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Spatial Distribution of Soil Nutrients in Berambadi Watershed of Chamarajanagar District, Karnataka for Sustainable Crop Production

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Abstract: The spatial distribution of soil nutrients was assessed in Berambadi watershed of Chamarajanagar district, Karnataka based on geo-statistics model. A total of 447 surface soil samples (0-20 cm) were collected at 250 m grid interval and analyzed. Semi variogram parameters (nugget, sill and range) for each soil property with best fitted models were identified based on minimum root mean square error (RMSE). Exponential, spherical and gaussian models were fit well for the soil properties. The nugget-sill ratio showed that the spatial variability of soil nutrients moderate spatial dependence (25-75 %) except soil pH and zinc (<25 % spatial dependence). The results of spatial distribution of nutrients showed that available phosphorus content was medium (23-56 kg ha^{-1}) in 57% of total geographical area and available potassium content was high (>330 kg ha^{-1}) in more than 60% of total geographical area of Berambadi watershed. Spatial distribution of soil nutrients is most important to know the status of soil fertility, which helps in adjusting the agricultural management measures for better crop production.

Key words: *Spatial distribution, soil nutrients, geo-statistics, semivariogram, kriging*

Introduction

Soil nutrients play an important role in soil fertility, vegetative restoration, land ecosystem structure and function. Soil nutrient content and its availability to the plants are greatly influenced by land use and management (Islam and Weli 2000; Wang Jun and Shaliqing 2007). Multi-nutrient deficiencies are common due to continuous applications of major nutrients (NPK) and neglect of micro-nutrients (El-Swaify *et al.* 1985; Rego *et al.* 2003; Sharma *et al.* 2009), which affects sustainability and nutritional security. Hence, attention has to be paid to identify the extent of problem and suggest corrective measures for deficiencies of nutrients in various cropping systems (Rego *et al.* 2005; Sahrawat *et al.* 2007; Manna *et al.* 2011).

Spatial variability and severity of nutrients deficiency can be estimated by using geostatistical interpolation techniques (Tesfahunegn *et al.* 2011; Tripathi *et al.* 2015). Spatial distribution of soil nutrients can be generated by different interpolation techniques namely, Inverse Distance Weighted (IDW), Radial Basis Functions (RBF), Local Polynomial Interpolation (LPI), Ordinary Kriging (OK) and Empirical Bayes (EBK) (Johnston *et al.* 2001). Among the methods of interpolation, ordinary kriging is most common geo-statistical method for estimation of the spatial distribution of soil nutrients (Pang *et al.* 2011). Kriging is

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most suitable when there is a spatially correlated distance or directional bias in the data compared to other interpolation methods. Kriging also uses the calculation of spatial autocorrelation to determine the weights that should be applied at various distances and it is widely used in soil science and geology. In this context, the present study is proposed to investigate the soil fertility status of Berambadi watershed, Chamarajanagar district, Karnataka using geo-statistical approach to bring more informed decisions to improve soil fertility and crop productivity of this region.

Materials and Methods

Study area

The study was carried out in the Berambadi watershed (11°43'49" to 11°48'11" N; 76°32'31" to 76°36'14" E) spread over 2655 ha (Fig. 1) situated in the Chamarajanagar district of Karnataka state at an elevation ranging from 829-940 m above MSL. The annual precipitation is 734 mm, of which around 35% rainfall is received during south–west monsoon and 36 % received during north-east monsoon. The average annual temperature is 23.7 °C and the length of growing period ranges from 90 to 120 days. The soil moisture regime is ustic and soil temperature regime is isohyperthermic. The major geological formation is granite and gneiss. The area covers rainfed lands with the main crops being maize, sorghum, pigeonpea, cotton, mango with other crops.

