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Mapping risk of soil phosphorus deficiency using geostatistical approach: A case study of Brahmaputra plains, Assam, India

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ABSTRACT

Analysis and interpolation of spatial variability of soil properties is very important for site specific management. The objective of this study was to determine the spatial distribution and degree of risk of phosphorus (P) deficiency in Goalpara district, Assam using statistics and geostatistics. A total number of 1397 soil samples were collected from 1953 km^2 area using 1 km×1 km grid at 0-25 cm depth and analyzed for Bray-1 P. Data set was positively skewed, therefore log-transformation was applied in order to achieve normality in the data set. Geostatistical analyses were carried out, including experimental variogram and model fitting and cross-validation. The ordinary kriging estimate map of P showed that the availability of P for plants was low in 78.6% area of the district. Another 6.0% area was ranked medium, while only 3.4% area was mapped with the high in available P. The probability map produced based on indicator kriging showed that the probability of deficiency of available P in the higher class [0.9 - 1.0] is 53%, whereas, probability greater than 0.5 accounted 99% of the total area of the district. This means that there is chance of 99% area of the district showing P deficiency in crops. The standard deviation (SD) map generally showing the SD values are high for the points having the true values high. Thus, the study will help in to minimize both yield loss and environmental threats such as eutrophication due to under or over dose of P fertilizer application.

1. INTRODUCTION

Phosphorus (P) is one of the three major nutrients required in crop nutrition, the other two being nitrogen (N) and potassium (K). P plays a vital role in the life cycle of plant, right from the stimulation of root growth to proper seed filling and seed setting, in addition to being an indispensable constituent of genetic material (Khasawneh *et al.,* 1986). It is also known to play a role in photosynthesis, breakdown of carbohydrate and transfer of energy through ATP and ADP compounds in various metabolic transformations.

Information on P fertility status of soils is of great importance, since it helps to determine the level of P fertilizer to be applied to crops. The information is equally useful for P fertilizer distribution and planning at both macro and micro levels. Natural and anthropogenic activities are both important in determining the complex spatial variation of P deficiency in soil, *viz.* soil pH and parent material, mineralogy and existing climatic condition of the study area. In acid soils the concentration of iron and aluminum ions greatly exceeds that of the phosphate ions consequently, forming the insoluble phosphate. This leaves only minute quantity of the phosphate ion immediately available for plants.

Geostatistical methods can provide reliable estimates at unsampled locations provided that the sampling interval resolves the variation at the level of interest (Kerry and Oliver, 2004). In the last two decades, the application of geostatistical methods by soil scientists focused on predicting spatial variability of soil properties with different kriging methods. Kriging is one of the important techniques to arrest the spatial variability of the soil parameters having auto correlation. Variography and kriging have been used in India to study the distribution of soil properties (Santra *et al.,* 2008; Reza *et al.,* 2010; Pal *et al.,* 2010), and assessment of ground water quality (Adhikary *et al.,* 2010; Adhikary and Biswas, 2011). In practice, kriging will often be the precursor to some management decision. The kriged estimates of the concentrations of pollutants may be used to plan soil remediation, for example. Estimates of the concentration of a nutrient may be used to plan spatially variable application of fertilizer (Schepers *et al.,* 2000). Such management decisions may often be based on threshold values of a soil property. For example, if the concentration of available (Bray-1) P in the soil is larger than 15 mg kg^{-1} then no fertilizer input of P is needed according to the University of Nebraska recommendations (Ferguson *et al.,* 2000). Fertilizer recommendations based on threshold values are widely used.

Land use planning may also take into consideration the threshold values of soil properties. Wood *et al.* (1990) reported soil salinity thresholds (electrical conductivity) that are used to determine land suitability for different crops in Israel. When a land manager wants to interpret a kriged map of a soil property with respect to some critical threshold value(s) then the uncertainty of these estimates becomes important. An estimate of the probability that the soil nutrients at a site not exceeding the advisory thresholds (conditional on the observed values at sample sites) may be more useful to the manager than a map of the estimated concentrations of the nutrient. The basic objectives of this study were 1) to determine the spatial variability of soil available P using ordinary kriging and 2) to describe the risk of P deficiency not exceeding a pre-selected threshold value using indicator kriging techniques.

