated by Ordinary Kriging (Spherical, Circular, and Gaussian). The performance of methods was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Goodness of prediction (G) obtained from a cross-validation procedure. The results showed that Circular, spherical, and Gaussian models were found best fit for available N, P, and K, respectively. All variables showed strong spatial dependence. Cross validation of kriged map showed that spatial prediction of soil nutrients using semi variogram parameters is better than assuming mean of observed value for any unsample location. Therefore it is a suitable alternative method for accurate estimation of soil properties in unsampled positions as compared to direct measurement which has time and costs concerned.

Keywords: Spatial variability, semivariogram, cross-validation, soil properties, GPS

Introduction

Soil is a dynamic natural body which is characterized by high degree of spatial variability due to combined effect of physical, chemical or biological processes that operate with different intensities at different scales (Goovaerts, 1998) ^[5]. Reports have shown that there is large variability in soil properties, crop yield, disease, weed etc., not only in large-sized fields (Godwin and Miller, 2003) ^[4], but also in small-sized fields (Bhattacharyya *et al.*, 2008) ^[1]. Soil macronutrients are essential to plants growth; maintain ecosystem and high crop yields. However, imbalance fertilization, deteriorate the precious soil environment particularly N and P can be potentially hazardous to water resources when their available components in soils are excessive, because available macronutrients can be transported off site in runoff due to rain or irrigation (Smith *et al.*, 1998; Phupaibul *et al.*, 2004) ^[16, 23] and subsequently degrades the fertility of soil and reduced the productivity. Several studies have documented that soil properties vary across agricultural fields, causing spatial variability in crop yields. Information on soil properties in crop field is very important and useful for fertilizer requirement and also to the specific management of the crop and soil. Understanding the distribution of soil properties in the field is important in refining agricultural management practices (McBratney and Pringle, 1999) ^[13] while minimizing environmental damage. Soil variability can be due to many processes acting and interacting across a continuum of spatial and temporal scales and is inherently scale dependant (Trangmar *et al.*, 1985) ^[18]. Knowledge of soil spatial variability and the relationships among soil properties is important for evaluating agricultural land management practices (Huang *et al.*, 1999) ^[7]. Among statistical methods, geo-statistical kriging-based techniques have been often used for spatial analysis (Deutsch, 2002) ^[3]. Spatial interpolation is therefore commonly used to generate soil property maps from discrete point-based data (Schloeder *et al.*, 2001) ^[15]. Robinson and Metternicht, 2006 tested the performance of spatial interpolation techniques (normal kriging and log normal kriging) for mapping soil properties and obtained acceptable results.

In the last two decades, the application of geo-statistical methods by soil scientists focused on predicting spatial variability of soil properties with different kriging methods over small to

Corresponding Author:**Rakesh Banwasi**

Department of Soil Science and
Agriculture Chemistry, College of
Agriculture, IGKV, Raipur,
Chhattisgarh, India

large spatial scale (Tsegaye and Hill, 1998; Lark, 2002) [19]. Traditional mapping method of soil parameters is of little help when the uncertainty associated to the estimated values at unsampled locations is required to support decision making. The geo-statistical methods consider the spatio-temporal variation of soil properties as a random process depending on both time and space (Goovaerts, 1999) [6]. Kriging is a geo-statistical interpolation technique that uses statistical properties of measured points for interpolation at unsampled locations (Isaacs and Srivastava, 1989) [8] and performance can be significantly affected by variability, spatial structure of data (Leenaers *et al.*, 1990) and by the choice of variogram models.

