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FULL-LENGTH RESEARCH ARTICLE

Spatial Heterogeneity of Soil Metal Cations in the Plains of Humid Subtropical Northeastern India

S. K. Reza[1] · Utpal Baruah[2] · S. K. Singh[3] · R. Srinivasan[1]

Abstract Analysis and interpolation of soil micronutrients are very important for site-specific management. The objective of this study was to determine the spatial distribution of iron (Fe), manganese (Mn), zinc (Zn) and copper (Cu) in the forest covered area of Chirang district, Assam, using statistics and geostatistics. A total of 607 soil samples from a depth of 0–25 cm at an approximate interval of 1 km were collected over the entire study area. The concentration of Fe, Mn, Zn and Cu ranged between 0.10–263.5, 0.50–149.5, 0.01–3.4 and 0.64–14.6 mg/kg, respectively, with mean values of 45.3, 19.6, 0.4 and 5.0 mg/kg, respectively. Analysis of semivariogram indicated that the Fe and Mn were well described with the spherical model, with the distance of spatial dependence being 5.83 and 1.95 km, respectively, while the Zn and Cu were well described with exponential model, with the distance of spatial dependence being 5.24 and 3.95 km, respectively. To define different classes of spatial dependence for the soil variables, the ratio of nugget and sill was used. Cu was strongly spatially dependent, with the nugget/sill being 0.202 in this given region, while Fe, Mn and Zn were moderately spatially dependent, with the nugget/sill being 0.347, 0.299 and 0.426, respectively. With the kriging analysis, the spatial distribution maps of contents of these four micronutrients in the study area were drawn with the ArcGIS software. It was found that the soils with higher content of Fe, Mn and Zn were mainly distributed in the upper area of the northern part of the study area, while the soils with higher content of Cu were mainly distributed in the center, decreasing toward the south, east and west.

Keywords Geostatistics · Spatial heterogeneity · Semivariogram · DTPA-extractable micronutrients

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Introduction

Knowledge of the availability of plants with micronutrients in soils is important for maintaining or improving forest, crop production and food quality. Micronutrients are required in small amounts by plants or animals for normal nutrition and health, and yet high concentrations of these or other trace elements can be toxic [24]. Zinc (Zn), copper (Cu), iron (Fe) and manganese (Mn) are referred as cationic micronutrients. Although micronutrients are required in minute quantities but have the same agronomic importance as macronutrients and play a vital role in the growth of plants, micronutrients also increase plant productivity, leaf and grain yield. Most of the micronutrients are associated with the enzymatic system of plants [2]. The deficiency of the micronutrients is one of the major limiting factors for

crop production causing considerable yield losses of economically important crops throughout the world [1].

Spatial heterogeneity is the complexity and variation of systems or their attributes, and heterogeneity of soil nutrients is ubiquitous in all natural ecosystems [3]. The spatial distribution pattern of the concentration of an element in soil is controlled by various geochemical processes. Studies of the spatial patterns are beneficial for further analysis of the processes, and as a result, increased knowledge of such geochemical processes is achieved. Meanwhile, describing the spatial patterns quantitatively with soil indices is one way of going from qualitative to quantitative analysis [5]. Soils are characterized by a high degree of spatial variability, even in intensively managed ecosystems [5, 9, 10]. Rational soil management requires an understanding of how soil properties vary across the land. By using soil sampling and analysis of relevant soil properties, we can develop maps that would help to identify areas of particular interest and to plan suitable management plans for increased productivity and quality of vegetation. Inherent in this process is the assumption that a soil property measured at a given point represents the surrounding unsampled neighborhood [25]. The validity of this assumption depends on the spatial variability of the soil property.

Geostatistics provides the means to characterize and quantify 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 has been used to characterize spatial variability and map a variety of soil properties at scales ranging from centimeters to kilometers, and it may prove useful across even greater distances, at the scale of the whole country [26]. There have been several studies dealing with spatial variability of soil properties based on GIS and geostatistics. Variography and kriging have been used in India to study the distribution of soil physical properties [17], soil chemical properties [15, 16], boron [6] and soil salinity [14].

Estimation, characterization and comparison of spatial variation of micronutrients of soil are important issues in the site-specific crop management, precision farming and sustainable agriculture. Hence, this paper deals with the spatial variation of soil fertility factors in the plains of Chirang district, Assam. Through analysis of variations of soil available Zn, Cu, Mn and Fe, the study would reveal the spatial variability of these micronutrient cations in the study area and would help in taking suitable sampling size and appropriate micronutrient management practices.

