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Application of Geostatistical Techniques in Spatial Variability Mapping of Soil Fertility– A Review

Tapan Gorai[1]; Mani Bhushan[2]*; Shashi Bhushan Kumar[3]

[1]Assistant Professor – cum - Junior Scientist, Bhola Paswan Shastri Agricultural College, Purnea City, Purnea, Bihar -854302, India, (Bihar Agricultural University, Sabour, Bhagalpur) Phone: 7781035140, E-mail: tapanbankura@rediffmail.com

[2]*Corresponding author: Assistant Professor – cum - Junior Scientist, Bhola Paswan Shastri Agricultural College, Purnea City, Purnea, Bihar -854302, India, (Bihar Agricultural University, Sabour, Bhagalpur) Phone: 9162205525, E-mail: m.bhushan008@gmail.com

[3]Associate Professor-cum-Senior Scientist, Department of Soil Science and Agricultural Chemistry, Bihar Agricultural University, Sabour, Bhagalpur, Bihar

Abstract: Soil fertility is one of the key factors of agricultural crop production. Spatio-temporal database and digital mapping of soil fertility at different scale from field level to country level has tremendous utility in development of agricultural sector. Geo-statistical tools in geographic information system (GIS) have potentiality to describe the spatial pattern using semiovariogram analysis and to carry out spatial interpolation of soil properties including macronutrients and micronutrients by kriging methods. Now–a-days, several kriging techniques like ordinary kriging, universal kriging, co-kriging, multivariate kriging, indicator kriging etc. are used for spatial interpolation of soil fertility parameter, based on nature and interrelationship of soil attributes and other external information. Farm and district level nutrient mapping are being effectively utilized for precision farming, increased input use efficiency, enhanced agricultural productivity, sustainability and environmental safety as well as policy making for fertilizer allocation in different states.

Keywords: Soil fertility, macronutrients, micronutrients, geo-statistics, semivariogram, kriging, spatial variability

1. Introduction

Soil is one of the precious natural resources which require generation of a spatial database and soil map for its best utilization in crop production and land use planning planning. Soil property variation within a field often has been described by classical statistical methods assuming a random distribution (Goovaerts 1998; Conant and Paustian 2002). In many instances, spatial variation is not random but tends to decrease as distances diminish between points in space (Webster 2000). Geostatistics provides descriptive tools such as semivariograms to characterize the spatial pattern of continuous and categorical soil attributes. Various interpolation kriging techniques capitalize on the spatial correlation between observations to predict attribute values at unsampled locations using information related to one or several attributes (Goovaerts 1999). Increasingly geo-statistical techniques are being used to characterize and quantify spatial variation, and have been applied to estimate the variance of interpolated values (Isaaks and Srivastava 1989; Gaston *et al.* 2001; Stenger *et al.* 2002).

Spatial variability of soil properties is scale-dependent. Farm scale and village scale soil fertility mapping, using spatial analysis tool and subsequent site specific fertilizer and amendment recommendations for precision farming has been reported in several countries (Jin and Jiang 2002; Iqbal *et al*. 2005; Mondal and Basu 2009; Iho and Laukkanen 2012). District level mapping of spatial variability of soil fertility parameter (Sharma *et al*. 2006; Mahesh Kumar *et al*. 2011) are useful to improve agricultural productivity and for policy making about proper allocation of fertilizer input for different districts in India. The resource inventory data of soil fertility are necessary for a better understanding of the nature and extent of nutrient deficiencies and toxicities in soils, plants, livestock and humans (White and Zasoski 1999). Spatial and temporal monitoring of soil quality parameter can be done by GIS techniques as the spatial and non-spatial database of any locality is being stored, analysed, retrieved and displayed as per user's need. In the context of scientific applicability of geostatistical techniques for generation of thematic map of soil fertility parameter in agriculture field, the present attempt is made to review the research works of spatial variability mapping of soil fertility for future dimension of research and development in agriculture.