Geographic information systems (GIS), as new technology, for improving sampling design by utilizing the spatial dependence of soil properties within a sampling region and useful to illustrate the spatial interrelationship of soil data which reduces error, biasness and increase the accuracy of data for interpolation (Oliver, 1987). Characterization of soil spatial variability would be a key step towards development of site specific technology that will help the farmers to select the most appropriate soil and water management practices to optimize crop production across the field (Vieira and Gonzalez, 2003) [21]. The most important way to achieve the aforesaid target is to prepare soil maps through spatial interpolation of point-based measurements of soil properties after deriving the structure of spatial variation (Santra *et al.*, 2008) [14]. Therefore, their proper management is necessary to avoid deteriorating the environment while meeting the requirement of high crop productivity and farmer must be advised to use balanced fertilizers/manures, special soil amendment (if any) and accordingly adopt suitable cropping pattern. Hence it is necessary to evaluate the fertility status of the soil and promote the recommendations of soil test for balanced nutrition to maintain soil health. The information on spatial variability of soil properties at village or watershed level, particularly, in soils of basaltic terrain is meager. Therefore, the present study has been planned to assess the accuracy of geospatial techniques and to quantify the spatial variability of soil macronutrients in Miniwada Panchayat, Katol tehsil of Nagpur district of Maharashtra.

Materials and Methods

Study area

Bemetara block belongs to Bemetara district of Chhattisgarh and is located in the centre of Mahanadi basin. Geographically, it is located between 21° 58' to 22° 00' N latitude and 81° 28' to 81° 32' E, covering an area of 2841.65 ha (Fig 1). The study area is part of the Mahanadi Basin which is the 8th largest basin in the country with a catchment area of 139681.51 sq. km between 80° 30' to 86° 50' E longitude and 19° 21' to 23° 35' N latitude covering the states of Chhattisgarh and Odisha and comparatively smaller spread in Jharkhand, Maharashtra and Madhya Pradesh

Soil sample collection and analysis

Soil samples were collected grid wise at random with the help of Global Positioning System (GPS). A total of 182 soil samples were collected from the plough layer (0-25 cm) covering the entire study area. Available nitrogen (Subbiah and Asija, 1956) [17], available phosphorus (Olsen *et al.*, 1954) and available potassium (Hanway and Heidel, 1952) were determined by using standard procedures (Kumar *et al.*, 2018) [9].

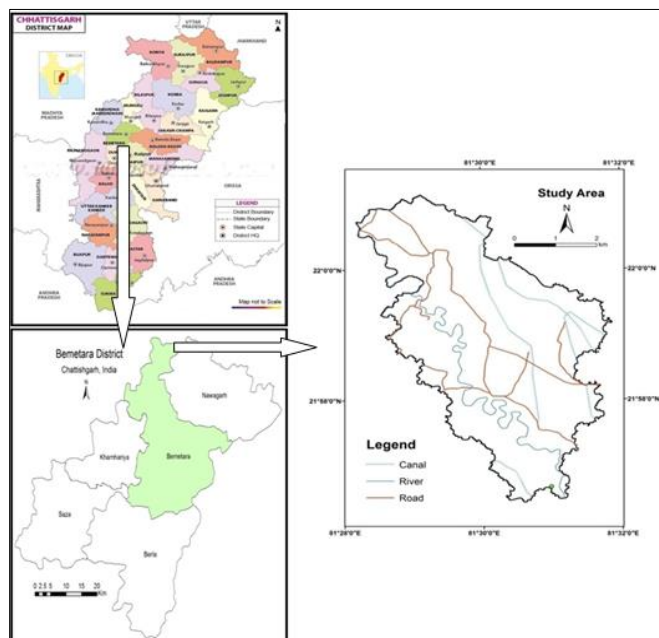


Fig 1: Location map of the study area

Geostatistical analysis of Soil properties

In general, geostatistical methods were used to estimate and map soil properties. It is based on the theory of recognized variables which was used to investigate the soil spatial variability. It is expressed by a Semivariogram which measures, the average dissimilarity between data separated by a vector h it is computed as half the average squared difference between the components of data pairs:

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

Where, $N(h)$ is the number of data pairs within a given class of distance and direction, $z(x_i)$ is the value of the variable at the location x_i and $z(x_i+h)$ is the value of the variable at a lag of h from the location x_i .