Materials and Methods

Site Characteristics

The area under study belongs to the forest covered area of Chirang district of Assam ($26°23'-26°40'$N, $90°32'-91°53'$E) covering an area 911 km^2. Topographically, it descends slightly from north to south across the study area. Climatically, this region belongs to the humid subtropical, with an annual average precipitation of 3000 mm, annual minimum temperature of 13 °C and maximum of 32 °C. The vegetation of the region is predominately characterized by dense semievergreen, evergreen and wet deciduous types owing mainly to the impact of heavy monsoonal rainfall, effective temperature and thick fertile soil cover. The principal varieties are Ikra (*Sccharum arundinaceum*), Nal (*Phragmites roxburghii*), Sal (*Shorea robusta*), Khair (*Acacia catechu*) and Sissu (*Dalbergia sisso*). According to soil survey report [19], there are four broad soil subgroups in the study area namely—Aeric Fluvaquents, Dystric Eutrochrepts, Typic Haplaquents and Typic Haplaquepts.

Soil Sampling, Processing and Analysis

A total of 607 soil samples from the surface layer (0–25 cm) at an approximate interval of 1 km grid (Fig. 1) were collected with the help of handheld global positioning system (GPS). Soil samples were air-dried and ground to pass through a 0.5-mm sieve. Soil pH in 1:2 soil/water suspension was determined using pH meter. Organic carbon and diethylenetriaminepentaacetic acid (DTPA) extractable micronutrients were determined by Walkley and Black [21] and Lindasay and Norvell [11], respectively. The concentration of micronutrients was determined by a Shimadzu AA6300 atomic absorption spectrophotometer.

Data Analysis

Exploratory data analysis was performed with SPSS (version 16) software. The data distributions were analyzed by classical statistics (mean, maximum, minimum, standard deviation, skewness, kurtosis and coefficient of variation). 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.

Fig. 1 Locations and grid map of the area of Chirang district, Assam, India
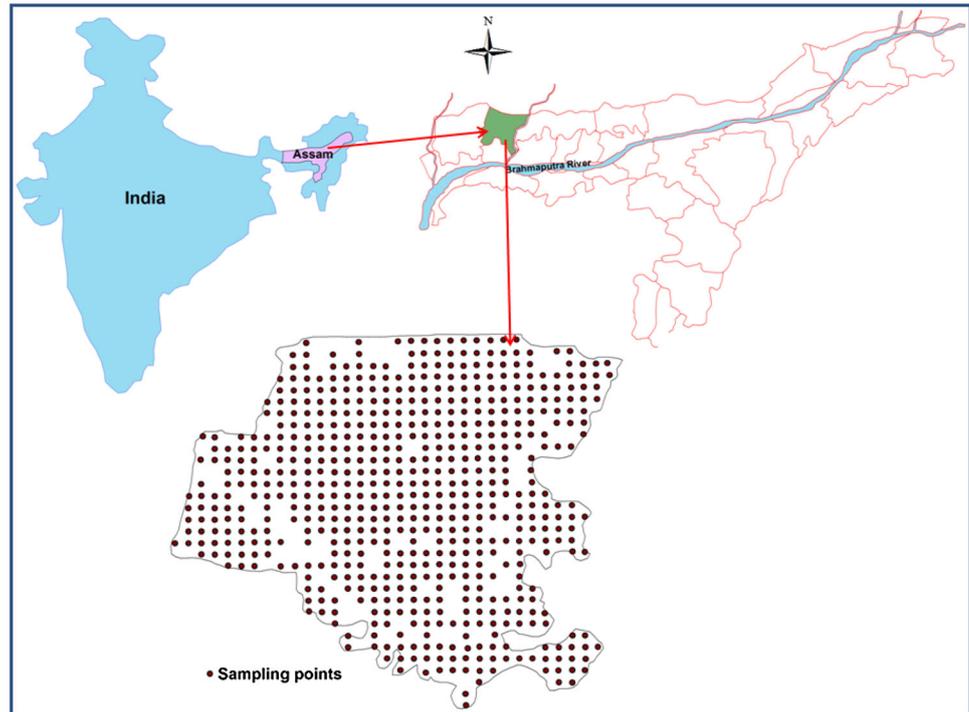
Geostatistical Analysis Based on GIS

