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ESTIMATION OF MICRONUTRIENTS IN THE SOIL

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ABSTRACT

In present paper, content of some important major micronutrients namely zinc, boron and iron were estimated at different unsampled locations in Sevapuri block of Varanasi district, Uttar Pradesh by using some Geostatistical techniques. Exponential and spherical semivariograms models were found the best on the basis of the higher values of R^2 and lower values of RSS. With the help of these variogram models and interpolating techniques spatial distribution maps of soil micronutrients were prepared and it was found that spatial dependence level of zinc and boron are moderate so they are deficient in the soil of Sevapuri block whereas spatial dependence level of Fe is strong, hence medium and deficient in the soil of Sevapuri block.

INTRODUCTION

Soil is an important part of agricultural system and ecosystem. Soil micronutrients play a major role to maintain soil health. Proportionate to primary and secondary nutrients, plants need a much smaller quantity of micronutrients. However, their importance is still great. A shortage of micronutrients can limit plant growth and crop yields. Too great a shortage could even because plant death, even with all other essential elements fully represented. An adequate attention is still necessary to pay in this area. Study conducted under GPS based soil fertility mapping project revealed that soils of Varanasi district are deficient in micronutrients namely Zn (46%), B (37%) and Fe (15%) (Singh, 2012). Determining soil variability and maintaining soil health is very much important for ecological modelling, environmental predictions, precise agriculture and management of natural resources (Hangshenget al., 2005; Wang, 2009).Temporal and spatial investigation of data and time series forecasting (Mishra and Singh 2013, Kumariet al., 2013, 2014a, 2014b, 2014c) is essential for understanding of soil spatial and temporal variability.Geostatistics is the strategy that considers spatial variance, location, estimation and distribution of samples.This study was done to investigate and map the spatial variability and to estimate micronutrients in the soil at differentunsampled locations by using data at sampled locations.

MATERIALS AND METHODS

The study area Sevapuri covers an area 16968 ha located at "UP-7 Eastern Plain Zone" agro climatic zone in VaranasiDistrict (25°16'55.23 north latitude and 82°5722.683 east latitude)of Uttar Pradesh, India. Varanasi lies in the middle Ganges valley of North India, in the Eastern part of the state of Uttar Pradesh (shown in Figure 1). The geographical area of Varanasi District is approximately 1530 sq. kilometres, total cropped area ('000 ha) is 157.096 (www.agricoop.nic.in).Secondary data of 72 soil samples were tested for deficiency of major micronutrients namely zinc (Zn), boron (B) and iron (Fe) (mg/kg) by (Singh, 2012). The UTM coordinates of soil samples were recorded for using in spatial analysis of major micronutrients in soil.

Geostatistics is based on spatial correlation between observations or samples and this correlation can be expressed with mathematical model which called variogram.The experimental semivariograms were calculated for the analysis of the spatial variability of micronutrients by using the equation:

$$y(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z(x_i) - Z(x_i + h) \right]^2 \qquad \text{...........................(1)}$$

Where: y(h) is experimental semivariance, N(h) is the number of pairs of measured values $Z(x_i)$ and $Z(x_i + h)$ are the values of regionalized variable at location x_i and x_{i+h}respectively separated by a vector (h).

Kriging interpolation

Kriging interpolation isone of the important geostatistical techniques. It is a powerful tool for determining spatial variability (Sauer *et al.,* 2006) and estimation (Pandey and Mishra, 1991, Mishra and Pandey, 1992). The prediction weights in Kriging interpolation (Krige, 1951) are based on spatial dependence between observations modelled by the variogram. Given spatial data $Z(s_i)$ that follows an intrinsically stationary process, *i.e.* having constant unknown mean μ, known spatial covari ance function $C = (h)$ for spatial lags $h = s_i - s_j$ and can be written as $Z(s_i) = \mu + \varepsilon(s_i)$, we typically want to predict values of major micronutrients at unobserved locations, $s_0 \in D$. Kriging method gives statistical weight to each observation so their linear structure's has been unbiased and has minimum estimation variance (Kumke *et al.,* 2005). This estimator has high application due to minimizing of error variance with unbiased estimation (Polhaman, 1993). In the case of an intrinsically stationary process with constant unknown mean, the ordinary Kriging (OK) method is used.

$$\hat{Z}(s_0) \quad \sum_{i\ 1}^{N} w_i Z(s_i) \quad \text{..(2)}$$

Now for finding best linear unbiased predictor (BLUP) variance of interpolation error will be minimized. Thus Mean square error of the variance of an ordinary Kriging was calculated using equation:

$$\sigma^2_{ok} \quad \sigma^2 \quad \sum_{i\ 1}^{N} w_i(\mathrm{cov}[Z(s_i), Z(s_0)] \quad \text{..........................(3)}$$

Where σ^2_{ok} variance of ordinary Kriging, λ is vector of weights and λ Lagrange multiplier.

