Chemical Science Review and Letters ISSN 2278-6783

Research Article

# Spatial variability of Soil Macronutrients on Basaltic landscape of Central India: A Geostatistical approach

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**Abstract**

A study was conducted to interpolate and to explore the analysis of spatial variability of major soil nutrients in Basaltic Terrain of Nagpur district, Maharashtra. A total of 235 soil samples (0-25 cm) were collected grid wise at an interval of 250 m using GPS. Soil chemical properties i.e. available nutrients (N, P and K) were measured in laboratory. After normalization, data were interpolated by Ordinary Kriging (Spherical, Exponential 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 Ordinary Kriging (Spherical Model) was the best method to estimate available N and K whereas Gaussian Model fits well with highest precision for estimation of available P in this area. Available P and K have displayed moderate spatial dependence whereas Available N 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

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## Introduction

Soil is a dynamic natural body, which is characterize by high degree of spatial variability due to combined effect of physical, chemical or biological processes that operate with different intensities at different scales [1]. Reports have shown that there is large variability in soil properties, crop yield, disease, weed etc., not only in large-sized fields [2], [3], but also in small-sized fields [4]. 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 [5-7] 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 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 [8] 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 dependent [9]. Knowledge of soil spatial variability and the relationships among soil properties is important for evaluating agricultural land management practices [10]. Among statistical methods, geo-statistical kriging-based techniques have been often used for spatial analysis [11]. Spatial interpolation is therefore, commonly used to generate soil property maps from discrete point-based data [12]. [13] tested the performance of spatial interpolation techniques (normal kriging and log normal kriging) for mapping soil properties and obtained acceptable results.

In recent years, geostatistics has been proven to effectively assess the variability of soil properties [14-20]. A semivariogram is use to describe the structure of spatial variability and plays a central role in the analysis of geostatistical data using the kriging method. It takes into account the spatial autocorrelation in data to create mathematical models of spatial correlation structures commonly expressed by variograms [21, 22]. The spatial distribution patterns of soil properties vary greatly depending on soil types, topography, climate, vegetation and anthropogenic activities. Soil mapping is a process in which the spatial variance of topsoil properties are estimated and exposed in a way that can be understood and analyzed by a wide range of users [23, 24]. A standard method for generating these maps is to sample the area of interest using a grid sampling design and then interpolate the measured variable values of the samples using one of the existing interpolation methods. The spatial interpolation methods make available a tool for estimating the values of soil variable at unsampled points using data from point observations [25, 26]. Data measurement accuracy, data density, data distribution and spatial variability are the factors having the greatest influence on interpolation accuracy [27]. The performance of an interpolation method is usually assess and compared using cross validation. The ultimate goal of cross validation is to increase credibility and gain sufficient confidence about an interpolation method, and to ensure that predictions reflect the most likely true outcome, particularly real spatial variability. The performance of interpolation techniques is evaluated using validation indices. A few validation indices include cross validation [28], mean prediction error [29, 30], mean absolute error, [31] mean squared prediction error, [12, 32], and root-mean-squared prediction error [29, 33]. Many studies recognized the importance of spatial structure in the interpolation [34, 35]. Nugget over sill ratio (*N*/*S*), which defines the proportion of short-range variability that cannot be described by a geostatistical model based on a variogram, has been used to quantify the strength of spatial structure. [36] used kriging method to estimate heavy metals and found that the used method is the best estimator for spatial prediction of metals. In another research, spatial distribution maps were constructed for EC and pH of soil extracts using ordinary kriging interpolation in the agricultural lands of Rhodope District, Northeastern Greece [37].

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 large spatial scale [38, 39]. 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 [40]. Kriging is a geo-statistical interpolation technique that uses statistical properties of measured points for interpolation at unsampled locations [41] and performance can be significantly affected by variability, spatial structure of data [34] 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 [42]. 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 [43]. 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 [44]. 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 aimed 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.