Experimental semivariogram value for each property was computed using ArcGIS 10.2.2. During pair calculation, maximum lag distance was taken half of the minimum extent of sampling area to minimize the border effect. Using the semivariogram model, basic spatial parameters such as nugget (C_0), partial sill ($C + C_0$) and range (m) was calculated. Nugget is the variance at zero distance, partial sill is the lag distance between measurements at which one value for a variable does not influence neighboring values and range is the distance at which values of one variable become spatially independent of another (Lopez-Granadoz *et al.*, 2002) [11]. Three commonly used semivariogram models were fitted for soil macronutrients (N, P and K). These are the Spherical, Exponential and Gaussian model. Expressions for different semivariogram models are below:

Spherical model:

$$\gamma(h) = C_0 + C \left[1.5 \frac{h}{a} - 0.5 \left(\frac{h}{a} \right)^3 \right], \text{ if } 0 \leq h \leq a, \quad (2)$$

$$= C_0 + C, \text{ otherwise}$$

Exponential model:

$$\gamma(h) = C_0 + C \left[1 - \exp\left\{-\frac{h}{a}\right\} \right] \text{ for } h \geq 0 \quad (3)$$

Gaussian model:

$$\gamma(h) = C_o + C[1 - \exp\{\frac{-h^2}{a^2}\}] \text{ for } h \geq 0 \quad (4)$$

In all these models, nugget, sill and range were expressed by C_o , $(C + C_o)$ and m , respectively. From spatial data on soil properties corresponding point feature file was prepared in ArcGIS. ArcGIS geo-statistical analyst extension was used to carry out exploratory variogram analysis and then extend this exploratory approach to spatial interpolation by way of kriging. Geo-statistical analysis consisting of variogram calculation, kriging, cross-validation and mapping was performed using the geo-statistical analyst extension of ArcGIS 10.2.2.

Sensitivity analysis

Accuracy of model was done by comparing the deviation of estimates from the measured data and performing a cross-validation test over the dataset. The best model was selected based on four criteria: the standardized mean nearest to zero, the smallest Root-Mean-Squared prediction Error (RMSE), the average standard error nearest the root-mean-squared prediction error and the standardized root-mean-squared prediction error nearest one were selected for each soil nutrient. The performance of interpolation techniques, in terms of the accuracy of predictions, was based on the comparison of the measure of accuracy, namely the Mean-Squared Error (MSE) and on one measure of effectiveness, namely the Goodness of Prediction Estimate (G). The G gives an indication of how effective a prediction might be. The expressions for Mean Absolute Error (MAE), Mean Square Error (MSE) and Goodness of prediction (G) are given below: MAE is a measure of the sum of the residuals (e.g. predicted minus observed) (Voltz and Webster, 1990) [20].

$$MAE = \frac{1}{N} \sum_{i=1}^N [z(x_i) - \hat{z}(x_i)] \quad (5)$$

Where, $\hat{z}(x_i)$ is the predicted value at location. Small MAE values indicate few errors. The MAE measure, however, does not reveal the magnitude of error that might occur at any point and hence MSE was calculated.

$$MSE = \frac{1}{N} \sum_{i=1}^N [z(x_i) - \hat{z}(x_i)]^2 \quad (6)$$

Squaring the difference at any point gives an indication of the magnitude, e.g. small MSE values indicate more accurate

estimation, point-by-point. The G measure gives an indication of how effective a prediction might be relative to that which could have been derived from using the sample mean alone (Schloeder *et al.*, 2001) [15].

$$G = \left(1 - \frac{\sum_{i=1}^N [z(x_i) - \hat{z}(x_i)]^2}{\sum_{i=1}^N [z(x_i) - M]^2} \right) \times 100 \quad (7)$$

Where, M is the sample mean. If $G = 100$, it indicates perfect prediction, while negative values indicate that the predictions are less reliable than using sample mean as the predictors. The comparison of performance between interpolations was achieved by using mean absolute error (MAE).