For the model fitting to the experimental semivariograms, the following models were considered: linear, spherical, exponential and Gaussian. The semivariogram is the plot of the semivarianceagainst the distance (lag). Theshapes of these variograms indicate whether the variables are spatially autocorrelated or not. Nugget (C_0), sill (C_0+C) and range of spatial dependence A are the descriptive parameters of semivariograms. The nugget variance (C_0) expresses the variability due to unseen patterns (sampling errors and scales shorter than minimum inter-sample distance). The difference of sill variance and the nugget variance is the structural variance (C). This term accounts for the part of the total variance that can be modelled by the spatial structure. Selection of models was made principally on visual fit, regression coefficient (R^2) and residual sum of square (SSR), which provided an indication of how well the model fits the semivariograms data. The software package GS9+(trial version) was used for geo-statistical analysis.The degree of spatial dependence (GD) was calculated using equation:

$$GD = (C_0/C + C_0)*100(4)$$

Nugget/sill ratio (called also nugget effect) is regarded as a crieteria for classifying spatially structured variation for a regionalized variable as well as gives goodness of prediction. The ratio is equal or lower than 25%, variable was considered to be strongly dependent; ratio between 25-75%, then moderately dependent and ratio>75%, weakly dependent.Usually, a strong spatial dependence of soil properties can be attributed to intrinsic factors and a weak spatial dependence can be attributed to extrinsic factors (Cambardella *et al.,* 1994). An ordinary Kriging was used for constructing of soil distribution maps to provide enough estimated data.

RESULTS AND DISCUSSION

This study attempts to estimate the status of micronutrients at unsampled locations by using Kriging interpolation method. Management of micronutrient behavior requires an understanding of how soil micronutrients vary across the land. Integrated nutrient management is important for sustainable agricultural production and protecting environment quality and has been widely investigated around the world.

Table1 shows that decision coefficients (R^2) of Zn, B and Fe are 0.792, 0.494 and 0.630 respectively. The results indicated that the theoretical models chosen preferably reflected the spatial structure characters. The geostatistical data showed that many of the variables studied have the best fit to Exponential and Spherical.

The C_0 in Table 1 is nugget value or spatial variability arising from the random components. C_0 of Zn was low but higher

Figure 1: Eastern plain zone, U.P.

Table 1: Semivariogram models and parameters of spatial distribution for soil micronutrients evaluated

Soil Micro -nutrients	Nugget C_0	SillC_0+ C	Spatial Dependence ratio(N/S)	Range (m)	Model	Model R^2	RSS	Spatial dependence level
Zn	0.149	0.535	27.85	50	Expo-nential	0.792	4.63E-03	Moderate
B	0.019	0.073	26.13	211	Expo-nential	0.494	6.78E-04	Moderate
Fe	0.088	0.538	16.36	190	Spherical	0.630	4.84E-02	Strong

