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Kriging Approach for Estimating Deficient Micronutrients in the Soil: A Case Study

Garima Shukla[1], G.C. Mishra[1]* and S.K. Singh[2]

[1]Section of Agricultural Statistics, Department of Farm Engineering, Institute of Agricultural Sciences, Banaras Hindu University, Varasnai-221005, India.
[2]Department of Soil Science and Agricultural Chemistry, Institute of Agricultural Sciences, Banaras Hindu University, Varanasi, Uttar Pradesh, India.

*Corresponding author: gcmishrabhu@gmail.com

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Abstract

Soil surveying, testing and mapping are important operations for knowing availability of nutrients and micronutrients in the soil and their optimum use for agricultural operation. The main objective of present study was to estimate the content of deficient micronutrients namely Zn, B and Fe in the soil of Kashi Vidyapeeth block of Varanasi District of Uttar Pradesh, (India) at different locations by using test results of sampled soils. The Kriging interpolation method (Krige, 1951) was used for preparing the maps to show spatial distribution of deficient micronutrients. The method can be used for recommending judicious applications of micronutrients for sustainable soil management.

Highlights

Kriging interpolation method was used to prepare various maps by which value of deficient micronutrients can be estimated at different locations.

Keywords: Kriging interpolation, variogram model, spatial distribution, micronutrients.

Soil management in sustainable agriculture is a challenge to achieve food security for the future, through proper nutrient management and appropriate soil conservation practices, sustainable natural resource management and biodiversity protection. Soil is a store house of water, macro and micronutrients to plants, filter for effluents-wastes, and habitat to organisms and is critical for recycling elements vital for plant growth. It plays a major role in determining the sustainable productivity of an agro-ecosystem. It is the foundation of survival for present and future generations (Kumar and Babel 2011). Without healthy soil good agriculture can never be thought. Micronutrients play a vital role in maintaining soil health and consequently productivity of crops. The micronutrients are present in small quantities in the soil and most of the crops are sensitive to deficiencies of these micronutrients. Micronutrient deficiency in soil has become wide spread in recent years consequently low crop yields, more so after the introduction of high yielding crop varieties coupled with the use of high analysis fertilizer and increased cropping intensity. The sustainable productivity of a soil mainly depends upon its ability to supply essential nutrients to the growing plants. Still inadequate attention is paid to the effects of micronutrient deficiencies in soils and crops on livestock and human deficiency diseases. Soil fertility maps are meant for highlighting the nutrient needs, based on fertility status of soils (and adverse soil conditions which need improvement) to realize good crop yields (Thakor *et al.* 2014).

Time Series forecasting methods particularly ANN methods have been developed when conventional statistical methods could not give satisfactory results due to restrictive assumptions incorporated in these methods (Mishra and Singh 2013, Kumari *et* al. 2013, 2014a, 2014b, 2014c). Study conducted under GPS and GIS 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). Obviously, estimating (Pandey and Mishra 1991) the content of soil micronutrients in particular area can be proved highly beneficial in guiding the farmers, manufacturers and planners in ascertaining the requirement of various fertilizers in making projections for increased requirement based on cropping pattern and intensity (Bell and Dell 2006). Therefore, present study was carried out to provide a reliable estimate of micronutrients status in soil in order to control direct and indirect losses of soil health, crop production and human health to take prior action for future.

Geostatistics has been proved to be one of the most effective methods in analysing the spatial variability of soil features (Tekin *et al.* 2011). The precision agriculture, therefore, largely depends upon the management of spatial variability in soil fertility which is a major production constraint (Srivastava *et al.* 2010). In GIS method, we can apply different spatial interpolation methods. Geostatistical interpolation techniques are based on statistics and are used for more advanced prediction surface modelling that also includes some measure of the certainty or accuracy of predictions. Kriging interpolation (Krige 1951) has been considered one of the best efficient spatial interpolation approaches for spatial estimation. In this method surrounding known values are taken as weights and these weights are based not only on the distance between the known points and the unmeasured point but also on the overall geostatistical relationships among the known points. Kriging is capable of producing a prediction surface and also providing some measure of the certainty of the predictions. It is an improvement over other spatial interpolation methods viz. IDW (Shepherd 1968) and Spline (Schoenberg 1973) because prediction estimates tend to be less biased and also because predictions are accompanied by prediction standard errors (quantification of the uncertainty in the predicted value).

