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Spatial Distribution of Soil Nitrogen, Phosphorus and Potassium Contents and Stocks in Humid Subtropical North-Eastern India

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Soil nitrogen (N), phosphorus (P) and potassium (K) are important macronutrients for crop production and productivity. Assessment of spatial distribution and stock of N, P and K in soil are the need of the hour for judicious nutrient management through precision agriculture. An attempt was made to prepare the spatial distribution map of available macronutrients in soil using geostatistical techniques. In total 150 geo-referenced surface soil samples (0-25 cm depth) were collected at 1 km × 1 km grid interval in three major land use systems *viz*., crop, plantation and agroforestry (like *Mangifera indica*, *Syzigium cumini*, *Shorea robusta*, *Tectona grandis*, *Acacia auriculiformis* and *Bambusa sp.*) from Bishalgarh block, Sepahijala district, Tripura of North-eastern India. Data indicates that soil bulk density (BD), and available N, P and K varied from 1.10 to 1.82 g cm^{-3}, 0.01 to 0.29 g kg^{-1}, 0.001 to 0.02 g kg^{-1} and 0.02 to 0.24 g kg^{-1}, respectively. Stock of N, P and K in these soils varied from 0.33 to 8.71, 0.02 to 0.69 and 0.72 to 8.52 Mg ha^{-1}, respectively. Perusal of dataset under different land use systems revealed that stock of available N, P and K in surface soil followed the order of plantation land > agroforestry land > cropland. Geostatistical analyses indicated that spherical model was best fitted for N and P content in soil, while exponential model was best fitted for K content. Similarly, stocks of N, P and K in soil could be best fitted by exponential model. The nugget/sill ratio indicates a strong dependence for N (5%), a weak spatial dependence for K stock (81%) and moderate spatial dependence for all other soil variables (51-69%). The spatial distribution maps of macronutrients in soil exhibited differential distribution pattern indicate the need of differential soil application rates in respect of N, P and K. Such study is of practical significance in managing soil resources through judicious application of fertilizers under precision agriculture.

Key words: Ordinary kriging, geostatistical analysis, spatial distribution, macronutrients, land use systems

Soil nitrogen (N), phosphorus (P) and potassium (K) are important macronutrients for crop growth and development. Crop yield and yield attributes are largely governed by the presence of these essential elements in soil. However, imbalance in soil nutrients adversely affects crop production and productivity. Therefore, systematic assessment and monitoring of soil nutrient status are important for identification of priority area in order to implement proper nutrient management practices. Such information is also important to refrain from excessive application of fertilizers, which would otherwise cause environmental degradation. Assessment of nutrient status with their variability in soil provides a scientific basis for judicious nutrient management in agriculture. With the modernization in agriculture, it is the need of the hour to adopt precision agriculture for better management of natural resources and utilization of inputs. Use of geostatistical techniques in mapping of soil nutrient status is important step towards precision farming.

Enhancing nutrient use efficiency through site-specific nutrient management has been a great challenge for the resource managers. Analysis of spatial variability of nutrients in soil has been a prerequisite for site-specific nutrient management (Reza *et al.* 2016a, 2017, 2018a). Adoption of such approach of assessing and predicting nutritional status

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in soil is of immense importance in improving input use efficiency, thus increasing productivity and reducing environmental risks (Yasrebi *et al.* 2009). The need of assessing spatial variability of nutrients in soil arises from the fact that soils are also varying from place to place even under similar agro-climatic condition. Variability in soil properties results mainly from the complex interactions between geology, topography and climate, as well as soil use and management (Liu *et al.* 2015). Therefore, assessing spatial variability of soil nutrients in relation to land use systems is highly relevant. It is worthwhile to mention that such information has relevance in land use planning.

Geostatistics is a technology to predict a soil variable at unknown locations using a property measured at a given place and time (Yasrebi *et al.* 2009). Based on this assumption, many techniques have been developed to predict the spatial variability of soil properties in the last few decades, such as ordinary kriging (OK), inverse distance weighting (IDW), artificial neural network and pedo-transfer functions (Reza *et al.* 2013, 2015; Veronesi *et al.* 2014). In recent years, OK has been widely used by many researchers for preparation of spatial variability maps of soil chemical properties (Behera *et al.* 2011; Reza *et al.* 2012a, 2012b) and soil physical properties (Reza *et al.* 2016b). However, the information on spatial variability of soil properties in relation to land use Tripura soils of India is limited (Choudhary *et al.* 2016).