2. Principles of Geo-statistics

Geostatistics is a class of statistics used to analyze and predict the values associated with spatial or spatiotemporal phenomena. It incorporates the spatial (and in some cases temporal) coordinates of the data within the analyses. Geostatistics has been applied in soil science for more than 30 years (e.g., Burgess and Webster 1980; Webster 1994; Zhang *et al*. 2000).

Geostatistical methods for interpolation start with the recognition that the spatial variation of any continuous attribute is often irregular to be modelled by simple, smooth mathematical function. Instead, the variation can be better described by stochastic surface. The attribute is known as regionalized variable. Interpolation with geostatistics is known as kriging, after D.G. Krige. Regionalized variable theory assumes that the spatial variation of any variable can be expressed as the sum of three major components. These are (a) a structural component, having constant mean or trend; (b) a random, but spatially correlated component, known as the variation of regionalized variable, and (c) a spatially uncorrelated random noise or residual error term.

Geostatistics provides tools to describe and predict spatial variation, and carry out spatial interpolation. It uses the (semi-) variogram to quantify the spatial variation of a regionalized variable. The fitted function to the experimental variogram provides the input parameters for spatial prediction by kriging (Krige 1951).

Semivariogram Analysis

A property is said to show spatial dependence or spatially correlation if the variation in the value of the property at any two locations is a function of their separation distance. Spatial variability is expressed by a semivariogram $\hat{\gamma}(h)$ which measures (Goovaerts 1998; Warrick *et al.* 1986) the average dissimilarity between data separated by a vector *h*. The empirical semivariance or classical semivariance (Matheron 1963) was computed as half the average squared difference between the components of data pairs:

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

Where $N(h)$ is the number of data pairs within a given class of distance and direction, $z(x_i)$ is the value of the variable at the location x_i and $z(x_i+h)$ is the value of the variable at a lag of h from the location x_i.

The semivariogram values were computed using geo-statistical software and plotted with lag distance *h*. The computed semivariogram values $\hat{\gamma}(h)$ for corresponding lag (h) were fitted with available theoretical semivariogram models (spherical, exponential, circular and Gaussian model) using weighed least square technique. Weight for each lag was directly proportional to the number of sampling pairs and inversely proportional to the standard deviation of experimental semivariogram values. Expressions for Spherical semivariogram models used in this study are given below.

$$\gamma(h) = C_0 + C\left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right], \text{if } 0 \le h \le a,$$

$$= C_0 + C, \text{otherwise}$$

In the semivariogram models, nugget, sill and range were expressed by C_0, $(C + C_0)$ and a respectively. Nugget variance is a measure of amount of variance due to error in sampling, measurement and other unexplained source of variance. Sill value is that value of semivariance when it becomes equal to the variance of sampled population (if it has no trend). Range is the distance at which the samples become spatially independent and uncorrelated to each other. Hence in order to understand the spatial structure of a given property, sample spacing should be one fourth or less of the range.

Important condition to be met before using a semivariogram model for interpolation is stationarity *i.e.* semivariogram at any separation distance is finite and does not depend on the location. If these conditions are not met, the measured property is said to be non-stationarity and kriging can't be used without removing the cause of non-stationarity in the data. When mean changes systematically with distance, it is often called as trend. The trend can be removed by fitting a regression model to data. Short range stochastic change in mean with location, is often referred as drift. The primary method to remove trend is use of universal kriging.

Kriging

Kriging (Krige 1951) is regarded as an optimal method of spatial prediction. Kriging is a moderately quick interpolator that can be exact or smoothed depending on the measurement error model. It is a theoretical weighted moving average:

$$\hat{z}(x_0) = \sum_{i=1}^{n} \lambda_i z(x_i)$$

Where $\hat{z}(x_0)$ is the value to be estimated at the location of x_0, $z(x_i)$ is the known value at the sampling site x_i and n is the number of sites within the search neighbourhood used for the estimation. The number n is based on the size of the moving window and is defined by the user. Kriging is different from other methods (such as inverse distance weighting), because the weight, $\boldsymbol{\lambda}_i$ is no longer arbitrary. The weights depend on the parameters of the variogram model and the sampling configuration and are decided under the conditions of unbiased and minimized estimation variance. The $\boldsymbol{\lambda}_i$ weights are chosen so as to minimize the estimation or error variance $\sigma_E^2(x_i) = var\{\hat{z}(x_i) - z(x_i)\}$ under the constraint of unbiasedness of the estimator. It is very flexible and allows us to investigate graphs of spatial autocorrelation. The flexibility of kriging can require a lot of decision-making. Kriging assumes the data come