The spatial dependency of soil properties was graded based on the nugget variance effect. The ratio of nugget variance to sill expressed in percentages $(C_o / C + C_o)$ can be regarded as criterion for classifying the spatial dependence of the soil parameters. If the ratio is equal or less than 25%, then the variable has strong spatial dependence, if it is between 25 and 75% considered as moderate spatial dependence, and the values equal or greater than 75% have weak spatial dependence (Cambardella *et al.*, 1994) [2].

Data analysis

Statistical results indicated that the soil macronutrients were normally distributed. Data sets were analyzed and maps were produced with GIS software ArcGIS and its extension of Spatial Analyst.

Results and Discussion

Distribution of soil fertility parameter

Before modelling the spatial distribution of any fertility property, the data is needed to be checked for normal distribution and the non-normal distributed parameters to be log transformed (Kumar and Sinha, 2018) [9]. The histograms of the soil fertility parameters are shown in figure 2. It shows that, the nitrogen and potassium were normally distributed. The same may be confirmed with the Shapiro-Wilk normality test (table 1). The parameter with non-normal distribution (phosphorous) was log-transformed before spatial modelling.

Table 1: Normality test for the soil fertility parameters using Shapiro-Wilk test

Fertility Parameter	W	P-value	Normal/ Non-normal
Nitrogen	0.98543	0.2114	
Phosphorous	0.94296	1.137e-06	
Potassium	0.97994	0.05562	

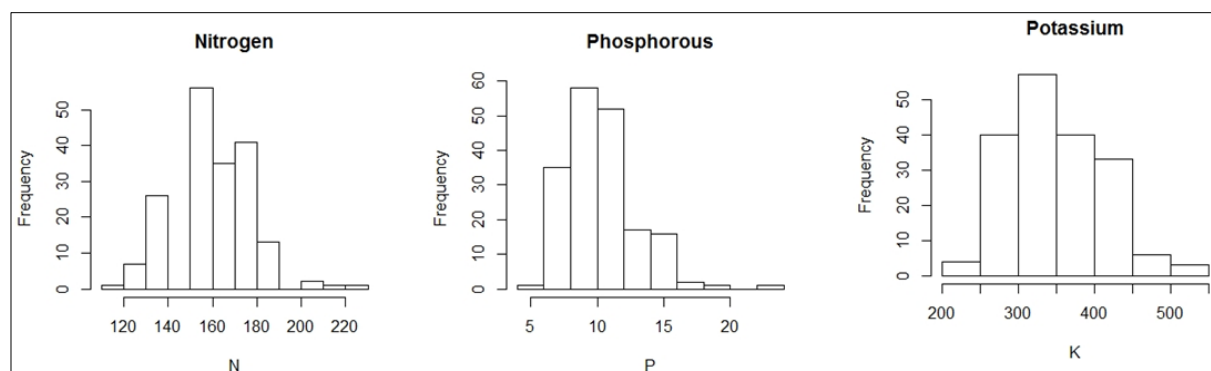


Fig 2: Histogram of the soil macronutrients

Descriptive statistics of soil parameters

The descriptive statistics of soil parameters are shown in Table 2. The available N, P, and K varied from 113 to 226 kg ha⁻¹, 5.56 to 22.4 kg ha⁻¹, and 243 to 508 kg ha⁻¹ with mean value of 159.6 kg ha⁻¹, 10.32 kg ha⁻¹, and 350.35 kg ha⁻¹, respectively. All the samples were found low in nitrogen. Majority of the samples were low to medium in phosphorous, medium to high in potassium. Based on CV, Gomes and Garcia (2002) proposed the classification: low (<10 %), medium (10–20 %); high (20–30 %) and very high (>30 %)