Kriging is a widely used method of geostatistical interpolation that assumes that no regional trend exists in the data. This method utilized the co-regionalization structure of soil properties and provided unbiased estimates and minimum variance [45].

## Materials and Methods

### *Study area*

Miniwada Panchayat is situated in Katol tehsil of Nagpur district, Maharashtra and lies between $21^0$ 08′ to $21^0$ 12′ North latitudes and $79^0$ 08′ to $79^0$ 15′ East longitudes with an area of 1621 hectares (**Figure 1**). The panchayat includes three villages namely Miniwada, Mhasala and Malkapur, which. The elevation ranges from 407 to 472 m (WGS 84 datum) above mean sea level (MSL). The geology of the area is basalt. The climate is mainly hot sub-tropical and general dryness throughout the year except during the south-west monsoon season. The mean annual temperature 28$^o$C and mean annual rainfall of 980 mm, which is lower than the average rainfall of 1205 mm of Nagpur district. The area qualifies for hyperthermic soil temperature regime and Ustic soil moisture regime.

### *Soil Sample Collection and Analysis*

Soil samples were collected grid wise at an interval of 250 m with the help of Global Positioning System (GPS). A total of 235 soil samples were collected from the plough layer (0-25 cm) covering the entire study area has shown in

**Figure 2**. Available nitrogen [46], available phosphorus [47] and available potassium [48] were determined by using standard procedures.