Keeping above things in view, a systematic study was carried out 1) to assess the spatial variability of available N, P and K and its stocks in soils of Bishalgarh block of Sepahijala district, Tripura, North-eastern India, and 2) to estimate the total N, P and K storage under different land use systems in the study area for land management and maintaining or improving productivity.

Materials and Methods

Study Area

The area under investigation belongs to Bishalgarh block, Sepahijala district, Tripura, North-eastern India (23°36′51″ - 23°45′02″ N latitude, 91°08′58″ - 91°23′00″ E longitude) covering an area of 17051 ha (Fig. 1). The area is characterized by humid subtropical climate with annual mean maximum temperature is 36 ºC and annual mean

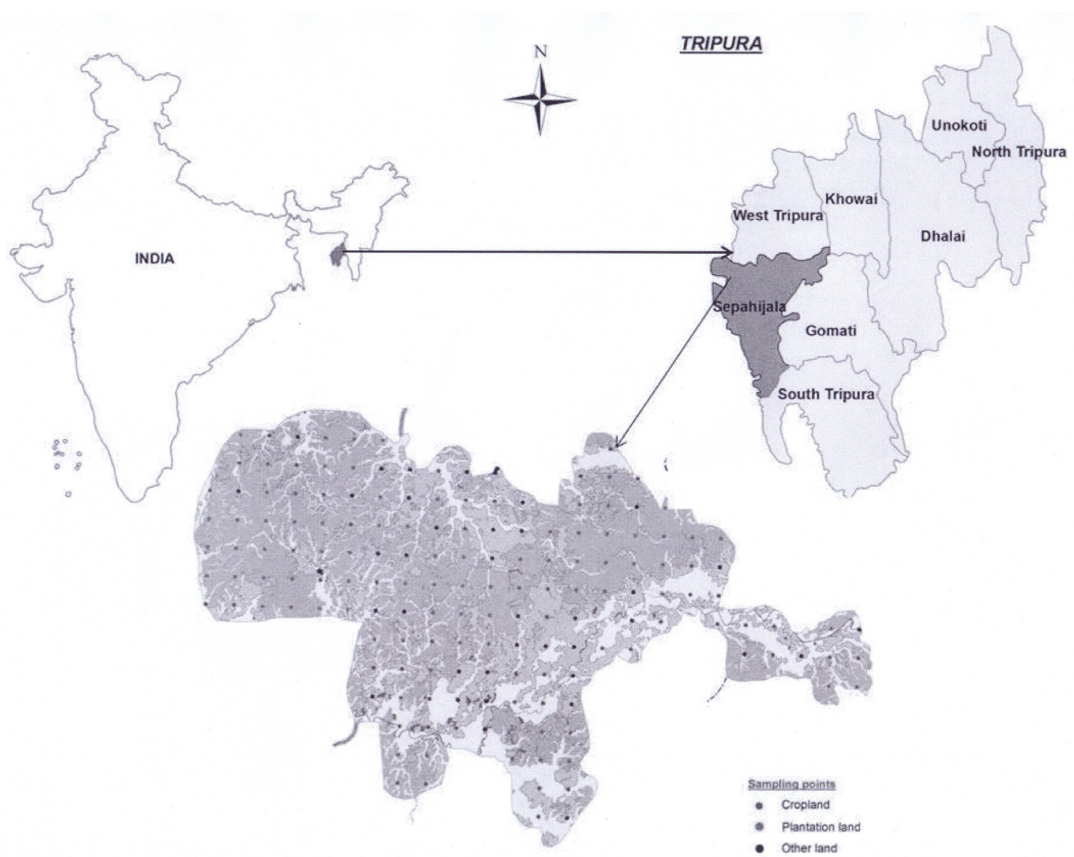

Fig. 1. Location and grid map of the study area

minimum temperature is 7 ºC. The mean annual rainfall is 2340 mm. Geomorphologically, the study area represents undulating terrain. Two major landforms namely, high lands (*tillas*) and valley land (*lungas*) are common in the study area. Soil resource information indicates the presence of five broad soil subgroups in the study area namely, Typic Hapludults, Typic Endoaqualfs, Fluvaquentic Dystrudepts, Aeric Endoaqualfs and Typic Endoaquents.