Spatial interpolation and GIS mapping techniques were employed to produce spatial distribution maps for the investigated DTPA-extractable micronutrients, and the software used for this purpose was ArcGIS v.10.1 (ESRI Co, Redlands, USA). In ArcGIS, kriging can express the spatial variation and allow a variety of map outputs, and at the same time minimize the errors of predicted values. Moreover, it is very flexible and allows users to investigate graphs of spatial autocorrelation. Kriging, as applied within moving data neighborhoods, is a non-stationary algorithm which corresponds to a non-stationary random function model with varying mean but stationary covariance [8]. In kriging, a semivariogram model was used to define the weights of the function [23], and the semivariance is an autocorrelation statistic defined as follows [13]:

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

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.

During pair calculation for computing the semivariogram, maximum lag distance was taken as half of the minimum extent of sampling area. 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-square error (RMSE) were selected for each soil property:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [z(x_i) - \widehat{z}(x_i)]^2} \tag{2}$$

The spherical and exponential models were best fitted to all the micronutrients. Expression for different semivariogram models used in this study is given below. Exponential model

$$\gamma(h) = C_0 + C_1 \left[1 - \exp\left\{-\frac{h}{a}\right\}\right] \quad \text{for} \quad h \geq 0 \tag{3}$$

Spherical model

$$\gamma(h) = C_0 + C_1 \left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right], \quad \text{if } 0 \leq h \leq a$$
$$= C_0 + C_1, \qquad\qquad\qquad \text{otherwise} \tag{4}$$

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 represents variation caused by stochastic factors, such as error in measurement, 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 [12].

Accuracy Assessment

Accuracy of the maps was evaluated through cross-validation approach [7]. 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 [20].

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

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.

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

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 [18].

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

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

Descriptive Statistics of DTPA-Extractable Micronutrients

Descriptive statistics for Fe, Mn, Zn and Cu were shown in Table 1. The maximum and minimum concentration of Fe, Mn, Zn and Cu were 263.5 and 0.10, 149.5 and 0.50, 3.4 and 0.01, and 24.6 and 0.64 mg/kg, respectively, with mean values of 45.3, 19.6, 0.4 and 5.0 mg/kg, respectively. The median of each micronutrient was lower than the mean, which indicates that the effects of abnormal data on sampling value were not great. All the soil properties exhibit a high variation (>50 %) according to guidelines provided by Warrick [22]. 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 [23]. Therefore, a logarithmic transformation was performed for all micronutrients because their skewness was greater than 1.

Relationships of DTPA-Extractable Micronutrient to Controlling Factors

To examine the relationships between the analyzed micronutrients and controlling factors (pH and organic carbon), a correlation table (Pearson correlation coefficients) was established. The maximum and minimum value of pH was 6.6 and 4.0 with mean values of 6.1, and organic carbon 3.06 and 0.29 % with mean value 1.16 %. As shown in Table 2, between the soil pH value and these micronutrient elements, there are significant and negative correlations with Fe, Mn and Zn in the soils at the 0.01 level. The correlation coefficients were −0.65, −0.31 and −0.17, respectively. Between the soil organic matter and these micronutrient elements, there are (1) highly significant and positive correlations with Mn at the 0.01 level, and the correlation coefficient is 0.11 and (2) significant and positively a correlation with Fe at the 0.05 level, and the correlation coefficient is 0.08. Similar observations were also reported by Chen et al. [4] for the Xiangcheng tobacco planting area of Henan Province, China.

Semivariogram Analysis of Micronutrients

Semivariogram analysis was used to characterize and quantify spatial variability and root-mean-square error

Table 1 Descriptive statistics of the DTPA-extractable micronutrients ($n = 607$)

Micronutrients	Max	Min	Mean	Median	SD	CV (%)	Skewness	Kurtosis	Distribution pattern
Fe (mg/kg)	263.5	0.10	45.3	40.1	35.9	79	1.3	6.5	Log
Mn (mg/kg)	149.5	0.50	19.6	10.6	24.1	123	2.7	10.9	Log
Zn (mg/kg)	3.4	0.01	0.4	0.4	0.4	88	2.5	14.2	Log
Cu (mg/kg)	24.6	0.64	5.0	4.0	3.6	71	2.4	10.0	Log