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from a stationary stochastic process, and some methods assume normally-distributed data. Kriging uses statistical models that allow a variety of map outputs including predictions, prediction standard errors, probability, etc.

There are several kriging techniques such as simple kriging, ordinary kriging, block kriging, non-linear kriging like lognormal kriging; kriging using extra information such as stratified kriging, co-kriging, kriging with trend *i.e.* universal kriging, multivariate kriging; probabilistic kriging such as indicator kriging. Multivariate kriging is the application of geostatistics to multivariate transformation, such as result of regression model, principal component transformation, reciprocal averaging, or fuzzy-k-means.

Assessment of spatial interpolation methods

The spatial interpolation method like ordinary kriging and simple kriging was evaluated through a leave-one-out cross-validation approach (Davis 1987). Mean Error is the average value of residuals *i.e.* difference between predicted and observed values. Average Standard Error is the average of the prediction standard errors. The performance of each spatial interpolation method was assessed using the root-mean-squared error (RMSE) and root mean squared standardized error (RMSSE) (ESRI 2011).

The predictions are unbiased, indicated by a mean prediction error close to zero. The predictions do not deviate much from the measured values, indicated by root-mean-square error and average standard error that are as small as possible. The RMSSE measures the goodness of fit of the theoretical estimate of error (Bishop and Lark 2008). If the correct semivariogram model is used, the RMSSE values should be close to 1 (Lark 2000). The best suited interpolation option is the one which give lowest RMSE and also its average standard error (ASE) nearest to root mean square prediction error or alternatively root mean square standardized error (RMSSE) nearest to one.

3. Soil Fertility and Spatial Variability

Soil fertility is affected by several factors including land use history, cropping pattern, relief position, and parent material under a specified climate. Even within a given soil plot, the spatial distribution of soil chemical properties is altered by agriculture, particularly by the application of fertilizers, amendments and tillage systems in the upper 100 mm depth of the soils (Camacho-Tamayo *et al*. 2008).

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Advances including the global positioning system (GPS), geographic information systems (GIS), atomic absorption spectroscopy (AAS), inductively coupled plasma (ICP) spectrometry, geo-statistics, and precision agriculture facilitate soil macro & micronutrients mapping and provide quantitative support for decision and policy making to improve agricultural approaches for balanced crop nutrition (Warrick *et al*. 1986; White and Zasoski 1999). Goovaerts (1999) described the applications of geostatistical tools to the description of spatial pattern, modelling spatial variation, spatial prediction, modelling local uncertainty and stochastic simulation of soil properties. Soil macronutrient fertility map (Jalali 2007; Xing-Yi *et al*. 2007; Binita *et al*. 2009) and micronutrients fertility maps (White and Zasoski 1999; Singh 2008) had been developed using GIS software.

Farm scale mapping of soil physical properties was investigated by several researchers. Santra *et al*. (2008) developed kriged map of soil properties such as clay content, silt content, bulk density, organic carbon content, water content at field capacity and permanent wilting point in IARI farm, New Delhi. Hole-effect semivariogram model was found the best to fit the experimental semivariogram of organic carbon content due to its periodic variation over two dimensional spaces wheras the semivariogram of other soil properties are best fitted with Gaussian model at IARI farm soils. In an another study, Amirinejad *et al*. (2011) assessed and generated map of spatial variation of soil physical health in a farm, Kherali Bhav village, Uttar Pradesh. They observed that soil physical health of the farm was medium to good for paddy cultivation but was not suitable for succeeding wheat crop mainly because of increased bulk density and reduced field saturated hydraulic conductivity, non-capillary porosity and available water retention capacity of the farm during wheat growth.

