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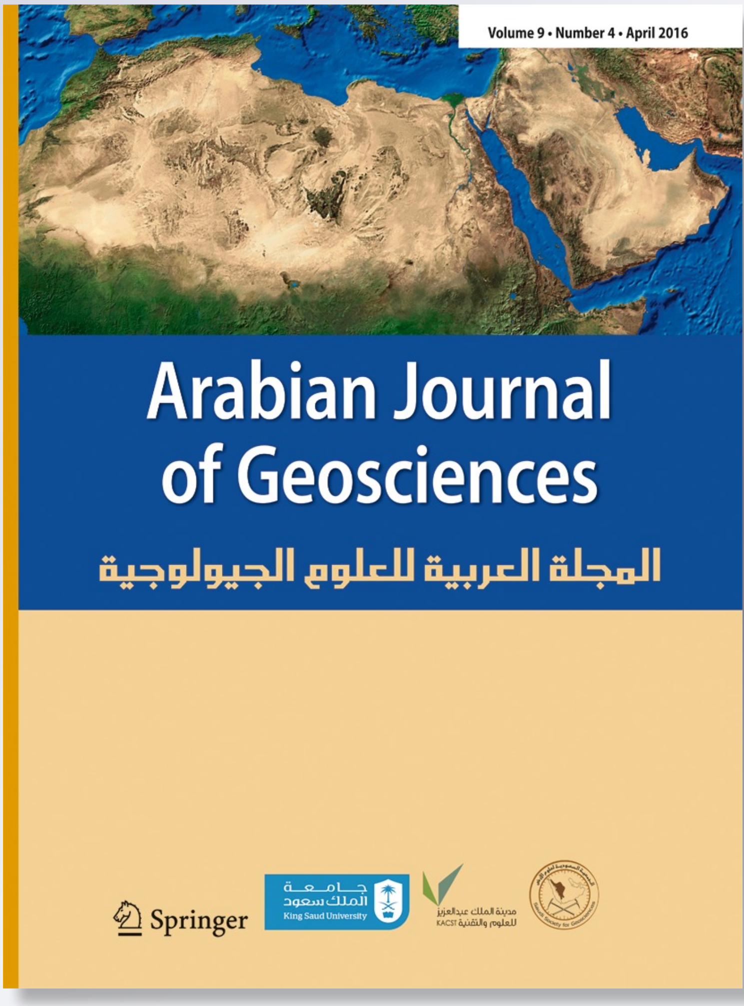

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ORIGINAL PAPER

Spatial variability of soil properties using geostatistical method: a case study of lower Brahmaputra plains, India

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Abstract Soil properties like pH, organic carbon (OC), available nitrogen (AN), available phosphorus (AP), and available potassium (AK) vary spatially from a field to a larger region scale and determine the soil fertility. This study addressed the spatial variability of soil properties in Brahmaputra plains, northeastern India using geostatistical method. For this, a total of 767 soil samples from a depth of 0–25 cm at an approximate interval of 1 km were collected over the entire Bongaigaon district of Assam. Data were analyzed both statistically and geostatistically on the basis of semivariogram. Soil properties showed large variability with greatest variation was observed in AP (86 %) where as the smallest variation was in pH (19 %). The semivariogram for all soil properties were best fitted by exponential models and showed a highest (2.7 km) range for OC and lowest (1.2 km) for AP. The nugget/sill ratio indicates a strong dependence for pH (12 %), moderate spatial dependence for available nutrients (53–72 %) and a weak spatial dependence for OC (77 %). Evaluation of spatial maps indicated that except for AN due to high root mean square error (61.8), kriging could successfully interpolate other soil properties. Soil pH highly negatively correlated with OC (−0.330**) and AN (−0.228**) and highly positive correlated with AP (0.334**) and AK (0.164**). A highly significant correlation was also found between OC and AN (0.490**).