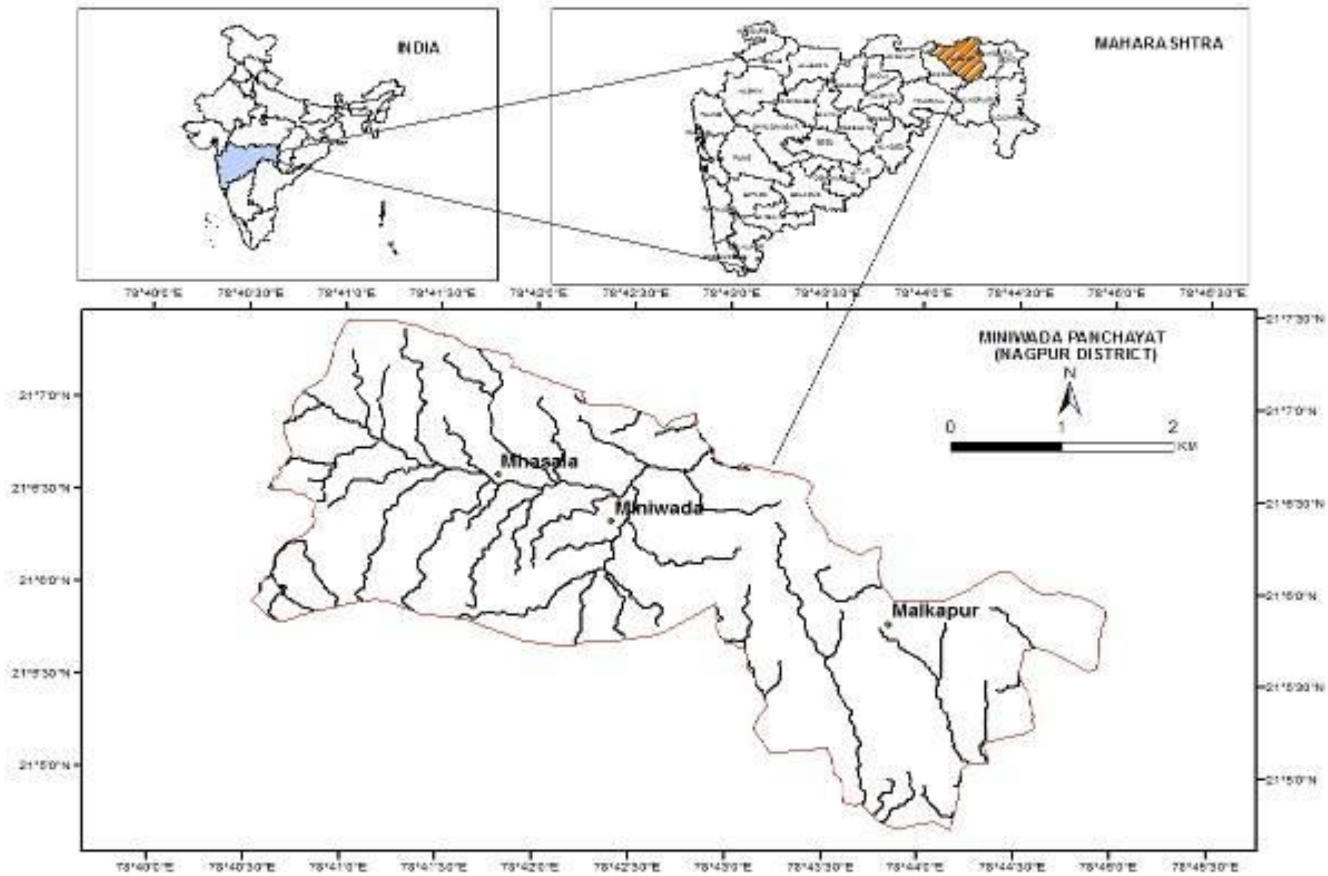



**Figure 1** Location map of the study area

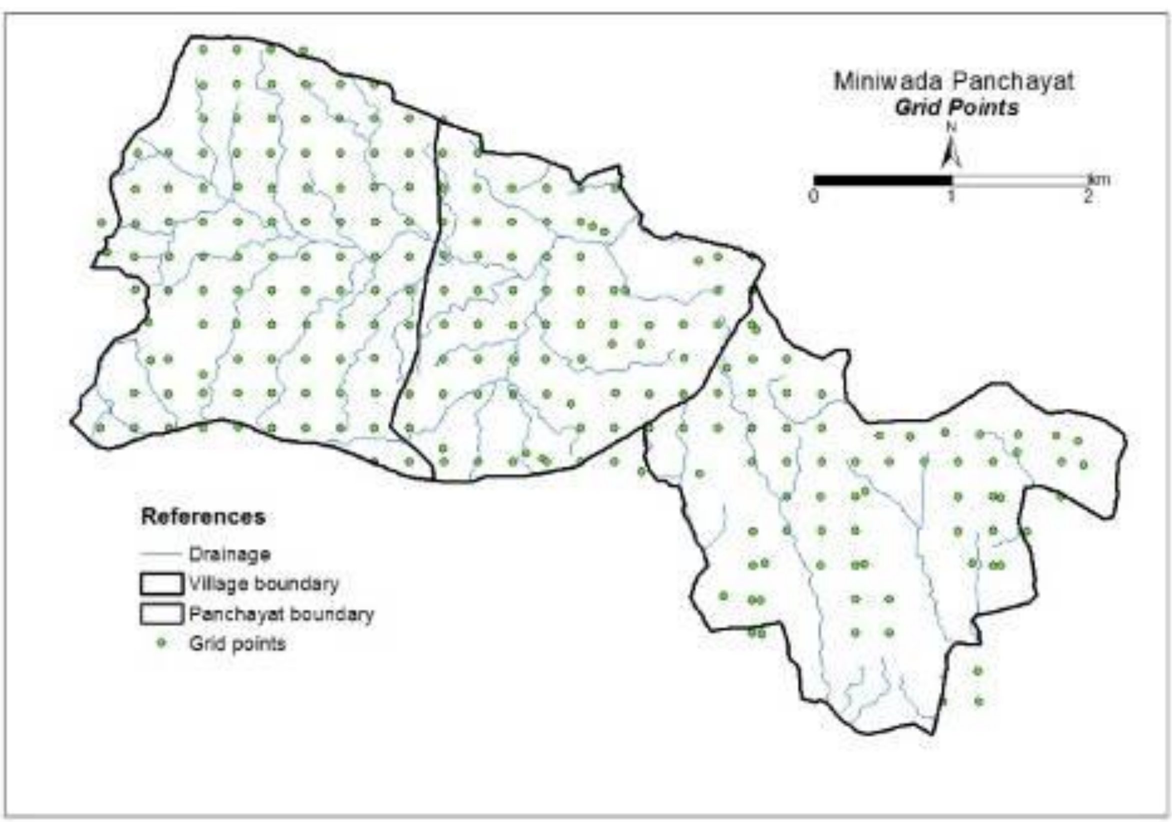



**Figure 2** Distribution of sampling points in Miniwada Panchayat

### *Geostatistical analysis of Soil properties*

In general, geostatistical methods were used to estimate and map the 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:

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

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 [49]. 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*

$$\gamma(h) = C_o + C[1.5\tfrac{h}{a} - 0.5(\tfrac{h}{a})^3], \quad \text{if } 0 \le h \le a, \quad (2)$$
$$= C_o + C, \text{ otherwise}$$

*Exponential model*

$$\gamma(h) = C_o + C[1 - \exp\{\tfrac{h}{a}\}] \quad \text{for } h \ge 0 \quad (3)$$

*Gaussian model*

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

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) [32].

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

Where, $z(x_i)$ 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.

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

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 [12].

$$G = \left(1 - \frac{\sum_{i=1}^{N}[z(x_i) - z(x_i)]^2}{\sum_{i=1}^{N}[z(x_i) - \mathrm{M}]^2}\right) \text{x } 100 \qquad (7)$$

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 ($C_0$ / C+ $C_0$) 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 [24].