Land Use Systems

A land use/land cover (LULC) map of the study area was prepared using IRS Resourcesat 2 LISS IV data through visual interpretation in geographical information system (GIS) environment in order to delineate the existing land use systems. Three broad land use systems were identified *viz*., cropland including single and double crop (rice, pigeon pea, black gram, rapeseed-mustard, potato and *rabi* vegetables), plantation land including rubber and tea plantation and agroforestry land comprising homestead cultivation of trees like mango (*Mangifera indica)*, jamun (*Syzigium cumini*), sal (*Shorea robusta*), teak (*Tectona grandis*), acacia (*Acacia auriculiformis*) and bamboo (*Bambusa* sp.).

Soil Sampling and Analysis

For collection of soil samples, grids of 1 km × 1 km interval were overlayed on the LULC map of the study area (Fig. 1) and 150 georeferenced surface (0-25 cm) soil samples were collected using handheld global position system (GPS). Number of soil samples collected from cropland, plantation land and agroforestry land were 43, 71 and 36, respectively.

Soil samples were air-dried, ground and sieved to pass to through 2-mm sieve. Bulk density (BD) of samples for each grid points was obtained using standard procedure (Black and Hartge 1986). The available N was determined following Subbiah and Asija (1956) method. Available K was extracted with 1 *N* NH_4OAc and then measured by flame photometer. Phosphorus was determined colorimetrically using standard procedure (Bray and Kurtz 1945).

The N, P and K density were calculated with the following equation (Guan *et al*. 2015):

$$\text{N density (P or K) (Mg ha}^{-1}\text{)} = \frac{\text{N (P or K) (g kg}^{-1}\text{)} \times \text{BD (g cm}^{-3}\text{)} \times \text{soil depth (cm)}}{10} \quad \ldots(1)$$

For estimation of total N, P and K stocks under various land use systems in the block, mean values of N, P and K density and area under each land use categories were used.

$$\text{N or P or K stock (Gg)} = \frac{\text{N density or P density or K density (Mg ha}^{-1}\text{)} \times \text{Area under each land use (ha)}}{10^3} \quad \ldots(2)$$

Statistical and Geostatistical Analyses

The descriptive statistical analysis including minimum, maximum, mean, standard deviation, coefficient of variation (CV), skewness and kurtosis were analyzed. The normal frequency distribution of data was verified by the Kolmogorov-Smirnov (K-S) test. Analysis of variance (ANOVA) was performed to test the effect of land uses on BD, available N, P and K. Fisher's t-test was performed to examine the significant differences between means. The Pearson correlation coefficient was also performed between the variables.

Spatial interpolation and GIS mapping techniques were employed to produce spatial distribution maps for the investigated soil properties. The software used for this purpose was ArcGIS v.10.1 (ESRI Co, Redlands, USA). The semivariogram analyses were carried out before application of ordinary kriging interpolation as the semivariogram model determines the interpolation function (Goovaerts 1997) as given below.

$$\gamma(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}[z(x_i) - z(x_i + h)]^2 \quad \ldots(3)$$

where, $z(x_i)$ is the value of the variable z at location of x_i, h the lag and N(h) the number of pairs of sample points separated by h.

Different semivariogram models were evaluated to select the best fitted model with the data. Best-fit model with minimum root mean square error (RMSE) were selected for each soil property:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2} \quad \ldots(4)$$

The spherical, exponential and Gaussian models were best fitted to all the soil properties. Expression for different semivariogram models used in this study is given below:

Spherical model:

$$\gamma(h) = C + C_0\left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right] \text{ for 0 h a otherwise } C + C_o \quad \ldots(5)$$

Exponential model:

$$\gamma(h) = C_0 + C\left[1 - \exp\{-\frac{h}{A}\}\right] \text{ for h} \geq 0 \qquad \ldots(6)$$

where, h = lag interval, C_0 = nugget variance ≥ 0, C = structure variance ≥ C_0, and A = range parameter.