Keywords Spatial variability · Kriging · Semivariogram · Accuracy assessment · Soil properties

Introduction

Site-specific management of pH, organic carbon (OC), available N (AN), available P (AP), and available K (AK) has received considerable attention due to potential benefits of increasing input use efficiency, improving the economic margins of crop production and reducing environmental risks (Yasrebi et al. 2008). Hence, knowledge about the spatial variability of these soil properties is crucial when managing soil fertility by refining agricultural management practices and by improving land use sustainability (Wang et al. 2003). Spatial and temporal variability is recognized to be inherent to agricultural production systems. Variability in soil properties results mainly from the complex interactions between geology, topography and climate, as well as soil use (Quine and Zhang 2002; Emadi et al. 2008; Liu et al. 2015). In addition, variability may also occur as a result of land use and management strategies (Safari et al. 2013). As a consequence, soils can exhibit marked spatial variability at the macro-scale and micro-scale (Brejda et al. 2000; Vieira and Paz Gonzalez, 2003).

Developing accurate application maps for site-specific fertilization is critical in implementing precision farming technology. Therefore, spatial variability map showing soil properties (pH, organic carbon, nitrogen, phosphorus, and potassium) will make it possible to reduce fertilizer use, costs, and environmental pressure (Lopez-Granados et al. 2002). Geostatistics provides the means to characterize and quantify

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spatial variability, use this information for rational interpolation, and estimate the variance of the interpolated values. Variance estimation provides valuable information on the sampling density and configuration necessary to estimate a property to a specified precision. Geostatistics is a technology for estimating the soil property values in nonsampled areas or areas with sparse samplings (Yao et al. 2004). These nonsampled areas can vary in space (in one, two, or three dimensions) from the sampled data (Zhu et al. 2005). Geostatistical techniques incorporating spatial information into predictions can improve estimation and enhance map quality (Mueller and Pierce 2003). Several geostatistical methods have been used by the researchers for developing the spatial variability maps of soil properties, depending upon the requirements and situations of field experiments. Kriging is a useful tool to predict and interpolate data between measured locations (Burgess and Webster 1980; Reza et al. 2010, 2012a; Arfaoui and HédiInoubli 2013; Marko et al. 2014; Shahbeik et al. 2014).

In recent years, geostatistics has been widely used by many researchers for preparation of spatial variability maps of soil properties like soil texture (Safari et al. 2013), total soil nitrogen and phosphorus (Wang et al. 2009), soil available phosphorus (Reza et al. 2012b), soil organic carbon (Lui et al. 2006), soil quality (Sun et al. 2003), and soil physical properties (Santra et al. 2008; Reza et al. 2015). Thus, the objective of this study was to determine the spatial variability of selected soil properties, such as pH, organic carbon content (OC), available N (AN), available P (AP), and available K (AK), with the classical statistics and geostatistical analysis for Bongaigoan district of Assam, India.

Materials and methods

Study area

The area under investigation belongs to the Bongaigaon district of Assam (26° 09′ 0″–26° 31′ 30″ N, 90° 22′ 30″–90° 52′ 15″ E) covering an area 1725 km^2 (Fig. 1) in lower Brahmaputra plains, northeastern India. The topography of the district represents mostly plain lands and sub-divided into very gently to gently sloping plain, level to nearly level active flood plain, and moderately to steeply sloping side slope. The climate in the district is moderate during the winter and in summer it is hot. The maximum temperature is 32 °C during July and August; a minimum temperature falls up to 13 °C in the month of January. Annual rainfall is 2500–3500 mm and about 75 % of rainfall is from South West monsoon. There are three broad soil subgroups in the district according to Soil Taxonomy (USDA) namely Dystric Eutrochrepts, Typic Udipsamments, and Typic Udifluvents (NBSS&LUP 1999).

Soil sampling and analysis

A total of 767 soil samples were collected from the surface (0–25 cm) at an approximate interval of 1 km grid (Fig. 1) with the help of hand-held global positioning system (GPS) over the entire Bongaigoan district of Assam. Soil samples were air-dried and ground to pass through a 2-mm sieve. AK was extracted with 1 M NH_4OAc and then measured by atomic absorption spectrophotometer. Bray-1 P was determined (Bray and Kurtz 1945) by colorimetric spectrophotometer. AN was determined by Subbiah and Asija (1956), OC by Walkley and Black (1934) and pH with glass electrode in a 1:2.5 soil/water suspension.

Statistical analysis

The main statistical parameters, including mean, median, standard deviation, coefficient of variance, and extreme maximum and minimum values, which are generally accepted as indicators of the central tendency and of the data spread, were analyzed. The Pearson correlation coefficients were estimated for all possible paired combinations of the response variables to generate a correlation coefficient matrix. These statistical parameters were calculated with EXCEL® 2007 and SPSS 15.0.