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

Table 2 Correlation matrix of micronutrients and controlling factors

	pH	OC	Fe	Mn	Zn	Cu
pH	1.00					
OC	−0.86**	1.00				
Fe	−0.65**	0.08*	1.00			
Mn	−0.31**	0.11**	0.45**	1.00		
Zn	−0.17**	−0.02	0.16**	0.10*	1.00	
Cu	−0.15**	0.03	0.06	0.09*	−0.05	1.00

** Correlation is significant at the 0.01 level (two-tailed), * Correlation is significant at the 0.05 level (two-tailed)

Table 3 Geostatistical parameters of the fitted semivariogram models for DTPA-extractable micronutrients

Micronutrients	Fitted model	Nugget (C_0)	Sill ($C + C_0$)	Range[a] (A)	Nugget/sill (%)	RMSE[b]
Fe	Spherical	0.592	1.706	5.83	0.347	33.49
Mn	Spherical	0.395	1.317	1.95	0.301	18.84
Zn	Exponential	0.434	1.018	5.24	0.426	0.32
Cu	Exponential	0.074	0.367	3.95	0.202	2.48

[a] Range in km, [b] root-mean-square error

(RMSE) was used for different theoretical semivariogram models to fit the experimental semivariogram values for each micronutrient (Table 3). Analysis of the isotropic variogram indicated that the Fe and Mn semivariograms were well described with the spherical model, with the distance of spatial dependence being 5.83 and 1.95 km, respectively, while the Zn and Cu were well described with exponential model, with the distance of spatial dependence being 5.24 and 3.95 km, respectively.

Nugget (C_0) usually expresses the variations caused by experimental error or a smaller sampling scale. A bigger C_0 value shows that a certain smaller scale process cannot be ignored. Sill indicates the variation caused by the system on the whole. The ratio of C_0/sill indicates the percentage of the variation caused by stochastic factors to the total variation of the system. A higher value indicates that the stochastic factor plays a major role in the variation. From the point of view of structural factors, the ratio of C_0/sill can manifest the autocorrelation among many systematic variables. If C_0/sill <25 %, it means that there exists a strong spatial autocorrelation; if C_0/sill changes from 25 to 75 %, it suggests there exists a moderate spatial autocorrelation; if C_0/sill >75 %, it indicates that there is only a weak spatial autocorrelation [25]. Cu was strongly spatially dependent, with the C_0/sill being 0.202, showing that variations was controlled mainly by internal factors, and that both the external factors (cropping system, fertilization, etc.) and internal factors (climate, parent material, topography, soil type, etc.) play important roles in the variation, whereas Fe, Mn and Zn were moderately spatially dependent, with the C_0/sill being 0.343, 0.301 and

0.426, respectively, suggesting that the effects of structural factors have been partly covered by the stochastic factors. The anthropogenic activity weakened the spatial autocorrelation of soil fertility factors, and both developed gradually at the same time, which explained adequately that the spatial variation of micronutrients is the synthetically result of structural factors as well as stochastic factors [27].

Kriging Interpolation

Spatial distribution map of all the micronutrients prepared through ordinary kriging is presented in Fig. 2. Kriging interpolation showed that all of those four micronutrients possessed obvious spatial heterogeneity. The mean content of Fe and Mn were 45.3 and 19.6 mg/kg, respectively, which are higher than the critical limits (4.5 and 3.5 mg/kg, respectively) [11]. The soil with higher content of Fe and Mn were mainly distributed in the upper part of the study area. The mean content of available Zn was 0.4 mg/kg, which is lower than the critical limit (0.6 mg/kg). The soil with higher content of Zn was found in the upper parts of the investigated area, while the soils with higher content of Cu were mainly distributed in the center, and decreasing toward the south, east and west. The higher content of Zn in the upper parts may be due to higher organic matter content and low pH in the upper parts in the study area.

Accuracy Assessment

Table 4 showed the evaluation indices resulting from cross-validation of spatial maps of DTPA-