Table 2: Descriptive statistics of the soil nutrients

	Minimum	Max	Range	Mean	SD	Kurtosis	Skewness	Standard Error	Median	CV
N	112.94	225.79	112.85	159.59	18.05	0.42	0.35	1.33	163.07	11.31
P	5.56	22.4	16.84	10.32	2.7	1.85	1.02	0.2	9.86	26.14
K	243.21	508.14	264.93	350.35	60.08	-0.31	0.49	4.44	340.76	17.15

Semivariogram of soil properties

In order to identify the possible spatial structure of different soil properties, semivariograms were calculated and the best models that describe these spatial structures were identified. Root mean square error (RMSE), Root mean square standardized prediction error (RMSSE) and Mean standardized error (MSE) for different theoretical semivariogram models to fit the experimental semivariogram values for each soil property are given in Table 3. The performance of four models (Circular, Spherical, Exponential

and Gaussian) has been compared. According to the cross-validation parameters, generally all three models performed fairly well but exponential was the best model. Among different theoretical models tested, the spherical model was found best fit for phosphorous, Gaussian model was found best fit potassium whereas; circular model was the best for nitrogen. The best fit models had been identified based of the criteria of highest precision and lowest error for estimation of these nutrients.

Table 3: Parameters for different theoretical semivariogram models used to fit the experimental semivariogram of soil properties

Soil properties	Semivariogram model	RMSE ^a	MSE ^c	RMSSE ^b	ASE
Nitrogen	Circular	18.2996	-0.0546	1.0128	17.9637
	Spherical	18.3648	-0.0485	1.0164	17.9610
	Exponential	18.3201	-0.0411	1.0091	18.0738
	Gaussian	18.3795	-0.0483	1.0166	17.9680
phosphorous	Circular	2.6512	-0.0203	0.9269	2.9401
	Spherical	2.6495	-0.0203	0.9249	2.9403
	Exponential	2.6589	-0.0138	0.9124	2.9834
	Gaussian	2.6522	-0.0181	0.9193	2.9506
Potassium	Circular	55.1744	-0.0090	1.0044	54.8985
	Spherical	55.2075	-0.0087	1.0071	54.7834
	Exponential	55.6307	-0.0074	1.0274	54.1328
	Gaussian	54.7053	-0.0117	0.9748	56.0625

Semivariogram parameters (range, nugget and partial sill) for each soil parameter with the best-fitted model are presented in Table 4. The range expressed as distance that could be

interpreted as the diameter of the zone of influence that represented the average maximum distance over which a soil property of two samples was related.

Table 4: Semivariogram parameters (ordinary kriging interpolation) of soil properties

Soil Parameter	Semivariogram model	Range (m)	Nugget (Co)	Partial Sill (C)	Co+C (Sill)	NS ratio
Nitrogen	Circular	220.354	115.507	187.912	303.42	0.38
Phosphorous	Spherical	185.019	0.001	0.070	0.07	0.02
Potassium	Gaussian	2190.060	2959.648	10166.281	13125.93	0.23

At distances less than the range, measured properties of two samples became similar with decreasing distance between the two points. Nugget (Co) defines the micro-scale variability and measurement error for the respective soil property, whereas partial sill (C) indicates the amount of variation, which can be defined by spatial correlation structure. According to the classification of Cambardella *et al.*, 1994^[2] nugget to sill ratio for available N, phosphorous, potassium, and iron was strong whereas for manganese it was low. The other parameters were showing moderate spatial dependency. The cross validation of the observed and predicted values for each parameter is shown in the figure 3. The figures showed

strong and significant correlation between measured and predicted values for K and moderate, but significant for N and P. The model fitness may also be confirmed with the distribution of the residuals (figure 3). The distribution of the residuals were found to be distributed normally along the 1:1 line for pH, OC, K, Fe, and Cu. This showed the fitness of model to be good.