Geostatistical analysis based on GIS

Geostatistical techniques are often used to characterize the spatial patterns of spatially dependent soil properties, both isotropically and anisotropically (Western et al. 2004). Geostatistical analysis uses the semivariogram to quantify the spatial variation of a regionalized variable and derives important parameters used for kriging spatial interpolation (Krige 1951; Matheron 1963). The semivariogram is half the expected squared difference between paired data values z(x) and z(x + h) to the lag distance *h*, by which locations are separated (Webster and Oliver 2001):

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

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.

Anisotropic semivariograms did not show any differences in spatial dependence based on direction, for which reason isotropic semivariograms were chosen. Circular, spherical, exponential, and Gaussian models were fitted to the empirical semivariograms. Best-fit model with minimum root mean

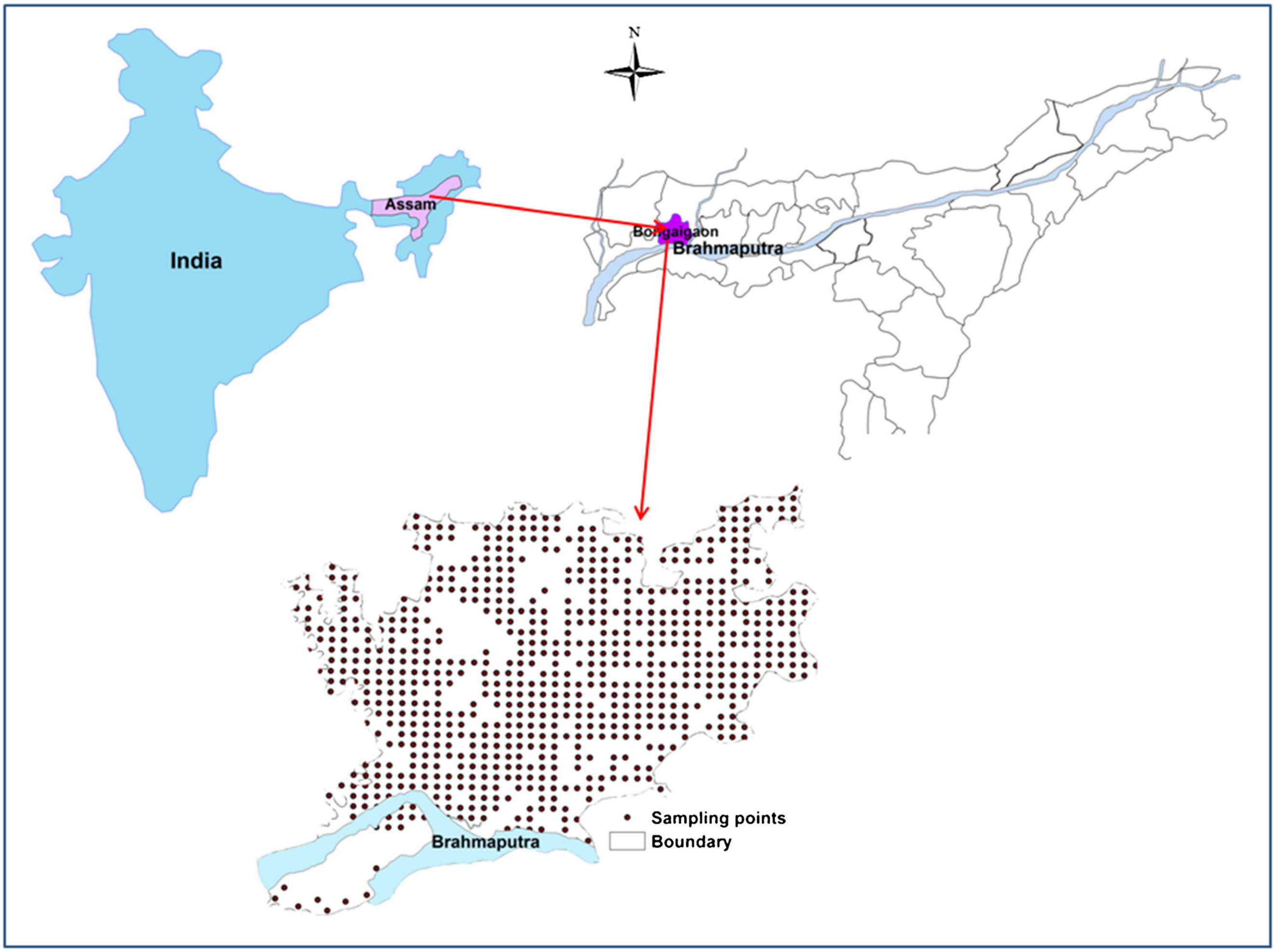

Fig. 1 Location and grid map of the study area

square error (RMSE) (Eq. 2) were selected for each soil property:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[Z(X_i) - \hat{Z}(X_i)\right]^2} \quad (2)$$

The exponential model was best fitted to all the soil properties defined by Eq. 3 (Deutsch and Journel, 1998):

$$\gamma(h) = C_o + C_1\left[1 - \exp\left\{-\frac{h}{a}\right\}^2\right] \text{ for } h \geq 0 \quad (3)$$

Using the model semivariogram, basic spatial parameters such as nugget(C_0), sill ($C + C_0$) and range (A) were calculated which provide information about the structure as well as the input parameters for the kriging interpolation. Nugget is the variance at zero distance, 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). Geostatistical analysis consisting of semivariogram calculation, cross-validation, and mapping was performed using the geostatistical analyst extension of ArcGIS v.9.3.1 (ESRI Co, Redlands, USA).

Accuracy of the soil maps was evaluated through cross-validation approach (Davis 1987). 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. MAE is a measure of the sum of the residuals (Voltz and Webster 1990).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left[Z(X_i) - \hat{Z}(X_i)\right] \quad (4)$$

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 will be calculated,

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left[Z(X_i) - \hat{Z}(X_i)\right]^2 \quad (5)$$

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).

$$G = \left[1 - \frac{\sum_{i=1}^{N}\left[z(x_i) - \hat{z}(x_i)\right]^2}{\sum_{i=1}^{N}\left[z(x_i) - z\right]^2}\right] \times 100 \tag{6}$$

Where z 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).

Results and discussion

Classical statistics of soil properties