Fig. 2 Spatial distribution maps of DTPA-extractable micronutrients **a** Fe, **b** Mn, **c** Zn and **d** Cu
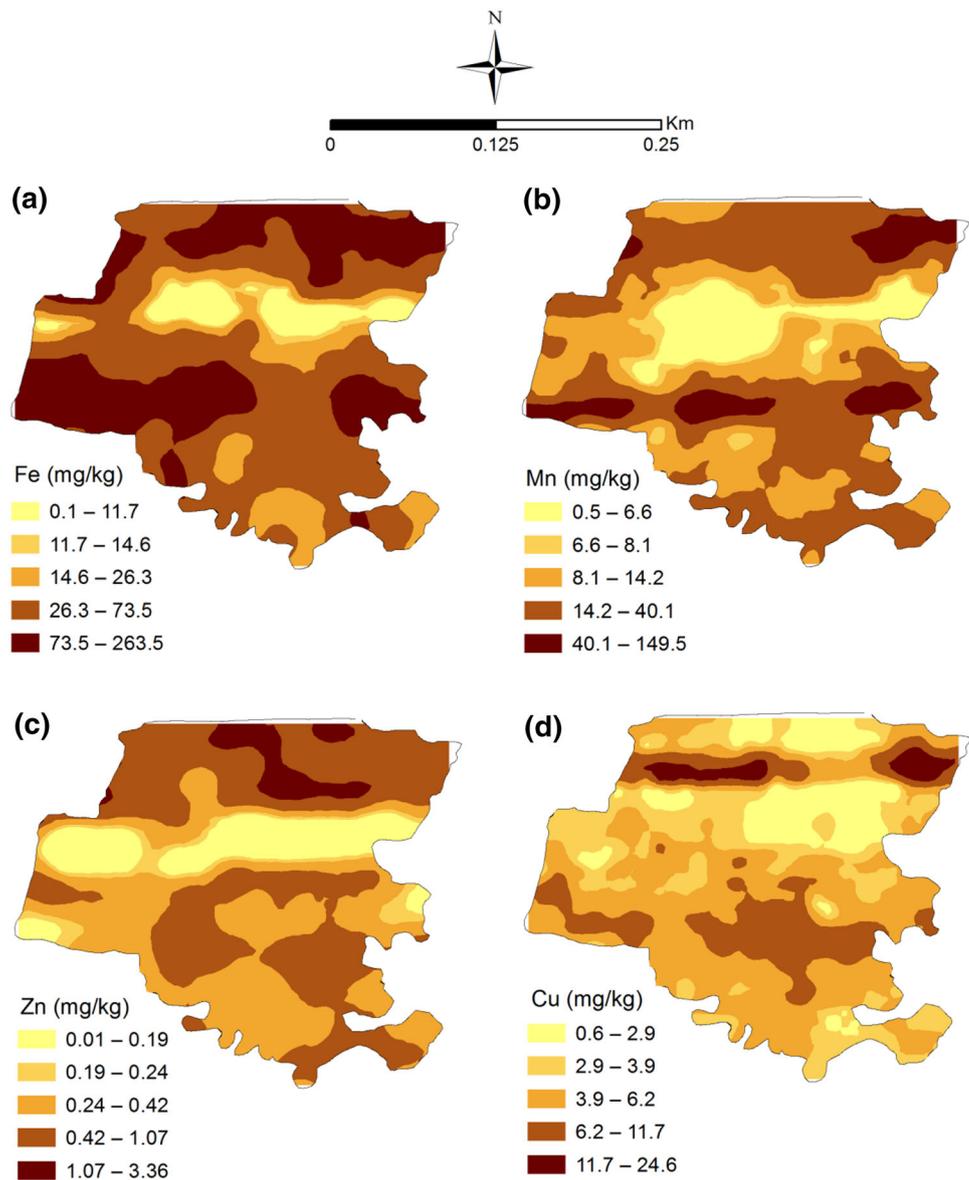
Table 4 Evaluation performance of kriged map of soil properties through cross-validation

Micronutrients	Mean absolute error	Mean square error	Goodness of prediction
Fe	11.44	1121.8	12.7
Mn	0.231	354.9	38.9
Zn	0.033	0.104	27.5
Cu	0.036	6.162	55.3

extractable micronutrients. It was observed that Zn had low MAE and MSE than other micronutrients. 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 distribution.

Conclusions

Geostatistics and GIS are essential tools to analyze geo-referenced information and advance our understanding of spatial variability of soil nutrients. Information on spatial variability is currently being exploited using techniques such as precision farming to improve input use efficiency and to decrease adverse environmental effects. The generation of maps for DTPA-extractable micronutrients is the most important and first step in precision agriculture. These maps will measure spatial heterogeneity and provide the

basis for controlling spatial variability. The findings of this study showed that all micronutrients namely, Fe, Mn, Zn and Cu had spatial autocorrelations. In general, the geo-statistical method on a large scale could be accurately used to evaluate spatial heterogeneity of DTPA-extractable mi-cronutrient cations in the plains of Northeastern India.

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