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Estimation of Temporal and Spatial Changes in Micronutrients in The Soil Using Geostatistical Analysis

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ABSTRACT

Investigation of temporal and spatial changes is essential in soil because of its heterogeneous, diverse and dynamic system. 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 analysis. After normalizing the data, geo-statistical analyses were used to illustrate spatial variation and then spatial distribution maps of micronutrients were prepared. On the basis of these maps amount of micronutrients at unsampled location were estimated by using data of sampled locations.

Keywords: Soil micronutrients, Geostatistical analysis, Variogram Models, Spatial distribution maps.

INTRODUCTION

Soil is an important part of agricultural system and ecosystem. As time and space change soil properties also change continuously (Rogerio *et al.*, 2006). Soil micronutrients play a major role to maintain soil health. 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 and even cause 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 necessary for ecological modelling, environmental predictions, precise agriculture and management of natural resources (Hangsheng *et al.*, 2005; Wang *et al.*, 2009).Soil micronutrients play a direct role in ecosystem processes such as plant growth and carbon cycle (Roberston *et al.*, 1997). Spatial and temporal investigation of data and time series forecasting (Mishra and Singh 2013, Kumari *et al.*, 2013, 2014) is essential for understanding of soil spatial and temporal variability. Geostatistical science is the strategy that considers spatial variance, location, estimation and distribution of samples (Pohlmann, 1993). Kriging interpolation is one of the important geostatistical techniques. It is a strong tool for determining spatial variability (Sauer *et al.*, 2006) and estimation (Pandey and Mishra, 1991, Mishra and Pandey, 1992). It is based on mathematical and statistical functions. This technique estimates unknown points based on autocorrelation and their spatial structure of measured points. This study was done to investigate spatial variability and to estimate micronutrients in soil at different unsampled 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 Varanasi District (25°16'55.2" north latitude and 82°5722.68" east latitude) of Uttar Pradesh, India. The holy city Banaras lies in the middle Ganges valley of North India, in the Eastern part of the state of Uttar Pradesh (Fig. 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.

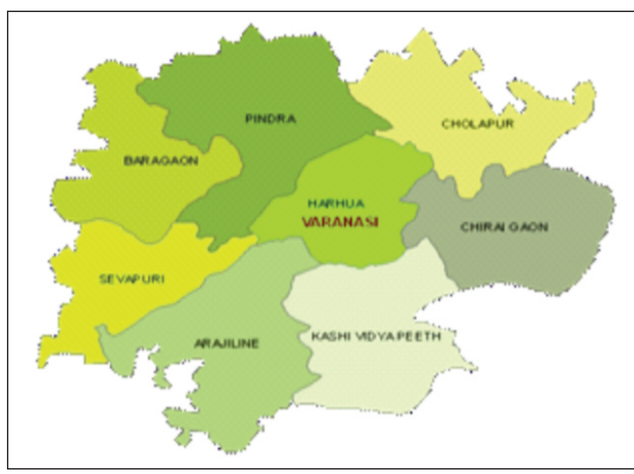

Fig. 1: Sevapuri Varanasi India: The study area

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

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

Where: y(h) is experimental semivariance, N(h) is the number

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of pairs of measured values Z(xi) and Z(xi+h) are the values of regionalized variable at location xi and xi+ h respectively separated by a vector (h).The prediction weights in Kriging interpolation (Krige, 1951) are based on spatial dependence between observations modelled by the variogram (Shukla *et al.,* 2015). Given spatial data Z(si) that follows an intrinsically stationary process, i.e. having constant unknown mean μ, known spatial covariance function for spatial lags h = si – sj, and can be written as Z(si)=U =E(si), we typically want to predict values of major micronutrients at unobserved locations, So eD. Kriging is a method that enables prediction of a spatial process based on a weighted average of the observations. Kriging method is a statistical estimator that gives statistical weight to each observation so their linear structure's has been unbiased and has minimum estimation variance (Kumke *et al.,* 2005). Minimizing of error variance with unbiased estimation this estimator has high application (Pohlmann, 1993). In the case of an intrinsically stationary process with constant unknown mean, the ordinary Kriging (OK) method is used.

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

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.

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

Where σ^2_{ok} variance of ordinary Kriging, w' 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 semivariance against the distance (lag). The shapes of these variograms indicate whether the variables are spatially autocorrelated or not. Nugget (C0), sill (C0+C) and range of spatial dependence A are the descriptive parameters of semivariograms. The nugget variance (C0) 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 (RSS), which provided an indication of how well the model fits the semivariograms data. The software package GS+(trial version) was used for geo-statistical analysis. The degree of spatial dependence (GD) was calculated using equation:

GD=(C0/C+C0)*100 (Eq. 4)

Nugget/sill ratio (called also nugget effect) is regarded as a criterion 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. This method is the best to detect amount of micronutrients content with pictorial representations in the soil on the basis of few data values. Integrated nutrient management is important for sustainable agricultural production and protecting environment quality and has been widely investigated around the world.

Table1 showed that decision coefficients (R2) of Zn, B and Fe are 0.792, 0.294 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 C0 in Table 1 is nugget value or spatial variability arising from the random components. C0 of Zn was low but higher than other two variables. C0 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.

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

Soil Micro - nutrients	Nugget C_0	Sill (C_0+C)	Spatial ependence 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	0.294	6.78E-04	Moderate
Fe	0.088	0.538	16.36	190	Spherical	0.630	4.84E-02	Strong

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 C0/(C0+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.* (2009). 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.