### *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

### *Descriptive Statistics of Soil Parameters*

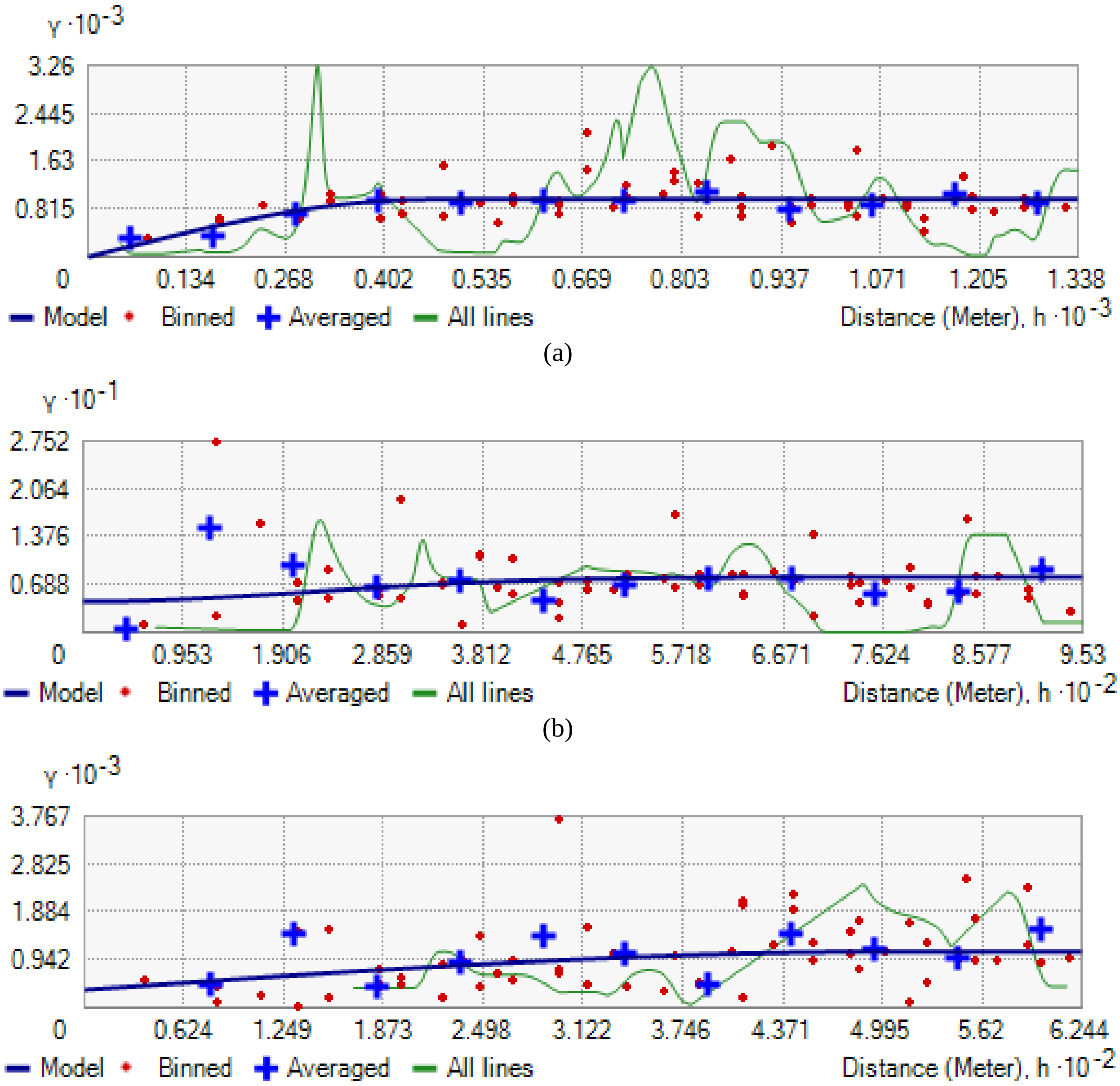
The descriptive statistics of soil parameters are shown in **Table 1** which suggested that they were all normally distributed. The available N, P and K varied from 112.69 to 275.94 kg/ha, 2.1 to 19 kg/ha and 91 to 241 kg/ha, respectively. The greatest and the smallest standard deviation were observed in the available potassium (33.38) and available phosphorus (2.77), respectively. Skewness is the most common form of departure from normality. If a variable has positive skewness, the confidence limits on the variogram are wider than they would otherwise be and consequently, the variances are less reliable. Alogarithmic transformation is considered where the coefficient of skewness is greater than one [17].

**Table 1** Descriptive statistics of soil parameters (0-25 cm) depth of 235 soil samples

| Parameters | Distribution | Minimum | Maximum | Mean | Median | Std. dev. | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| Avail. N (kg/ha) | Normal | 112.69 | 275.94 | 182.18 | 183.27 | 31.82 | -0.019 | 3.00 |
| Avail. $P_2O_5$ (kg/ha) | Normal | 2.1 | 19 | 9.36 | 9.2 | 2.77 | 0.544 | 3.85 |
| Avail. $K_2O$ (kg/ha) | Normal | 91 | 241 | 156.79 | 154 | 33.38 | 0.164 | 2.37 |

### *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 (**Figures 3** and **4**). 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 2**. The performance of three models (Spherical, Exponential and Gaussian) has been compared. According to the cross-validation parameters, generally all three models performed fairly well but Spherical was the best model. Among different theoretical models tested, the Spherical model was found as the best fit in case of available N and available K whereas Gaussian model was the best for available P, because it had the highest precision and lowest error for estimation of these nutrients.