Descriptive statistics of each soil properties are shown in Table 1. The median of each soil properties was lower than the mean, which indicates that the effects of abnormal data on sampling value were not great. There was difference in the CV of the soil properties. The greatest variation was observed in AP (86 %) where as the smallest variation was in pH (19 %). Other researchers also documented a smaller variation of soil pH compared to other soil properties (Sun et al. 2003). This may be attributed to the fact that pH values are log scale of proton concentration in soil solution, there would be much greater variability if soil acidity is expressed in terms of proton concentration directly. 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. A logarithmic transformation is considered where the coefficient of skewness is greater than one (Webster and Oliver 2001). Therefore, a logarithmic transformation was performed for AP and AK parameters as their skewness was greater than 1.

Geostatistical analysis

The semivariogram parameters obtained from the best fitted model are given in Table 2. For all the soil properties, semivariogarms of could be fitted best by exponential model. This model is one of the usual models in the study of soil properties (Cambardella et al. 1994; Vieira and Paz Gonzalez, 2003). However, soil properties displayed differences in their spatial dependence. The range for pH, OC, and AP were 2.0, 2.7 and 1.2 km, respectively, however for AN and AK was 2.1 km; thus, the length of the spatial autocorrelation is much longer than the sampling interval of 1 km. Therefore, the current sampling design is appropriate for this study and it is expected that a good spatial structure will be shown on the interpolated map. All soil properties showed positive nugget, which can be explained by sampling error, short range variability, random and inherent variability. To define different classes of spatial dependence for the soil variables, the ration the nugget and sill was used (Cambardella et al. 1994). The variable is considered to have a strong spatial dependence if the ratio less than 25 %, and has a moderate spatial dependence if the ratio is between 25 and 75 %; otherwise, the variable has a weak spatial dependence. The nugget/sill ratio showed a strong spatial dependence for the soil pH (12 %), which might be attributed to the strong leaching process of soil nutrients in this subtropical region and to the parent material with a high exchangeable Al (Sun et al. 2000). AN, AP, and AK were moderate spatially dependent (53–72 %), imprinted by intrinsic factor (soil forming process) and extrinsic factors (soil fertilization and cultivation practices) (Cambardella et al. 1994). Some other researchers had also found the moderate spatial dependence of soil properties (Safari et al. 2013; Liu et al. 2015). OC exhibited weak spatial dependence (77 %), this indicated that the spatial patterns of this soil properties was mainly influenced by extrinsic factors such as fertilization and rainfall redistribution induced by canopy (Liu et al. 2015).