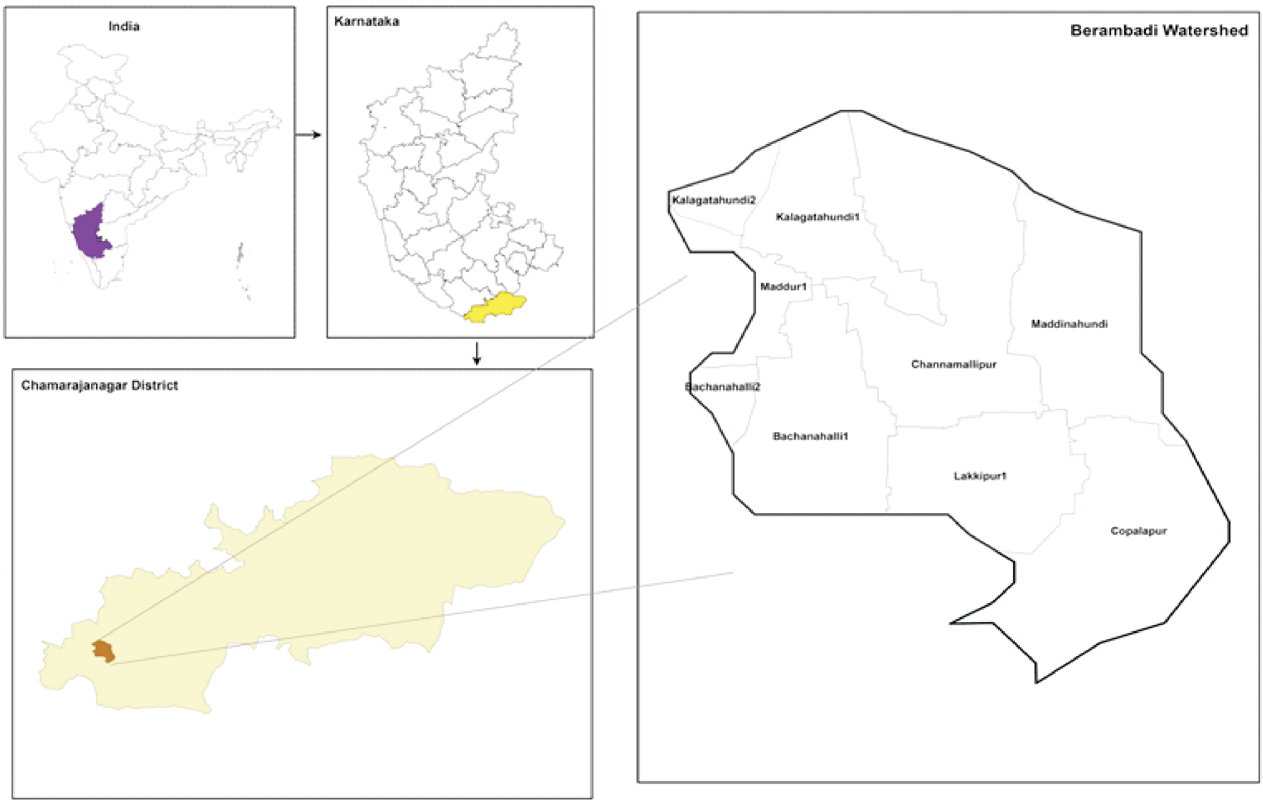

Fig.1. Location map of study area

Soil sampling and analysis

A total of 447 surface soil samples (0-20 cm) were collected at 250 m grid interval with the help of Global Positionig System (GPS) during 2015. Collected soil samples were air dried and processed. Soil pH (1:2.5) and electrical conductivity (EC) were analyzed in soil water suspension as described by Jackson (1962). Organic carbon was estimated by Walkley and Black (1934) method. Available phosphorus was determined by Olsen *et al.* (1954) method (pH >6.5). Available potassium was analysed by flame photometer after extraction with 1*N* ammonium acetate (Richards 1954). The available sulphur was extracted by 0.15 % $CaCl_2$ and estimated the sulphate content by turbidimetric procedure (Tabatabai 1982). Available boron was estimated by using Azomethine-H reagent (Keren 1996). Micronutrient cations (Zn, Cu, Fe and Mn) were analyzed by DTPA extraction method with pH 7.3 and estimated the micronutrients contents by Atomic Absorption Spectrophotometer (Lindsay and Norwel 1978).

Geostatistical analysis

The mean, minimum, maximum, standard deviation (SD), kurtosis, skewness and coefficient of variation (CV) values for each soil properties were computed. According to Carvalho *et al.* (2002), kurtosis and skewness are indicative of a normal frequency distribution. The ratio of standard deviations and averages is the variation coefficient, which reflects the discrete degree of samples. If the ratio is less than 0.1, it shows that the data exhibits weak spatial variability. If the ratio is above 0.1 and less than 1.0, it shows that the data exhibits medium spatial variability. If the ratio is above 1.0, it shows that the data exhibits strong spatial variability (Hu *et al.* 1999). To find out the relationship between soil properties and available nutrients, pearson's correlation coefficients were computed. Spatial interpolation and GIS techniques were used to produce spatial distribution of soil nutrients by using ArcGIS v.10.1 (ESRI Co, Redlands, USA). One of the most important interpolation methods is kriging as it predicts unknown values from data observed at known locations. This method uses variogram to express the spatial variation and kriging method reduces the error of predicted values which are determined by measuring the spatial distribution of the predicted values (Li *et al.* 2000). A variogram is a description of the spatial continuity of the data. The experimental variogram is a discrete function calculated using a measure of variability between pairs of points at various distance. Kriging allows users to study graphs of spatial autocorrelation. It can be applied within moving data neighbourhoods, is a non-stationary algorithum which corresponds to a non-stationary random function with changeable mean but stationary covariance (Deutsch and Journel 1992).