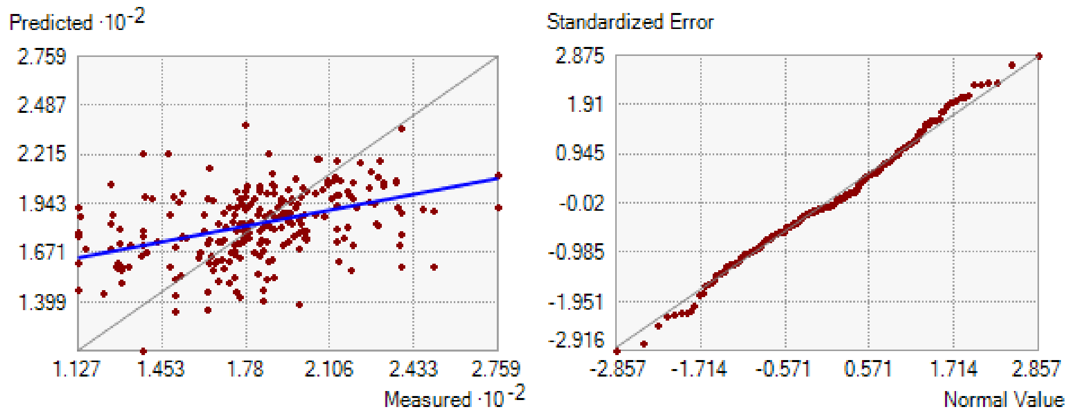

(c)

**Figure 3** Semivariogram of soil macronutrients (a) Available N; (b) Available P and (c) Available K

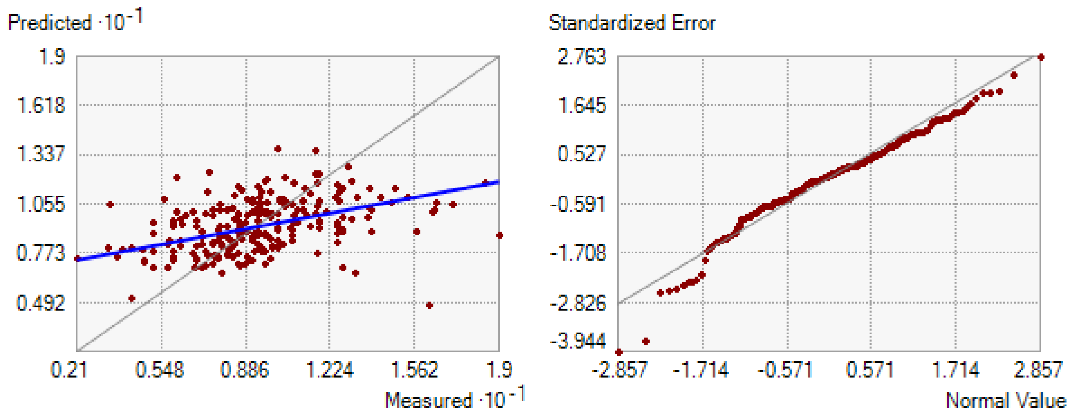
Semivariogram parameters (range, nugget and partial sill) for each soil macronutrient with the best-fitted model are presented in **Table 3**. The range expressed as distance could be interpreted as the diameter of the zone of influence that represented the average maximum distance over which a soil property of two samples was related. At distances less than the range, measured properties of two samples became similar with decreasing distance between the two points. Thus, the range provided an estimate of areas of similarity. Nugget ($C_o$) 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. The interpolation maps of all ordinary kriging soil macronutrients are shown in **Figure 5**. According to the classification of [24] nugget to sill ratio for available N is strong whereas for available P and K had a moderate spatial dependency.