Soil fertility maps

Based on the best fitted semivariograms models, the krigged maps for all the soil parameters were generated. The maps are shown in the figures 4. The soils were low in nitrogen and

phosphorous in the entire study area. The low nitrogen and phosphorous status of the soils in Bemetara district was also reported by IGKV (2013). In the similar kind of landforms and soils in Kavardha district (near to the study area), low

nitrogen status have been reported (Kumar *et al*, 2014). Soil potassium was high and medium in the study area with higher values in the flood plains.

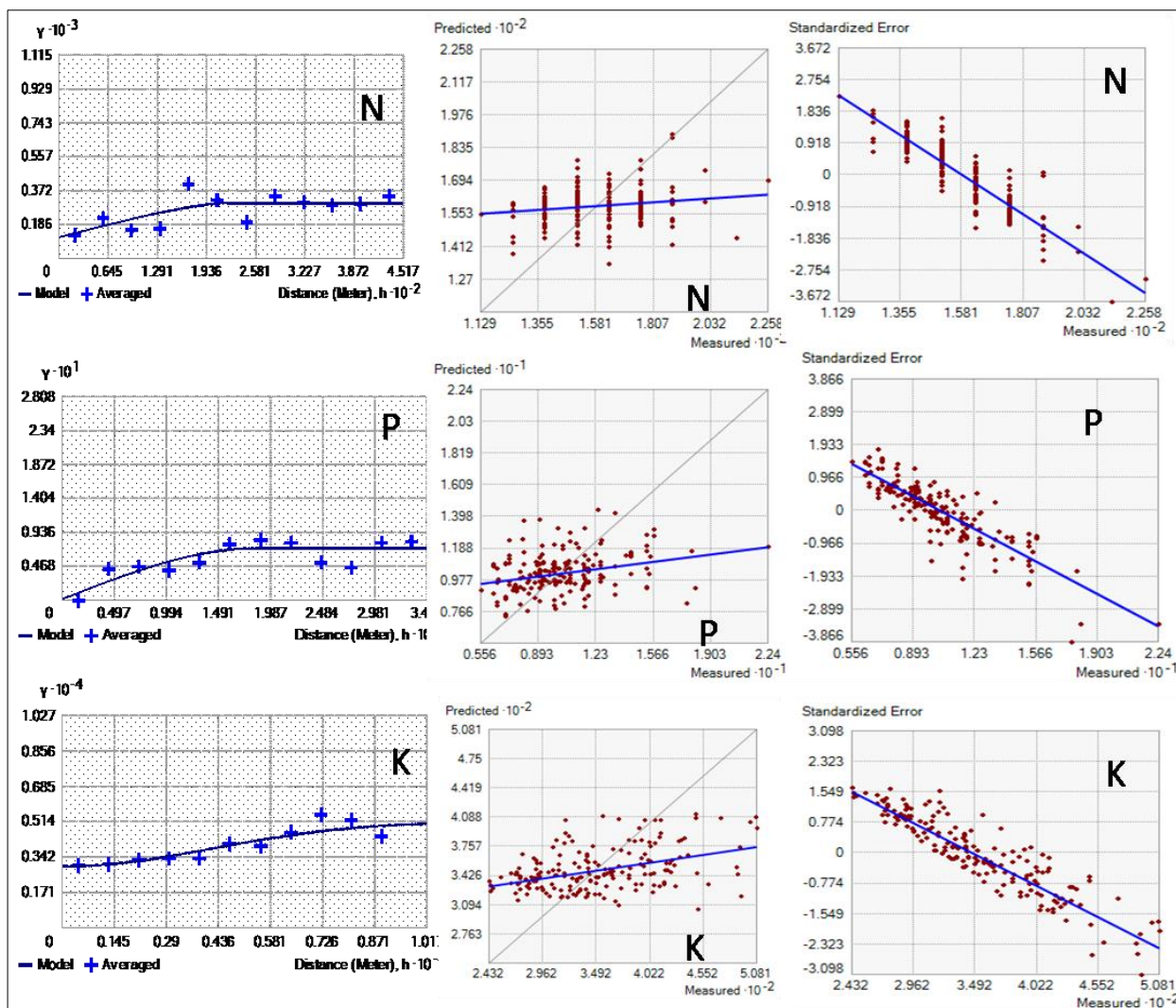


Fig 3: Semivariogram (left), cross validation (middle), and distribution of residuals (right) of soil macronutrients (a) Available N; (b) Available P and (c) Available K