The parameters of the exponential model were used for kriging to produce the spatial distribution maps of soil properties of the study area. Spatial maps of pH and OC

Table 1 Descriptive statistics for pH, organic carbon (OC), available nitrogen (AN), available phosphorus (AP), and available potassium (AK) (*n* = 767)

Parameters	Min	Max	Mean	Median	SD	CV (%)	Skewness	Kurtosis	Distribution pattern
pH	4.1	8.0	5.7	5.3	1.1	19	0.30	−1.49	Normal
OC (g kg^{-1})	0.4	36.5	10.7	9.7	5.5	51	0.97	1.52	Normal
AN (mg kg^{-1})	22.3	419.0	170.8	159.3	69.1	40	0.38	−0.46	Normal
AP (mg kg^{-1})	0.2	64.4	11.8	8.9	10.2	86	1.93	4.64	Log
AK (mg kg^{-1})	12.1	293.8	53.7	47.5	28.7	53	2.45	10.95	Log

Min minimum, *Max* maximum, *SD* standard deviation, *CV* coefficient of variation

Table 2 Geostatistical parameters of the fitted semivariogram models for soil properties

Soil properties	Fitted model	Nugget (C_0)	Sill ($C+C_0$)	Range[a] (A)	Nugget/sill (%)	RMSE[b]
pH	Exponential	0.173	1.405	2.0	0.123	0.713
OC	Exponential	21.99	28.34	2.7	0.771	4.860
AN	Exponential	3354	4996	2.1	0.671	61.78
AP	Exponential	0.499	0.927	1.2	0.538	9.505
AK	Exponential	0.159	0.220	2.1	0.723	27.28

[a] Range in km

[b] Root mean square error

(Fig. 2a, b) and AN, AP, and AK (Fig. 3a–c) prepared through kriging showed that pH value in the southern and eastern part of the study area was in neutral to alkaline range along with the Brahmputra river and the value in the northwest quadrant was strongly acidic (<4.5 pH), while AP had inverse distribution may be due to fixation of phosphorus with exchangeable Al and Fe in low pH. OC and AN had a large similar spatial variability, both the soil properties decreased in the southern part of the study area and increased in central and southeast quadrant, while AK had inverse distribution may be due to landscape.

Table 3 showed the evaluation indices resulting from cross-validation of spatial maps of soil properties. It was observed that**,** pH had low MAE and MSE however, for OC, AN, AP, and AK relatively large MAE and MSE were observed. These results are in close conformity with the findings of Reza et al. (2010). For all the soil properties, the G value was greater than 0, which 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 reasonable to describe the spatial variation of pH, OC, AN, AP, and AK. However, the RMSE value for AN was especially large, prediction of AN was especially poor suggesting that exponential model of kriging was unreliable for this parameter.