***Ordinary Kriging and Cross Validation***

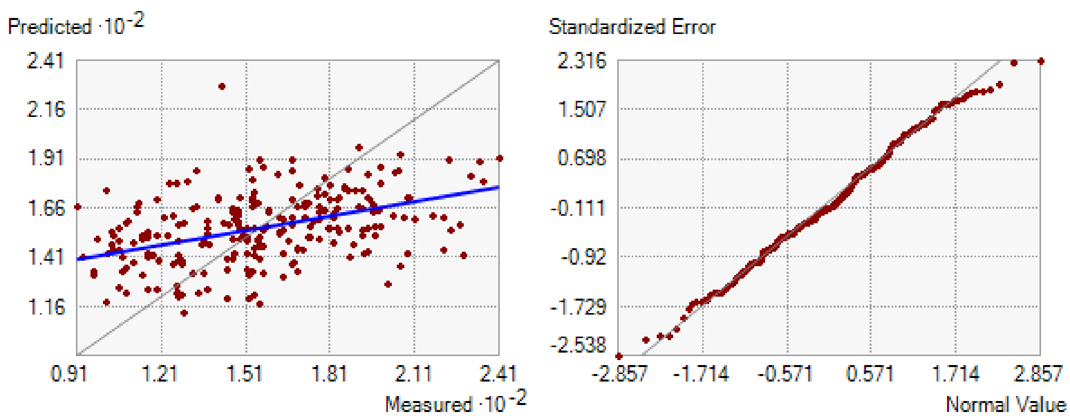
Spatial maps prepared through ordinary kriging using the semivariogram parameters were cross-validated by leaving one sample out and predicting for that sample location based on rest of the samples. Evaluation indices resulting from cross-validation of spatial maps of soil properties are given in **Table 4**. For all soil parameters the *G* value was greater than zero, it indicates that spatial prediction using semivariogram parameters is better than assuming mean of observed value as the property value for any unsampled location. This also shows that semivariogram parameters obtained from fitting of experimental semivariogram values were fairly reasonable to describe the spatial variation.




(a)




(b)




(c)

**Figure 4** Cross validtion and QQ plot of soil macronutrients (a) Available N; (b) Available P and (c) Available K

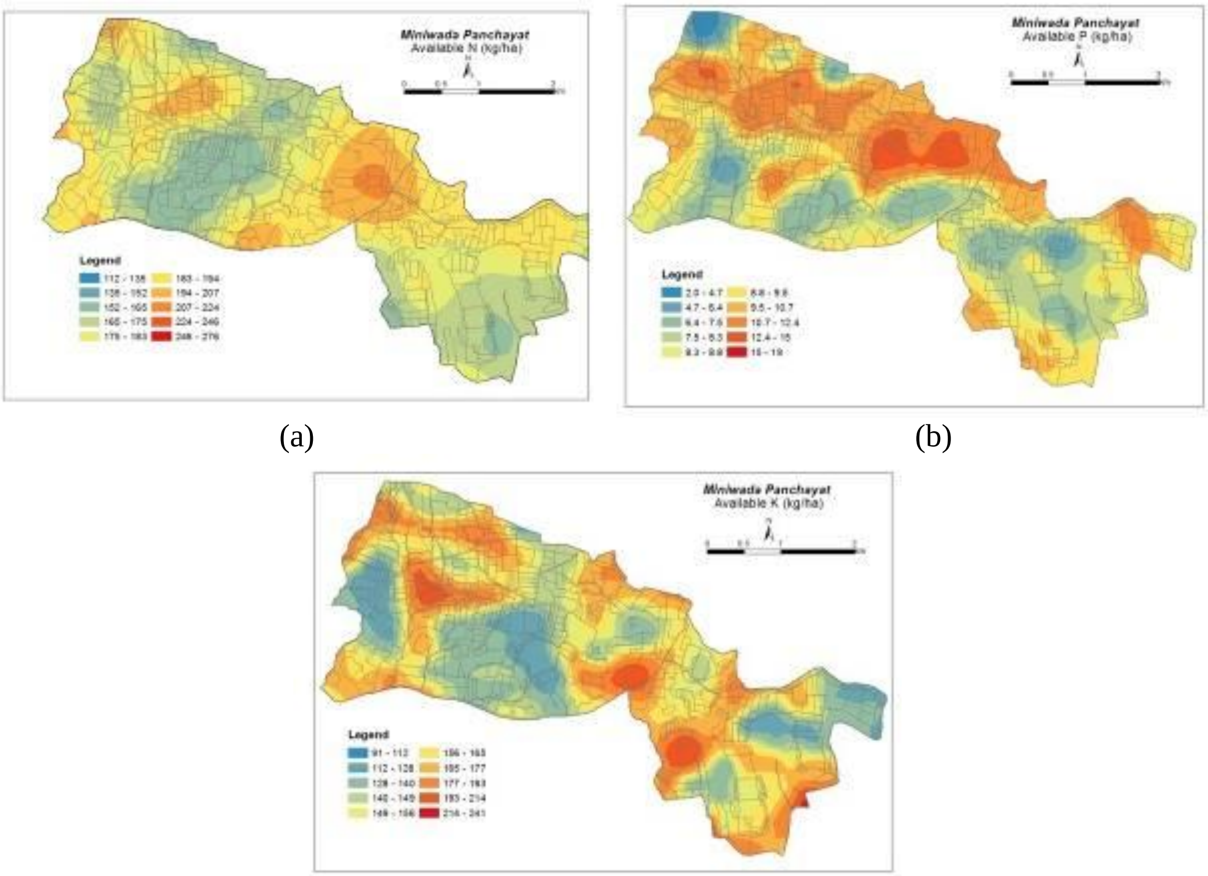
**Table 2** Parameters for different theoretical semivariogram models used to fit the experimental semivariogram of soil properties