Using the model semivariogram, basic spatial parameters such as nugget (C_0), sill (C + C_0) and range were calculated which provide information about the structure as well as the input parameters for the kriging interpolation. The nugget/sill ratio and the range are the parameters which characterize the spatial structure of a soil property. The range defines the distance over which the soil property values are correlated with each other. A low value of nugget/sill ratio and a high range generally indicates that high precision of the predicted value of property can be obtained (Cambardella *et al*. 1994). The nugget/sill ratio was used as the criterion to classify the spatial dependence of variables. Ratio values lower than or equal to 0.25 were considered to have strong spatial dependence, whereas values between 0.25 and 0.75 indicate moderate dependence and those greater than 0.75 show weak spatial dependence (Cambardella *et al*. 1994).

Accuracy of maps was evaluated through cross-validation approach (Reza *et al*. 2010). Among three evaluation indices used in this study, mean absolute error (MAE), and mean squared error (MSE) measure the accuracy of prediction, whereas goodness of prediction (G) measures the effectiveness of prediction (Utset *et al.* 2000). The MAE is a measure of the sum of the residuals (*e.g.* predicted minus observed).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)] \qquad \ldots(7)$$

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

$$MSE = \frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2 \qquad \ldots(8)$$

Squaring the difference at any point gives an indication of the magnitude, for example, 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).

$$G = \left[1 - \frac{\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2}{\sum_{i=1}^{N}[z(x_i) - \overline{z}]^2}\right] \times 100 \qquad \ldots(9)$$

where, *z* is the sample mean. G is one of the methods used for accuracies of interpolated maps (Tesfahunegn *et al.* 2011). Accuracies of interpolated maps of studied soil properties were checked by G values. Positive G values indicate that the map obtained by interpolating data from the samples is more accurate than an area average. Negative and close to zero G values indicate that the area-scale average predicts the values at unsampled locations as accurately as or even better than the sampling estimates.

Results and Discussion

Descriptive Statistics

Descriptive statistics for each soil properties are shown in table 1. The values of BD ranged from 1.10 to 1.82 g cm^{-3} with the mean value of 1.47 g cm^{-3}. The mean values of N, P and K content were 0.11, 0.01 and 0.06 g kg^{-1}, respectively. The stocks of available N, P and K ranged from 0.33 to 8.71, 0.02 to 0.69 and 0.72 to 8.52 Mg ha^{-1}, respectively and the corresponding mean values were 4.10, 0.24 and 2.13 Mg ha^{-1}, respectively. The values of CV for soil properties ranged from 10.9 to 66.7%. The value of CV for BD revealed lowest variability (CV <25%). Other researchers also documented smaller variation of BD compared to other soil variables (Zhang *et al.*

Table 1. Descriptive statistics for soil variables (n=150)

Soil variables	Mean	Minimum	Maximum	SD*	CV (%)**	Skewness	Kurtosis	Distribution pattern
Bulk density (g cm^{-3})	1.47	1.10	1.82	0.16	10.9	-0.29	-0.33	Normal
Nitrogen (g kg^{-1})	0.11	0.01	0.29	0.04	36.4	0.40	1.42	Normal
Nitrogen stock (Mg ha^{-1})	4.10	0.33	8.71	1.54	37.6	0.21	0.26	Normal
Phosphorus (g kg^{-1})	0.01	0.001	0.02	0.004	40.0	0.95	0.38	Normal
Phosphorus stock (Mg ha^{-1})	0.24	0.02	0.69	0.15	62.5	1.01	0.44	Log
Potassium (g kg^{-1})	0.06	0.02	0.24	0.04	66.7	1.92	4.40	Log
Potassium stock (Mg ha^{-1})	2.13	0.72	8.52	1.30	61.0	1.89	4.33	Log