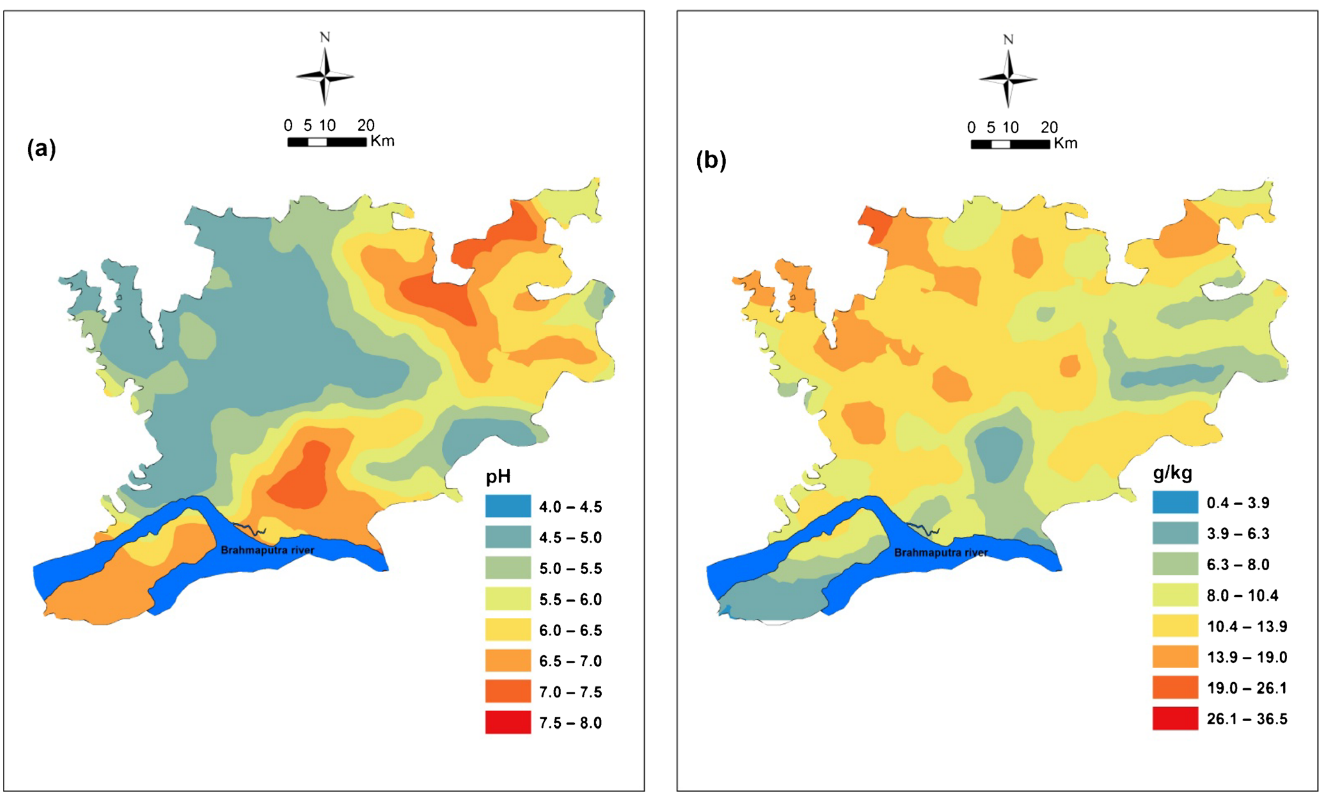

Fig. 2 Spatial variability maps for **a** pH and **b** organic carbon (*OC*) (g kg^{-1})