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2. MATERIALS AND METHODS

Site Description

The area under study belongs to the Goalpara district of Assam (25º53"-26º30"N, 90º-91º05"E) covering an area of 1953 km^2 (Fig. 1). The climate is humid subtropical. The maximum temperature is 33ºC during July and August and minimum temperature falls up to 7ºC in the month of January. Annual rainfall is 2169 mm and about 80% of rainfall is from South West monsoon. According to soil survey report there are eight broad soil subgroups in the district namely Aeric Fluvaquents, Aeric Haplaquepts, Aeric Haplaquents, Typic Udifluvents, Typic Kandihumults, Typic Haplumbrepts, Dystric Eutrochrepts and Typic Paleudults (Sen *et al.,* 1999).

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

Soil Sampling and Analysis

A total of 1397 surface soil samples were collected from a depth of 0-25 cm (plough layer) using a square 1 km × 1 km grid from the entire district with the help of hand-held global positioning system (GPS) (Fig. 1). The samples were air-dried, ground to pass through a 2-mm sieve and Bray-1 P was determined (Bray and Kurtz, 1945) by colorimetric spectrophotometer.

Geostatistics

Ordinary kriging

Ordinary kriging was used as spatial interpolation methods for preparation of estimated map of available phosphorus. The experimental semivariogram values were calculated from directly measured data using measurement of moment (MoM) approach (Matheron, 1965). 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).

$$\gamma(h)=\frac{1}{2}\,E[z(x)\text{-}z(x+h)]^2 \qquad \text{…......(1)}$$

The usual computing equation for the variogram is:

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

Where $z(x_i)$ is the value of the variable Z at location of x_i, h is the lag distance and N(h) is the number of pairs of sample points separated by h. For irregular sampling, it is rare for the distance between the sample pairs to be exactly equal to h. Therefore, the lag distance h is often represented by a distance band.

During pair calculation for computing the semivariogram, maximum lag distance was taken as half of the minimum extent of sampling area. In this study, omnidirectional semivariogram was computed for available phosphorus because no significant directional trend was observed. Best-fit model with smallest nugget values with minimum root mean square error (RMSE) was selected. Using the model semivariogram, basic spatial parameters such as nugget (C_0), sill ($C+C_0$) and range (a) was calculated. Nugget represents variation caused by stochastic factors, such as error in measurement. Lag reflects the range that soil has in spatial variations; within which soil fertility factors have correlations. Sill is the maximum in different sampling distances. Four commonly used semivariogram models were fitted. These are the spherical, exponential, Gaussian and hole-effect model.

Performance and cross validation of ordinary kriging

Predictive performance of the fitted model was checked on the basis of cross validation test. The values of coefficient of determination (R^2), mean error (ME), mean squre error (MSE), kriged reduced mean error (KRME) and kriged reduced mean square error were estimated to ascertain the performance of the used model (Sarangi *et al.,* 2005). The predictive value of model was ascertained from the estimated values approaching 0 or 1.

Indicator kriging

Risk of P deficiency not exceeding a pre-selected threshold value was assessed by using indicator kriging. Indicator kriging is a nonlinear geostatistics where the conventional linear kriging estimators are applied to the data after a nonlinear transformation. Here the nonlinear transform is to a discrete (binary) indicator variable. These techniques have been widely applied by soil scientists (*e.g.* Van Meirvenne and Goovaerts, 2001).

Let us assume that a soil property z at location x take value $z(x)$. In geostatistics, we treat this value as a realization of the random function $Z(x)$. An indicator transformation of $z(x)$ can be defined by

$$\blacktriangleleft_c(x) = 1 \quad \text{if } z(x) \leq z_c, \quad 0 \quad \text{otherwise,} \qquad \ldots\ldots\ldots(3)$$

Where z_c is a threshold value of the property. In indicator geostatistics, $\blacktriangleleft_c(x)$ is regarded as a realization of the random $\square_c(x)$,

$$\square_c(x) = 1 \text{ if } z(x) \leq z_c, \quad \text{else } 0. \qquad \ldots\ldots\ldots(4)$$

It can be seen that

$$\text{Prob}[Z(x) \leq z_c] = E[\square c(x)] = G[Z(x); z_c,] \qquad \ldots\ldots\ldots(5)$$

Where Prob[], E[] denote, respectively, the probability and the expectation of the terms within the square brackets, and $G[Z(x); z_c]$ is the cumulative distribution function of $Z(x)$ at value z_c. The principal of IK is to estimate the conditional probability that $z(x)$ is smaller than or equal to a threshold value z_c, conditional on a set of observations of z at neighbouring sites, by kriging $\square_c(x)$ from a set of indicator-transformed data.