Farm scale mapping of soil physic-chemical properties was investigated by several researchers. Nayak *et al*. (2009) reported that the semivariograms of the soil physicochemical parameters such as pH, EC, organic C indicated moderate to strong spatial dependence except bulk density at 0-7.5 and 7.5-15 cm under *P. juliflora*. The experimental semivariograms of bulk density under *P. juliflora* were not spatially structured. The kriged and inverse distance maps provided the regions and loops of pH, EC, organic C and bulk density with distinct values and explained the quality of heterogeneity of reclamation under both the tree species.

Macronutrients

Zonal level of soil fertility mapping in several countries was conducted. For example, geostatistical analysis of soil nutrient properties in black soil of Northeast China indicated that structural factors, such as parent material, terrain, and water table, were the main causes of the spatial correlations. Strong spatial correlations were noted with total organic matter content (OMC), total N, total P, available N (AN), and available P (AP), while they were moderate for total K and available K (AK). The effective spatial autocorrelation of OMC, total N, total P, and AN ranged from 1037 to 1353 km, whereas the ranges of total K, AP, and AK were only from 6 to 138 km (Zhang *et al*. 2007). In another study at Ghataprabha Left Bank canal (GLBC) command area by Binita *et al*. (2009) generated soil fertility map to evaluate the status of major nutrients as affected by the different physiographic units. Due to intensive irrigated agriculture practiced in the command area, the nutrient status did not follow any distinct trend with respect to physiographic units and crops grown.

District level soil nutrient mapping indicates the soil fertility status and is required for policy planning and allocation of fertilizer resources in India. Sharma *et al*. (2008) prepared maps of macronutrient (NPK) in Amritsar district of north-west Punjab clearly indicated the specific locales, where deficiency of nutrients constrained crop production. Reza *et al*. (2012) also generated the spatial variability map of pH, organic carbon (OC), available nitrogen (AN) and available potassium (AK) of Goalpara district of Assam using conventional statistics and geostatistical approach. There is need of storage of this geospatial research work in common platform so that it can caters the geospatial services to users and policy maker.

Farm-scale and field scale mapping of soil fertility was also reported worldwide using geo-statistical techniques. The geostatistical techniques identified the nature of spatial dependency of soil fertility parameter and its spatial range. Camberdella *et al*. (1994) studied field scale distribution of soil properties at two sites within a watershed in central Iowa, USA and observed that soil organic carbon C, total N, pH, and macro-aggregation were strongly spatially dependent whereas microbial biomass C and N, bulk density and denitrification were found to be moderately spatially dependent. Fu-Sheng *et al*. (2006) reported that soil organic matter (SOM), soil total nitrogen (STN), total phosphorus (STP) and total potassium (STK) had a lower structural heterogeneity ratio and a longer range at Kezuohouqi County, Inner Mongolia Autonomous Region of China. In addition, STN had an isotropic spatial structure, whereas the others had an anisotropic spatial structure. It was also observed that the spatial distribution pattern of STN was far different from those of SOM, STP and STK in the locality.

Besides, several kriging interpolation techniques generated soil fertility map with good accuracy and precision. Castrignano *et al*. (2000) investigated the scale-dependent correlation structure of soil variables in central Italy by means of Factorial Kriging Analysis (FKA) developed by Matheron. Classical statistical and geostatistical analysis which showed that plant macro and micro-nutrients coming from fertilization had led to short-range variation, especially in Na, N, and CEC. The effects were superimposed on long-range processes, producing systematic patterns in soil fertility. In another study, Lopez-Granados *et al*. (2005) compared various prediction methods for mapping soil properties (texture, organic matter (OM), pH, phosphorus and potassium) for precision farming approach by incorporating secondary spatial information into the mapping. The best prediction method for mapping organic matter, pH and potassium was kriging with varying local means in combination with the spectral data from the blue waveband with the smallest mean square error (MSE) indicating the highest precision.