*Standard deviation; **Coefficient of variation

Table 2. Mean values of the soil variables used to estimate nutrients stocks in the different land use systems

Soil variables	Land uses		
	Crop	Agroforestry	Plantation
Bulk density (g cm^{-3})	1.44 (-0.02)*	1.46 (-0.03)	1.51 (-0.01)
Nitrogen (g kg^{-1})	0.109 (-0.007)	0.113 (-0.006)	0.112 (-0.004)
Phosphorus (g kg^{-1})	0.0059 (-0.0006)	0.0065 (-0.0006)	0.0067 (-0.0004)
Potassium (g kg^{-1})	0.055 (-0.004)	0.058 (-0.005)	0.062 (-0.004)

*Mean and standard error of mean

2015). The rest of the soil properties exhibited moderate (CV 25-75%) variability. Skewness values of -0.29 to 1.92 for different soil proprieties revealed that some soil properties were not normally distributed. Such variation and non-normal distribution of soil properties in the block may be due to different soil management practices including variation in fertilizer application and other crop management practices under different land use systems (Srinivasarao *et al*. 2014). Normality is not strictly required in geostatistical analyses but normal distribution may lead to more reliable results (Webster and Oliver 2001). Therefore, the data distribution was tested for normality using the Kolmogorov-Smirnov test. The data on K, K stock and P stock was not normally distributed (Table 1), and therefore subjected to a natural log transformation.

Significant differences in BD, P and K were observed between cropland and plantation (Table 2). The mean BD (1.51 g cm^{-3}), P (0.0067 g kg^{-1}) and K (0.062 g kg^{-1}) was higher in plantation land over cropland and agroforestry land. This may be due to the cultivation of rubber as plantation crops with no-tilled system (Mansor *et al*. 2015).

Geostatistical Analysis of Macronutrients and their Stocks

Semivariogram parameters (nugget, sill and range) for soil variables with best fitted model were identified based on minimum RMSE. Other researchers also used the similar methodology for selecting the best model for interpolation using kriging (Reza *et al*. 2016c, 2017, 2018b). Analysis of the isotropic variogram indicated that the N stock, P stock and K stock semivariograms were well-described by exponential model, with the distance of spatial dependence being 6100, 2300, 3570 and 2700 m, respectively, while the N and P semivariograms were well-described by spherical model, with the distance of spatial dependence being 2180 and 2160 m, respectively (Table 3).

Nugget values present undetectable experimental errors, field variation within the minimum sampling space and inherent variability. In this study, nugget values ranged from 0.00001 to 1.679 for different soil variables. The nugget was highest for N stock, which is ascribed to the fact that the selected sampling distance could not capture the spatial dependence well. The nugget/sill ratio values were 5, 69, 54, 51 and 81% for N, N stock, P, P stock, K and K stock, respectively, which indicates moderate spatial dependence for N, P and K, imprinted by intrinsic factor (soil forming process) and extrinsic factors (soil fertilization and cultivation practices) (Cambardella *et al*. 1994).

Spatial Distribution of Macronutrients and their Stocks

Spatial distribution maps of soil variables as prepared by OK showed that the N content in central and eastern portion was high. This may be due to the high OC content in central and eastern portion of the

Table 3. Geostatistical parameters of the fitted semivariogram models for soil variables

Soil variables	Fitted model	Nugget (C_0)	Sill ($C + C_0$)	Range* (A)	Nugget/Sill	RMSE**
Nitrogen	Spherical	0.001	0.020	2180	0.05	0.041
Nitrogen stock	Exponential	1.679	2.423	6100	0.69	1.433
Phosphorus	Spherical	0.00001	0.000016	2160	0.69	0.003
Phosphorus stock	Exponential	0.264	0.488	2700	0.54	0.148
Potassium	Exponential	0.246	0.486	2300	0.51	0.501
Potassium stock	Exponential	0.226	0.280	3570	0.81	1.701

*Range in m; **RMSE = Root mean square error block. The P content of the study area was scattered in distribution. The spatial distribution map of K content was found low in eastern portion of the block (Fig. 2).