A set of data on z is transformed to the indicator variable $\square_c(x)$ using Eq. (3). The variogram of the underlying random function $\square_c(x)$ is then estimated by

$$\gamma_{\square c}(h) = \frac{1}{2M_h} \square_{i=1}^{M_h} [\blacktriangleleft c(x_i) - \blacktriangleleft c(x_i + h)]^2 \qquad \ldots..(6)$$

Where M_h pairs of observations that are separated by the lag interval h. A set of estimates of this indicator variogram at different lags may then be modeled by one of the authorized continuous functions used to describe variograms (Webster and Oliver, 2001).

An estimate of the indicator random function may then be obtained for a location x by kriging from the neighbouring indicator-transformed data. IK is equivalent to simple kriging of the indicator variables $\blacktriangleleft_c(x)$ using the mean within the kriging neighbourhood as the expectation.

Geostatistical analysis consisting of variogram calculation, kriging, cross validation and mapping was performed using the geostatistical analyst extention of ArcGIS 9.3.2.

3. RESULTS AND DISCUSSION

Descriptive Statistics of Soil Phosphorus

Descriptive statistics for the analyzed 1397 soil samples for available soil phosphorus are summarized in Table 1. The minimum and maximum concentration of available P in the district was 1.30 and 94.31 kg P_2O_5 ha^{-1} with mean value of 13.76 kg P_2O_5 ha^{-1}. The median (10.07 kg P_2O_5 ha^{-1}) of available P was lower than the mean, which indicates that the effects of abnormal data on sampling value were not great. Available P exhibit a high variation (>50%) according to guidelines provided by Warrick (1998). There is extensive literature on the variation in soil P concentrations, and nearly all reported that P is among the most variable soil properties. Dobermann *et al.* (1995) suggested that P concentrations are variable because P is less mobile in soil than nearly all other solutes, tending to concentrate in patches and resist homogenization in water flow across the landscape. Although true at the fine scale, the small concentration of readily available P at the local scale might contribute to the small CV, as very strong biological demand and decomposition homogenize concentrations spatially. Skewness is the most common form of departure from normality. If a variable has positive

Table: 1
Descriptive statistics of Bray-1 P measured at soil depth 0-25 cm for 1397 soil samples

Distribution	Min.	Max.	Mean	Median	Standard deviation	Skewness	Kurtosis
Normal	1.30	94.31	13.76	10.07	13.16	2.54	11.31
Log	0.26	4.55	2.27	2.30	0.85	-0.40	2.75

Bold face values are the lowest value of skewness and kurtosis for available phosphorus

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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 performed for all micronutrients because their skewness was greater than 1.

Semivariogram of Soil Phosphorus

Investigation was carried out for systematic dependencies in the data. A physically and statistically acceptable covariance model is sought to describe the correlation among data. A spherical theoretical covariance model suitable for spatial fields was fitted to experimentally derived covariance values for log-concentration based on minimum RMSE value. This model is a function of the distance between any two spatial points (Journel and Huijbergts, 1978).

Semivariogram parameters (range, nugget and sill) for available P with best fitted model are presented in Table 2. The variogram of available P exhibits a very good structure, having very small nugget effect (C_0=0.66), showing that the sampling density is adequate to reveal the spatial structures. Furthermore, the range of 2.37 km implies that 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 displayed a good spatial structure will be shown on the interpolated map (Goovaerts, 1997). The range in geostatistical analysis indicates the size of patches. Smaller sized patches in the study soils suggest that biological processes play an important role in surface soils vs. geochemical processes (Augustine, 203).

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Table: 2
Semivariogram parameters of soil available phosphorus

Semivariogram model	Range (km)	Nugget (C_0)	Sill (C)
Spherical	2.37	0.66	0.947

Spatial Variation of Soil Phosphorus

Spatial map prepared through ordinary kriging using semivariogram parameters was cross-validated. Evaluation indices resulting from cross-validation of spatial map of soil phosphorus is given in Table 3.

Table: 3
Cross validation results of ordinary kriging of soil available phosphorus

ME	MSE	KRME	KRMSE
0.192	0.467	0.005	0.930

ME = Mean Error, MSE = Mean Square Error, KRME = Kriged Reduced Mean Error, KRMSE = Kriged Reduced Mean Square Error

Spatial map of soil phosphorus prepared through ordinary kriging are presented in Fig. 2. Spatial map indicated that the availability of phosphorus for plants was low (<34 kg P_2O_5 ha^{-1}) in 78.6% area of the district. Another 6.0% area was ranked medium (34-68 kg P_2O_5 ha^{-1}), while only 3.4% area was mapped with the high (>68 kg P_2O_5 ha^{-1}) available phosphorus (Table 4).