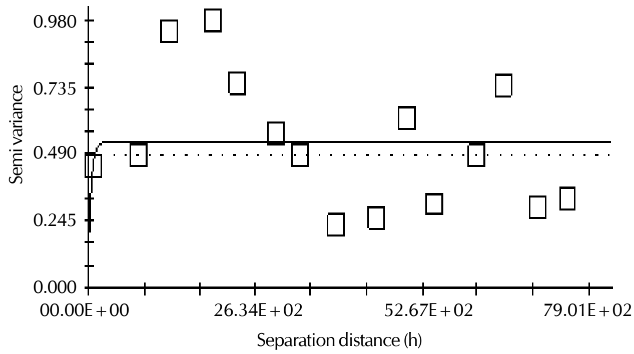

Figure 2: Semivariogram Model for Zn

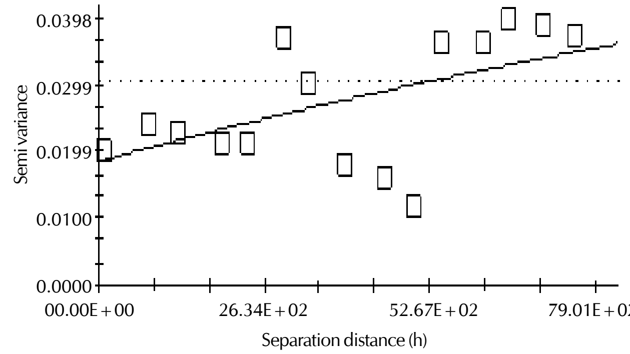

Figure 3: Semivariogram Model for B

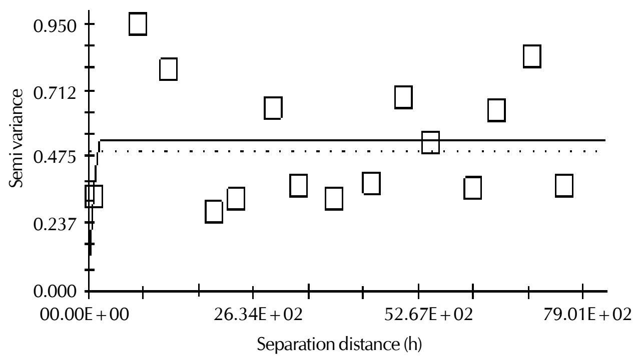

Figure 4: Semivariogram Model for Fe

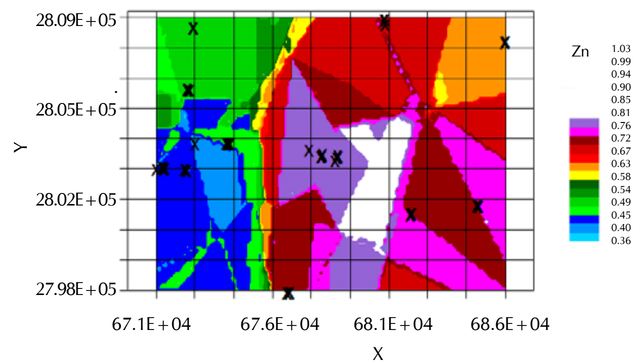

Figure 5: Spatial Distribution Map for Zn

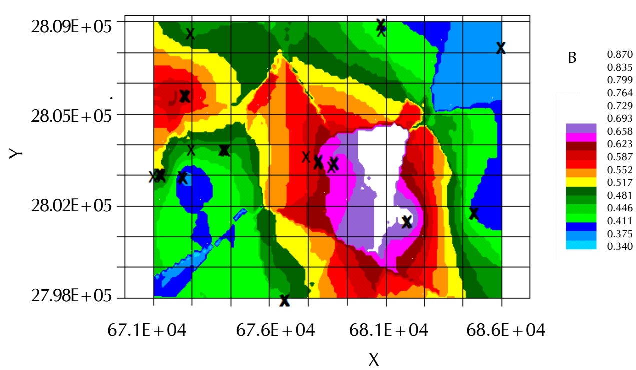

Figure 6: Spatial Distribution Map for B

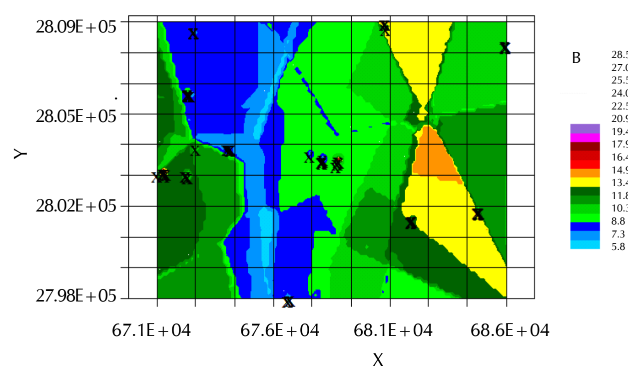

Figure 7: Spatial Distribution Map for Fe

than other two variables. C_0 of other micronutrients viz. B and Fe were quite small.In other words, a small nugget effect and close to zero indicates a spatial continuity between the neighbouring points. It was concluded that in the current scale of study, the variability of many soil micronutrients resulted from measurement errors and micro-scale processes were high.

Nugget/sill ratio (called also nugget effect) is used to classify spatially structured variation for a regionalized variable as well as gives goodness of prediction. It was observed that $C_0/(C_0+C)$ for Zn, B were between 25 % to 75%, so variables were considered moderately dependent and ratio observed for Fe was <25%, so it was considered as strongly dependent.

The geostatistical range (called the largest spatial correlation distance) reflected the autocorrelation range of variables and was related to the interaction between various processes of soil properties, which are affected at both observing and sampling scale. The soil micronutrients have spatial autocorrelation within the range; otherwise it does not exist.

Similar findings were observed by Wang *et* al. (2008). The range values Zn, B and Fe were also small as 50, 211 and 190m, respectively (Table1). The smaller range suggests smaller sampling intervals. Smaller ranges were obtained for Zn, B and Fe content.

The value of Residual sum of squares (RSS) i.e., the sum of squared errors (SSE) of estimation has been found small showing the observed data and estimated values.

Spatial dependence level of variables was found moderate and strong.

Figure 2, Figure 3 and Figure 4 are the semivariogram models for Zn, B and Fe, respectively.

On the basis of these semivariograms prediction weights were taken for Kriging interpolation method and spatial maps were generated. Spatial distribution maps of available micronutrients were developed by using these semivariogram models shown in Figure 5 for Zn, Figure 6 for B and Figure 7 for Fe.

With the help of these spatial distribution map amount of major micronutrients namely zinc (Zn), boron (B) and iron (Fe) at different unsampled locations of sevapuri block of Varanasi district, Uttar Pradesh(India) were estimated. The amount of these major micronutrients at sampled locations was used for further study. For spatial variability different semivariogram models were developed. Exponential and Spherical semivariogram models were found to be the best fit on the basis of model R^2 and RSS. It was also found that spatial dependence level of zinc and boron are moderate so they are deficient in the soil of Sevapuri block whereas spatial dependence level of Fe is strong, hence medium and deficient in the soil of Sevapuri block. Kriging interpolation method was used for generating spatial distribution maps.The results of this study can be used to make recommendations of best management, for maintaining soil health and modelling of soil and plant relationships in future studies.

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