The objective of the present study was to develop the model for estimating (Mishra and Pandey 1992) the value of deficient micronutrients at different locations in Kashi Vidyapeeth block of Varanasi district, Uttar Pradesh (India) by knowing the value of micronutrients in sampled locations and to study and map the spatial variability of micronutrients by using the Kriging Interpolation method.

Materials and Methods

Study Area

This study covers an area of 15896 ha located in Kashi Vidyapeeth block of Varanasi district, 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 coordinates of the area are between 25°16′55.2″ north latitude and 82057′22.68″ east latitude. Varanasi lies in "UP-7 Eastern Plain Zone" agro climatic zone. The geographical area of Varanasi District is approximately 1530 sq. kilometres, total cropped area ('000 ha) is 157.096 (www.agricoop.nic.in).

Figure 1: Map of Varanasi District

Methodology

The present study is based upon the secondary data of 42 soil tested for deficiency of micronutrients namely Zinc (Zn), Boron (B) and Iron (Fe) (mg/kg) tested by Singh (2012). For the analysis of the spatial variability of micronutrients, the experimental semivariograms were calculated with the help of GS+ using the equation:

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

Where: y (h) is experimental semivariance, N (h) is the number of pairs of measured values Z(x), $Z(x_i + h)$ separated by a vector (h). 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 covariance 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 the process at unobserved locations, $s_0 \in D$. Kriging is a method that enables prediction of a spatial process based on a weighted average of the observations. In the case of an intrinsically stationary process with constant unknown mean, the ordinary Kriging (OK) method is used.

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

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:

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

In matrix form

$$\sigma_{ok}^2 = \sigma^2 - w^{'}D \quad \ldots (4)$$

Where σ_{ok}^2 variance of ordinary Kriging, w' is vector of weights and Lagrange multiplier and D is the vector of covariances at the prediction location. Thus, experimental semivariance values were determined and the semivariogram model was fitted with the validation method "Jack-knifing". For the model fitting to the experimental semivariograms, the following models were considered: linear, spherical, exponential and Gaussian. The semivariogram is the plots of the semivariance against the distance (lag), and its shape indicates whether the variables are spatially conditional or not, e.g. there is spatial autocorrelation. The descriptive parameters of semivariograms are nugget (C_0), sill (C_0+C) and range, of spatial dependence A (Camberdella *et al*. 1994). The nugget variance (C0) expresses the variability due to unseen patterns (sampling errors and scales shorter than minimum inter-sample distance). The sill variance minus 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 degree of spatial dependence (GD) was calculated using equation:

$$GD= (C_0/C+C_0)*100 \quad \ldots (5)$$

It is also known as goodness of prediction. An ordinary Kriging was used for constructing of surface maps to provide enough estimated data.

Results and Discussion

Characterization and rational management of micronutrient behaviour require an understanding of how total and available 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.

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

Soil Prop/ Nutrients	Nugget (Co)	Sill (Co+C)	Spatial Dependence {C/ (Co+C)}*100	Range	Model	Model R^2	Residual Sum of Square
Zn	0.0076	0.0632	88.00	630	Spherical	0.510	2.32E-03
B	0.0235	0.2856	50.20	629.07	Gaussian	0.673	5.98E-06
Fe	0.334	0.669	49.93	150	Spherical	0.710	1.07E+00

Table 1 showed that decision coefficients (R^2) of Zn, B and Fe and other soil properties ranged between 0.510-0.710. 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 Spherical and Gaussian.

The C_0 in Table 1 is nugget value or spatial variability arising from the random components. C_0 of Fe was high, however, C_0 of other variables were quite small. It was concluded that in the current scale of study, the variability of many soil properties 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. If the ratio was equal or lower than 25%, variable was considered to be strongly dependent; if between 25-75%, then moderately dependent; and if >75%, weakly dependent. The strong spatial dependency of a soil property can be attributed to intrinsic factors, and weak spatial dependency to extrinsic factors. It was observed that $C_0/(C_0+C)$ for B and Fe contents were all between 25-75%which indicated that variation of available micronutrient contents were controlled both by intrinsic and extrinsic factors (eg. fertilization, Cultivation etc.). In this study ratio was 88% (>75%) for Zn i.e., these variables were weakly dependent and it also showed that semivariogram parameters obtained from fitting of experimental semivariogram values were fairly reasonable to describe the spatial variation.

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 630, 629.07 and 150m, 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.