The spatial distribution patterns of N, P and K stocks as predicted by OK were shown in fig. 3. The spatial distribution of nutrient stocks followed the distribution pattern of respective concentration of nutrients. The highest soil N stock was observed in the plantation land *i.e.* tilla land of the block. The lowest stock of P was estimated in the south-west portion of the block. On the contrary, K stock was higher in the south-west portion of the block. Such a spatial distribution pattern of nutrient stock indicates

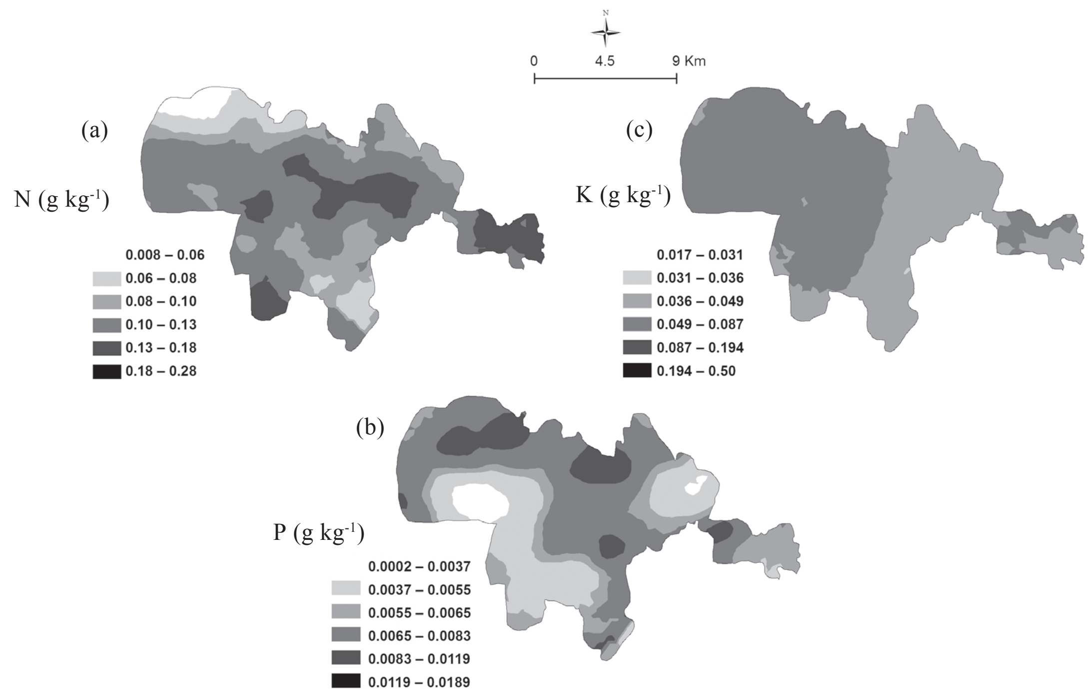

Fig. 2. Spatial distribution maps of (a) nitrogen (N), (b) phosphorus (P) and (c) potassium (K)