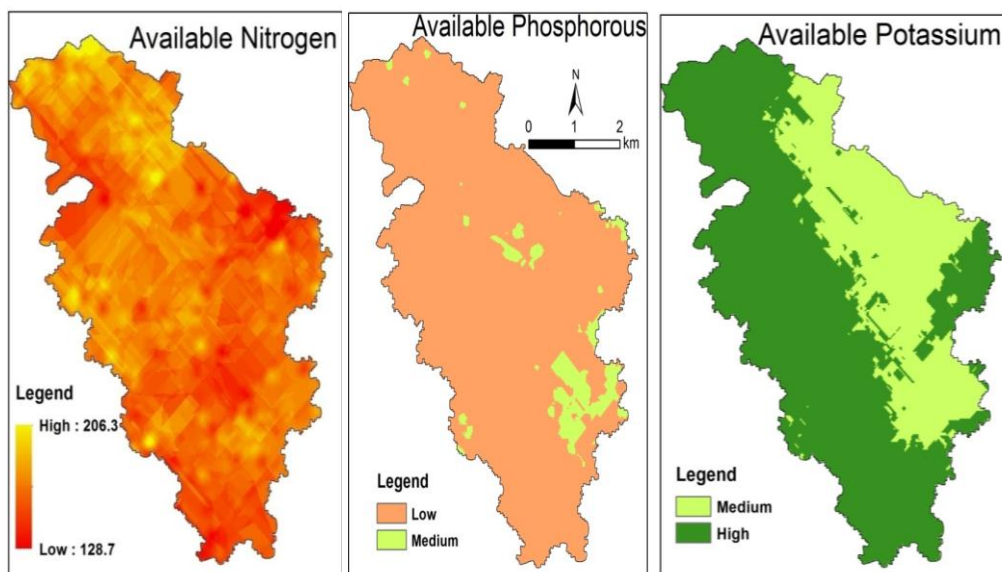


Fig 4: Kriged map of soil macronutrients (a) Available N; (b) Available P and (c) Available K

Conclusions

The generation of soil properties maps by kriging technique depicts their spatial variability and provides a strong base for site-specific nutrient management to optimize crop production and input use efficiency. Spatial variability of soil fertility was quantified through semivariogram analysis and interpolated through ordinary kriging using the best fit model. Results of this research indicated that geostatistics are more suitable methods for estimation of soil properties than other interpolation methods. Circular, spherical, and Gaussian models were found best fit for available N, P, and K, respectively. All the three variables were strongly spatially dependent. Cross-validation of kriged map shows that spatial prediction of basic soil properties using semivariogram parameters is better than assuming mean of the observed value for any unsampled location. The value of MAE and G for kriging as derived from geo-statistical analysis suggests that kriging technique may successfully be used for prediction and mapping the spatial distribution of soil parameters in the study area.