For monitioring of spatio-temporal soil fertility, GIS technology has tremendous potentiality. Sun *et al*. (2003) proposed a process to evaluate soil quality using the geo-statistical methods as a potential analysis tool for monitoring changes at a farm scale. A geo-statistical analysis showed that soil properties such as pH, organic matter, available P and K and their changes between 1985 and 1997 were spatially structured. The nugget-to-sill ratio indicated a strong spatial dependence for soil pH and a moderate spatial dependence for organic matter, available P and K.

Sensor based soil fertility analysis is key tool for real-time nitrogen management and generation of soil fertility map from lab based and spatially linked soil fertility data are important tools for site-specific nutrient management. Besides other technological advancement like non-destructive quick test of the nitrogen status of plants, new types of slow release and controlled release fertilizers, customized fertilizers and use of urease inhibitor and nitrification inhibitor etc had significantly improved fertilizer use efficiency (Xiang *et al*. 2008).

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Micronutrients

State level and regional level mapping of soil micronutrients in India was conducted for its spatial distribution. Detailed characterization of soils of Punjab with generation of GIS-aided thematic maps, carried out by Bali *et al*. (2010), indicated that 10% of the total geographical area of Punjab was affected by the Zn deficiency based on the existing critical limits. Behera *et al*. (2011) assessed the distribution pattern and variability of total and extractable Zn in cultivated acid soils of India through geostatistical analysis. Somasundaram *et al*. (2009) investigated the micronutrient status under different land use system in Chambal ravine lands and found that iron (Fe) and zinc (Zn) deficiencies are the major disorders in agricultural fields (marginal land) along the Chambal ravine systems.

Micronutrients status of several canal command area in India was also investigated using GIS technology. Nayak *et al*. (2006) reported that 10% of the area was found to be deficient in zinc, 5% in copper and iron whereas available manganese content was adequate in the area in the soils of Bara tract of Sardar Sarovar canal command located in Gujarat State, western India. At the sampled scale results showed that the micronutrients *viz.*, Zn, Fe and Cu followed normal distribution whereas Mn followed lognormal distribution. The measurements were spatially dependent and also present a distinct ordered spatial variation.

District level mapping of soil micronutrient was also conducted by several researchers. Minakshi *et al*. (2005) assessed the micronutrient status of soil in Patiala district using GIS and reported that about 11% (39,369 ha) of TGA of the district was deficient in Zn whereas only 4 and 5% of the area was deficient in Mn and Fe, respectively. Soil micronutrient maps of Amritsar district, prepared by Sharma *et al*. (2006), clearly delineated the micronutrient deficient area; and multi-micronutrient map suggested that deficiency of individual element was more prevalent as compared to that of two, three or four micronutrients. The study of Sood *et al*. (2009) revealed that in Muktsar district of Punjab, the 39, 7, 8 and 34 per cent of the total geographical area (TGA) of the district was deficient in Zn, Cu, Mn and Fe, respectively.

Field scale mappining of soil micronutrients were also been attempted by several researchers. Lin *et al*. (2009) characterized the spatial variability and distribution of micronutrients in rice grain and soil within a paddy field with unknown anthropogenic contamination in Deqing County, Zhejiang Province, China. The concentrations of the

DTPA-extractable micronutrients displayed strong spatial dependency, with a range distance of about 60 m.

4. Conclusions and Perspectives

In geostatistics, semi-variogram is used to quantify the spatial variation of regionalized variables such as soil fertility parameter. Subsequently, kriging uses statistical models that generates spatial distribution map including predictions, prediction standard error, probability map etc. Soil fertility maps at different scale from field level to country level can be developed using different kriging methods. The nature of spatial variation of soil fertility parameter and its distribution pattern is being utilized for policy planning as well as services toward farmers for higher and sustainable agricultural production with increased input use efficiency and environmental safety. Geographic information system has tremendous potentiality and prospects for maintenance of spatial and non-spatial database in relation to natural resources as well as agriculture at different scale for upgradation of Indian agriculture.

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