Table: 4
Delineated area under different classes of available phosphorus content

Available phosphorus class	Range (kg P_2O_5 ha^{-1})	Area (km^2)	% area of the district
Low	<34	1503	78.6
Medium	34-68	115	6.0
High	>68	65	3.4
Miscellaneous (Brahmaputra river, *etc.*)		228	11.9
Total		1911	100.0

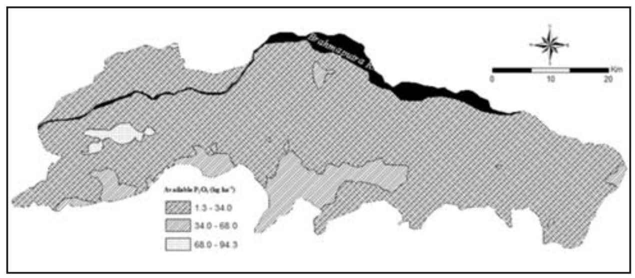

Fig. 2. Estimated map for available phosphorus (kg P_2O_5 ha^{-1}).

Risk of Soil Phosphorus Deficiency

Risk map of P deficiency not exceeding a pre-selected threshold value was prepared by using indicator kriging. A threshold value 34 kg P_2O_5 ha^{-1} was chosen, which represents soils with less than 34 kg P_2O_5 ha^{-1} is low in available P (Baruah and Barthakur, 1997)) showing deficiency symptoms for most of the crops and is recommended to receive large application rates to build up their P concentration. This threshold was used to create probability map (Fig. 3) in order to delineate the deficiency area of available P of the study area. The map showing the probability of deficiency of available P in the higher class [0.9 1.0] is 53%, whereas, probability greater than 0.5 accounted 99% of the total area of the district. This means that there is chance of 99% area of the district showing P deficiency in crops like some necrotic spots on leaves and the plants are dwarfed or stunted. P deficient plants develop very slowly in relation to other plants growing under similar environmental conditions but without P deficiency.

Kriging standard deviation (KSD) is the square root of the kriging variance. In this study, the KSD map for available P is shown in Fig. 4. This map shows the level of model errors. It is evident that the KSD was greater for high

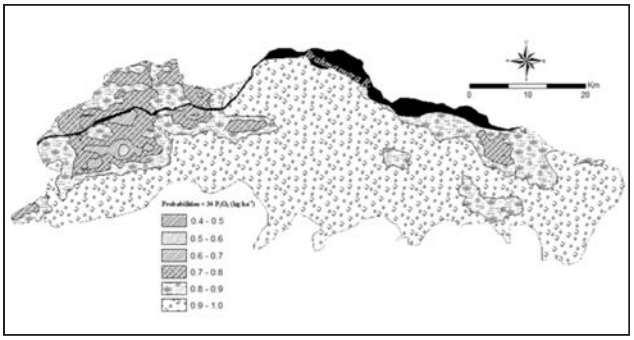

Fig. 3. Probability map for deficiency of available phosphorus.

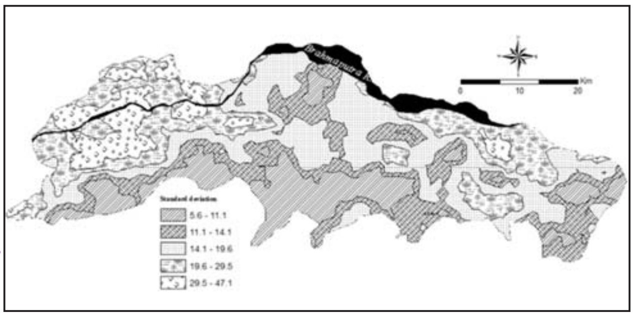

Fig. 4. Standard deviation error map for available phosphorus.

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estimated values of available P. In contrast, the error was smaller for small estimated available P values.

4. CONCLUSIONS

The spatial variability and risk of deficiency of P in Goalpara district of Assam was evaluated and mapped using geostatistical techniques. The raw data sets of available P are strongly positively skewed. The application of log-transformation was effective in normalizing the data. Spherical model was best fitted with strongly spatially dependent. A good variogram structure of available P is observed, revealing that there are clear spatial patterns of available P on the distribution map and also that the current sampling density is ample to reveal such spatial patterns. The kriging interpolated map has shown the availability of phosphorus for plants was low in 78.6% area of the district. Another 6.0% area was ranked medium, while only 3.4% area was mapped with the high in available phosphorus. The probability and standard deviation map produced based on indicator kriging interpolation provides useful information for deficiency areas identification and decision support. The map showing the probability of deficiency of available P in the higher class [0.9-1.0] is 53%, whereas, probability greater than 0.5 accounted 99% of the total area of the district. This means that there is chance of 99% area of the district showing P deficiency in crops.

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