References

- Bhattacharyya P, Tiwari AK, Bhatt VK. Spatial variation of soil strength in small hilly watershed of Shivalik-Himalayan region in India. *Ind. J Soil Conser.* 2008; 36(1):16-21.
- Cambardella CA, Moorman TB, Novak JM, Parkin TB, Karlen DL, Turco RF *et al.* Field scale variability of soil properties in Central Iowa soils. *Soil Science Society of America Journal.* 1994; 58:1501-1511.
- Deutsch CV. *Geostatistical reservoir modeling*, 1st edn. Oxford University Press, New York, 2002.
- Godwin RJ, Miller PCH. A review of the technologies for mapping within-field variability. *Biosystems Engin.* 2003; 84:393-407.
- Goovaerts P. Geo-statistical tools for characterizing the spatial variability of microbiological and physico-chemical soil properties. *Biology and Fert. Soils.* 1998; 27:315-334.
- Goovaerts P. Geostatistics in soil science: state of the art and perspectives. *Geoderma.* 1999; 89:1-45.
- Huang X, Skidmore EL, Tibke G. Spatial variability of soil properties along a transect of CRP and continuously cropped land. In: 10th International Soil Conservation Organization Meeting held, Purdue University and the USDA-ARS National Soil Erosion Research Laboratory, 1999, 641-647
- Isaaks EH, Srivastava RM. *An Introduction to Applied Geostatistics.* New York, NY: Oxford University Press, 1989.
- Nirmal Kumar, Sinha NK. *Geostatistics: Principles and Applications in Spatial Mapping of Soil Properties.* In G. P. Obi Reddy, S. K. Singh (eds.), *Geospatial Technologies in Land Resources Mapping, Monitoring and Management, Geotechnologies and the Environment* 21, Springer International Publishing AG, 2018.
- Kumar U, Mishra VN, Nirmal Kumar, Rathiya GR. *Methods of soil analysis*, Kalyani Publishers, Ludhiana, 2018. ISBN: 9789327288698
- Lopez-Granados F, Jurado-Exposito M, Atenciano S, Garcia-Ferrer A, Sanchez de la Orden M, Garcia-Torres L. *et al.* Spatial variability of agricultural soil parameters in southern Spain. *Plant Soil.* 2002; 246:97-105.
- Leenares H, Okx JP, Burrough PA. Comparison of spatial prediction methods for mapping floodplain soil pollution. *Catena.* 1990; 17:535-550.
- McBratney AB, Pringle MJ. Estimating average and proportional variograms of soil properties and their potential use in precision agriculture. *Precision Agric.* 1999; 1:125-152.
- Santra P, Chopra UK, Chakraborty D. Spatial variability of soil properties and its application in predicting surface map of hydraulic parameters in an agricultural farm. *Current Science.* 2008; 95:937-945.
- Schloeder CA, Zimmerman NE, Jacobs MJ. Comparison of methods for interpolating soil properties using limited data. *Soil Science Society of America Journal.* 2001; 65:470-479.
- Smith VH, Tilman GD, Nekola JC. Eutrophication: impacts of excess nutrient inputs on freshwater, marine, and terrestrial ecosystems. *Environmental Pollution* 100. 1998; (1-3):179-196.
- Subbiah BW, Asija GL. A rapid procedure for estimation of available nitrogen in soils. *Curr. Sci.* 1956; 25:259-260.
- Trangmar BB, Yost RS, Uehara G. Application of geostatistics to spatial studies of soil properties. *Advances in Agronomy.* 1985; 38:45-90.
- Tsegaye T, Hill RL. Intensive tillage effects on spatial variability of soil test, plant growth, and nutrient uptake measurement. *Soil Sci.* 1998; 163:155-165.
- Voltz M, Webster R. A comparison of Kriging, cubic splines and classification for predicting soil properties from sample information. *Journal of Soil Science.* 1990; 31: 505-524.
- Vieira SR, Gonzalez AP. Analysis of the spatial variability of crop yield and soil properties in small agricultural plots. *Bragantia, Caminas.* 2003; 62(1):127-138.
- Webster R, Oliver MA. *Geostatistics for Environmental Scientists.* John Wiley and Sons, Brisbane, Australia, 2001.
- Phupaibul P, Chitbuntanorm C, Chinoim N, Kangyawongha P, Matoh T. Phosphorus accumulation in soils and nitrate contamination in underground water under export-oriented asparagus farming in Nong Ngu Lauem Village, Nakhon Pathom Province, Thailand. *Soil Science and Plant Nutrition.* 2004; 50(3):385-393.