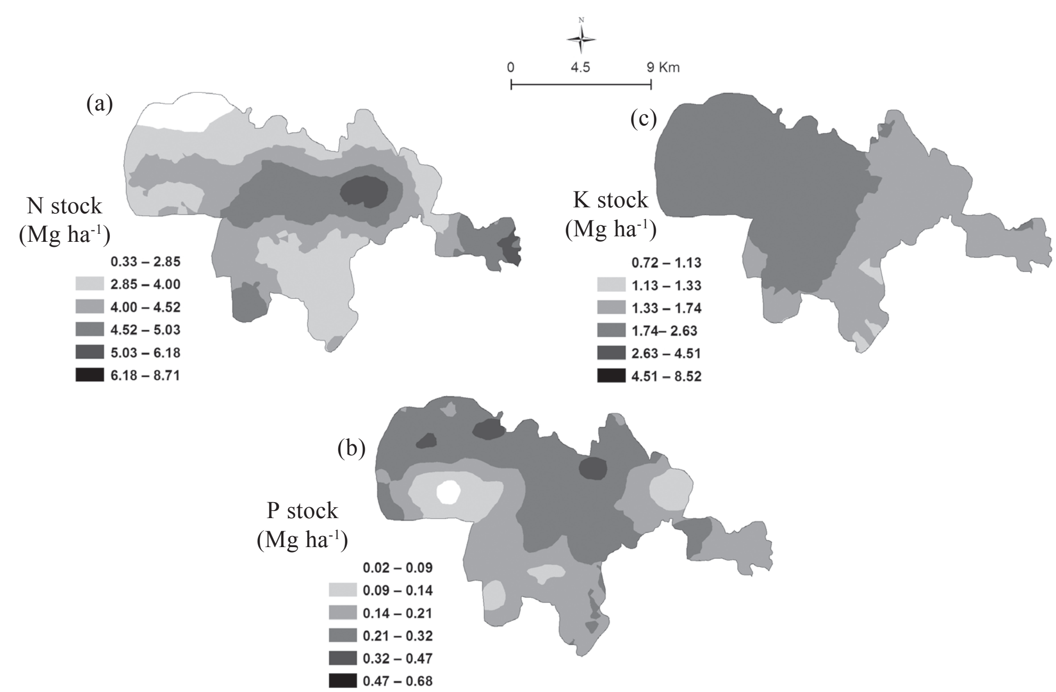

Fig. 3. Spatial distribution maps of (a) N stock, (b) P stock and (c) K stock

Table 4. Accuracy evaluation of ordinary kriged map of soil variables

Soil properties	Mean absolute error	Mean square error	Goodness of prediction
Nitrogen	0.0001	0.0016	7
Nitrogen stock	0.024	2.06	13
Phosphorus	0.000009	0.00001	46
Phosphorus stock	0.0005	0.0022	4
Potassium	-0.0015	0.0025	12
Potassium stock	-0.015	1.69	20

Table 5. Soil nutrients stocks in the different land use systems

Parameters	Land uses		
	Crop	Agroforestry	Plantation
Surface area (ha)	4361	4575	8115
Mean nitrogen stock (Mg ha^{-1})	3.84	4.12	4.26
Total of nitrogen (Gg)	16.75	18.85	34.57
Mean phosphorus stock (Mg ha^{-1})	0.21	0.24	0.25
Total of phosphorus (Gg)	0.92	1.10	2.03
Mean potassium stock (Mg ha^{-1})	1.95	2.08	2.30
Total of potassium (Gg)	8.50	9.52	18.66

differential management practices under different land use system.

The evaluation indices resulting from cross-validation of spatial distribution maps of soil variables showed in table 4. It was observed that, N stock and K stock had higher MSE than other soil variables. For all the soil variables, the G value was greater than 0, which indicates that spatial prediction using geostatistical technique is better than assuming mean of observed value as the property value for any unsampled location. This also shows that semi-variogram parameters obtained from fitting of experimental semivariogram values were reasonable to describe the spatial variation of all the studied soil variables.

Nutrient Stock in different Land Use Systems

Available N, P and K stocks in the topsoil (0-25 cm depth) of the block were 70.17, 4.05 and 36.68 Gg, respectively. The estimated stock values for plantation land, agroforestry land and cropland were 34.57, 18.85 and 16.75 Gg, respectively for N; corresponding values were 2.03, 1.10 and 0.92 Gg, respectively for P; and 18.66, 9.52 and 8.50 Gg, respectively for K (Table 5). The total stock of available N, P and K in the topsoil followed the order of plantation land > agroforestry land > cropland. Relatively lower nutrient stock in cropland may be due to the effect of intensive cropping under improper management practices.

Conclusions

The study indicates that geostatistical method is useful for evaluating spatial variability of soil parameters. Geostatistical analysis revealed that exponential and spherical semivariogram models best fitted for studied soil variables. The nugget/sill ratio values indicate a moderate spatial dependence for N, P and K contents. The spatial distribution maps of the macronutrients and their stocks in the study area indicate differential management practices are required depending on the variability in soil. The spatial distribution maps developed for soil properties could be serve as the primary guide for region-specific nutrient management. Further, the information generated in the study could be useful in monitoring nutritional status in the study area over a period of time.

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