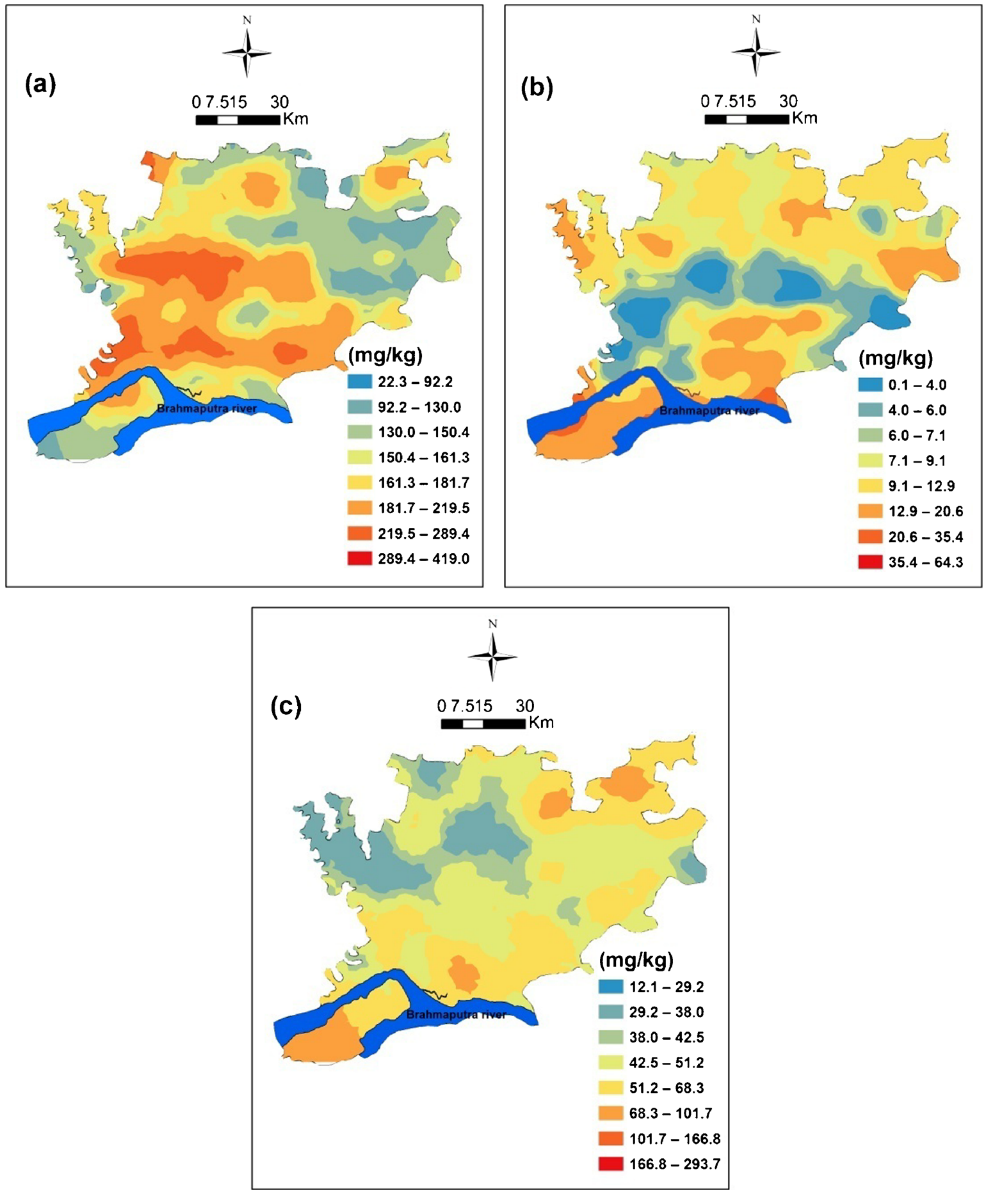

Fig. 3 Spatial variability maps for **a** available nitrogen (*AN*) (mg kg^{-1}), **b** available phosphorus (*AP*) (mg kg^{-1}), and available potassium (*AK*) (mg kg^{-1})

Relationship between soil properties

The Pearson linear correlation analysis results (Table 4) showed highly significant negative relationships of soil pH with OC (−0.330**) and AN (−0.228**) and highly significant positive relationships with AP (0.334**) and AK

Table 3 Evaluation performance of kriged map of soil properties through cross-validation

Soil properties	Mean absolute error	Mean square error	Goodness of prediction
pH	0.001	0.508	87
Organic carbon	0.016	23.22	24
Available N	0.155	3814	20
Available P	0.724	90.35	13
Available K	0.399	744.2	9

Table 4 Correlation coefficients among soil properties and their level of significance

Soil properties	pH	Organic carbon	Available N	Available P	Available K
pH	1.000				
Organic carbon	−0.330**	1.000			
Available N	−0.274**	0.490**	1.000		
Available P	0.334**	−0.155**	−0.131**	1.000	
Available K	0.164**	0.120**	0.071	0.072*	1.000

*Correlation is significant at $P = 0.05$, **Correlation is significant at $P = 0.01$

(0.164**). There have been reports on a positive relationship between OC and the capacity of the soil to supply essential plant nutrients including N and K (Rezaei and Gilkes 2005; Reza et al. 2011). Pearson linear correlation analysis indicated highly significant positive relationships of OC with AN (0.490**) and AK (0.120**) and highly significant negative relationships with AP (−0.155**). AN was found high significant negative correlation with AP (−0.131**), while AP was significantly correlated with AK (0.072*).

Conclusions

The summary statistics for soil properties were shown that there was difference in the CV of the soil properties. The raw data sets of AP and AK are strongly positively skewed and the application of log-transformation was effective in normalizing the data. Exponential model was best fitted with strongly spatially dependent and having spatial autocorrelations. The interpolated map has shown that pH value in the southern part of the study area was in neutral to alkaline range along with the river and the value in the southwestern quadrant was strongly acidic. OC and AN had a large similar spatial variability, both the soil properties decreased in the southern part of the study area and increased in central, southwest and southeast quadrant. In general, the geostatistical method on a large scale could be accurately used to evaluate spatial variability of soil properties.

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