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

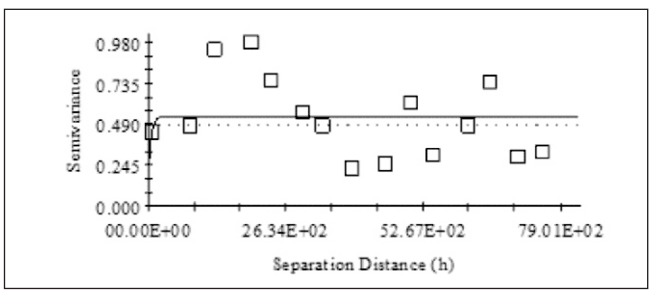

Fig. 2: Semivariogram Model for Zn

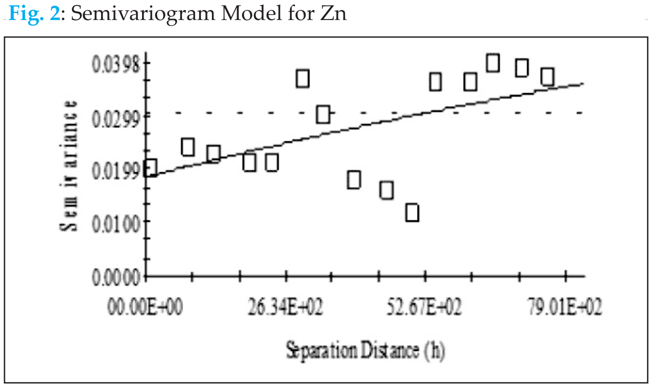

Fig. 3: Semivariogram Model for B

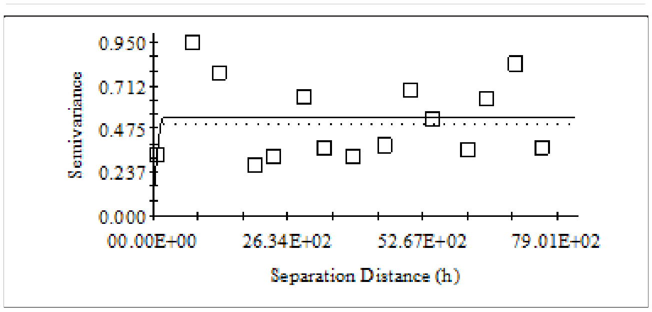

Fig. 4: Semivariogram Model for Fe

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 Fig. 7 for Fe.

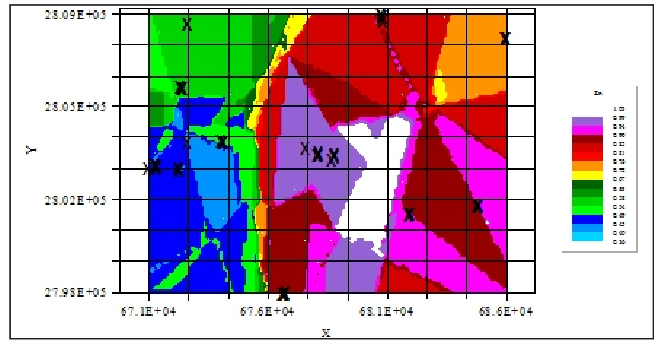

Fig. 5: Spatial Distribution Map for Zn

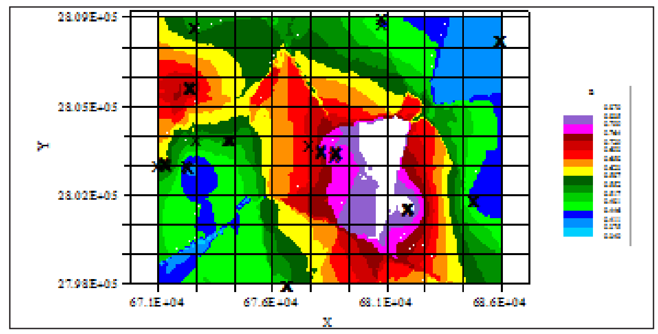

Fig. 6: Spatial Distribution Map for B

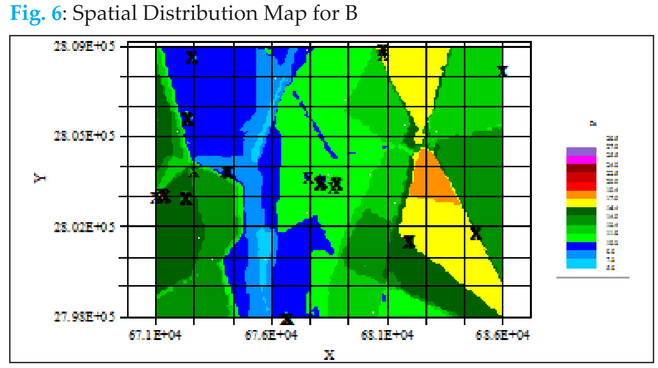

Fig. 7: Spatial Distribution Map for Fe

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 this study. For spatial variability different semivariogram models were developed.

CONCLUSION

Exponential and Spherical semi variogram models were found to be the best fit on the basis of model R2and RSS. Kriging interpolation method was used for generating spatial distribution maps. Results of present study can be used for making recommendations of best management, for maintaining soil health and modeling of soil and plant relationships in future studies.

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