| Soil properties | Semivariogram model | RMSE[a] | RMSSE[b] | MSE[c] |
|---|---|---|---|---|
| Avail. N | Spherical | 29.814 | 1.046 | 0.003 |
| | Exponential | 30.176 | 1.047 | 0.004 |
| | Gaussian | 29.892 | 1.062 | 0.006 |
| Avail. $P_2O_5$ | Spherical | 2.557 | 0.967 | -0.001 |
| | Exponential | 2.550 | 0.962 | -0.0007 |
| | Gaussian | 2.539 | 0.959 | -0.002 |
| Avail. $K_2O$ | Spherical | 30.151 | 0.963 | -0.009 |
| | Exponential | 30.214 | 0.961 | -0.012 |
| | Gaussian | 30.231 | 0.967 | -0.008 |

[a]Root Mean Square prediction Error; [b]Root Mean Square Standardized Error; [c]Mean Standardized Error

**Table 3** Semivariogram parameters (ordinary kriging interpolation) of soil properties

| Soil properties | Semivariogram model | Range (m) | Nugget ($C_o$) | Partial Sill (C) | $C_o$+C | NS ratio | Spatial dependence |
|---|---|---|---|---|---|---|---|
| Avail. N | Spherical | 462.78 | 0.06 | 983.99 | 984.05 | -0.00 | Strong |
| Avail. $P_2O_5$ | Gaussian | 522.81 | 4.44 | 3.520 | 7.957 | -0.56 | Moderate |
| Avail. $K_2O$ | Spherical | 513.34 | 353.66 | 749.912 | 1103.573 | -0.32 | Moderate |




(a) (b)

(c)

**Figure 5** Kriged map of soil macronutrients (a) Available N; (b) Available P and (c) Available K

**Table 4** Evaluation performance of Ordinary kriged map of soil properties through cross-validation

| Soil properties | Mean Absolute Error (MAE) | Mean Square Error (MSE) | Goodness of Prediction (G) |
|---|---|---|---|
| Avail. N | 0.125 | 888.85 | 11.8 |
| Avail. $P_2O_5$ | -0.010 | 6.446 | 15.60 |
| Avail. $K_2O$ | -0.426 | 909.08 | 18.07 |

## 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 the study indicate that geostatistical techniques are more suitable methods for estimation of soil properties than other interpolation methods. Spherical model was found best fit for available N and K, whereas Gaussian model was found best fit for available P. Available N was strongly spatially dependent, whereas, Available P and K were moderately 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.

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Publication History

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| Received | 17.12.2019 |
| Revised | 19.01.2020 |
| Accepted | 22.01.2020 |
| Online | 31.01.2020 |