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

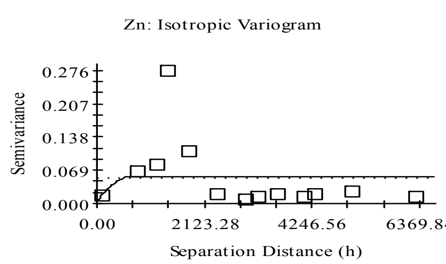

Figure 2. Variogram Model (Zn)

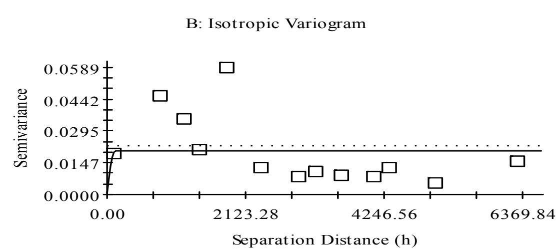

Figure 3. Variogram Model (**B**)

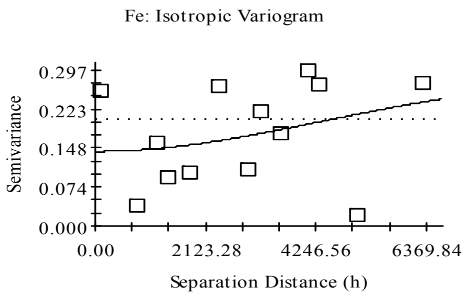

Figure 4. Variogram Model (Fe)

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

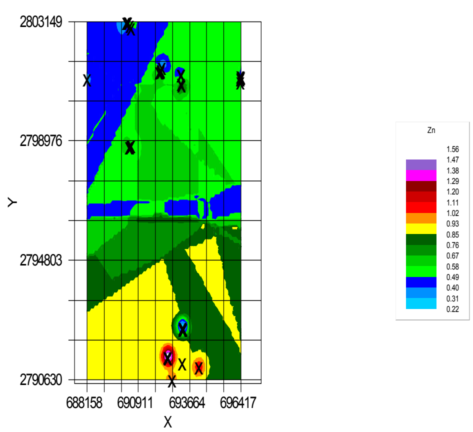

Figure 5. Spatial Distribution Map for Zn

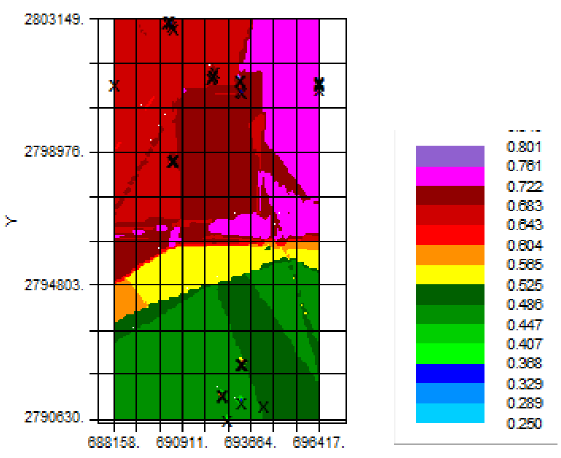

Figure 6. Spatial Distribution Map for B

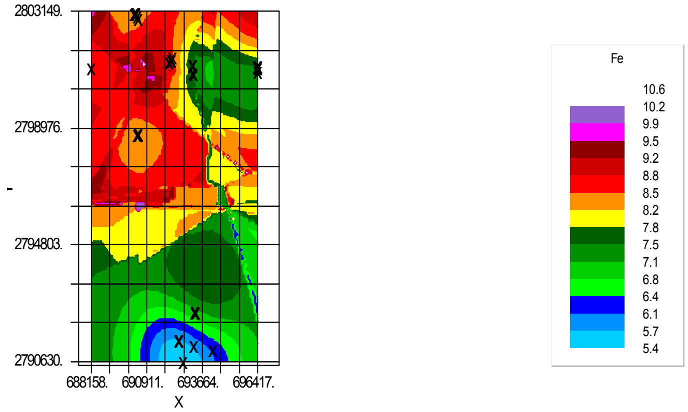

Figure 7. Spatial Distribution Map for Fe

Conclusion

The present paper aimed to estimate the amount of deficient micronutrients namely Zn, B and Fe at different locations of Kashi Vidyapeeth block of Varanasi district, Uttar Pradesh (India). The amount of these micronutrients available at sampled locations was used to develop the variogram models to describe spatial variability. Spherical and Gaussian variogram models were found to be the best fit on the basis of higher values of R^2 and lower values of RSS. Spatial distribution maps were generated by using Kriging interpolation method which would be useful for enabling the farmers to decide the amount of deficient micronutrients nutrients to be applied for economic returns based on the site specific micronutrients management.

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