Semivariogram model was used in the kriging to define the weights of the function (Webster and Oliver 2001), and the semivariance is an autocorrelation statistic defined as follows (Mabit and Bernard 2007):

$$r(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [(Xi - \hat{Z}(xi)]^2 \qquad (1)$$

where z (xi) is the value of the variable z at location of xi, 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 (*i.e.,* the behaviour of the variables that characterize them is not uniform in all directions) did not show any differences in spatial dependence based on direction, for which reason isotropic semivariograms (*i.e.,* the behaviour of the variables that characterize them is uniform in all directions) were chosen. Spherical, exponential and Gaussian models were fitted to the empirical semivariograms. Best-fitted model with minimum root mean square error (RMSE) were selected for each soil nutrients:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} [Z(xi - \hat{z}(zi)]^2 (2)}$$

The exponential, spherical and guassian models were best fitted to all the soil properties. Expression for different semivariogram models used in this study is given below:

Exponential model:

$$r(h) = Co + C1\left[1 - \exp\left\{-\frac{h}{a}\right\}\right] \; for h \geq 0 \tag{3}$$

Spherical model:

$$r(h) = Co + C1\left[1.5\frac{h}{a} - 0.5\;(\frac{h}{a})3\right], 0 \leq h \leq= Co + C1 \tag{4}$$

Guassian model:

$$r(h) = Co + C1\left[1 - \exp\left\{-\frac{h2}{A2o}\right\}\right] fohh \geq 0 \tag{5}$$

Using the semivariogram model, basic spatial parameters such as nugget (C0), sill (C1 + C0), and range (A) was calculated which provides 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 neighbouring values, and range is the distance at which values of one variable become spatially independent of another (Lopez-Granados *et al.* 2002).

The ratio between nugget and sill value is the nugget effect, when the ratio is less than 25%, it shows that soil nutrients present strong spatial dependence, when the ratio is in the range from 25% to 75%, it shows a medium dependence and the ratio is more than 75%, it shows relatively weak spatial dependence (Sun *et al.* 2002).

Results and Discussion

Description statistics of soil chemical parameter pH, EC and OC

The descriptive statistics of pH, EC and organic carbon (OC) are given in table 1. The pH ranged from 4.60 to 8.99 and electrical conductivity ranged from 0.01 to 2.53 dS m^{-1}. The organic carbon content ranged from 0.08 to 1.86% in Berambadi watershed. The coefficient of variation for OC, EC and pH are 16.0%, 94.8%, and 39.7%, respectively with medium spatial variability (Gomes and Garcia 2002). Kurtosis and skewness of pH is negative, whereas, EC and OC are positive.

Table 1. Descriptive statistics of soil chemical and nutrients parameters

Parameters	pH	EC (dS m^{-1})	OC (%)	P_2O_5 (kg ha^{-1})	K_2O (kg ha^{-1})	S (mg kg^{-1})	B (mg kg^{-1})	Cu (mg kg^{-1})	Fe (mg kg^{-1})	Mn (mg kg^{-1})	Zn (mg kg^{-1})
Mean	6.87	0.18	0.68	38.5	367.5	9.65	0.55	1.67	19.6	21.4	0.58
Maximum	8.99	2.53	1.86	316	1524.1	47.2	1.87	16.5	91.7	121.8	6.26
Minimum	4.60	0.01	0.08	2.29	67.4	0.72	0.01	0.26	2.32	1.80	0.02
S.D	1.10	0.17	0.27	45.2	228.7	6.16	0.36	1.21	15.1	15.1	0.66
Kurtosis	-1.23	78.7	0.47	9.17	3.19	5.53	0.001	64.2	1.66	6.33	29.4
Skewness	-0.02	6.53	0.55	2.59	1.59	1.59	0.71	6.39	1.31	1.81	4.47
CV (%)	16.0	94.8	39.7	117.5	62.2	63.9	65.8	72.0	76.8	70.3	112.7

Note: SD: Standard Deviation; CV: Coefficient of Variation

Descriptive statistics of major and micro nutrients

The descriptive statistics of major and micro nutrients are given in table 1. The P_2O_5 values ranged from 2.29 kg ha^{-1} to 316.0 kg ha^{-1} with a mean of 38.5 kg ha^{-1}and K_2O values ranged from 67.4 kg ha^{-1} to 1524.1 kg ha^{-1}with a mean of 367.5 kg ha^{-1}. Available sulphur ranged from 0.72 mg kg^{-1} to 47.2 mg kg^{-1}. The high phosphorus (316.0 kg ha^{-1}) and sulphur (47.2 mg kg^{-1}) contents might be due to samples collected from the plots receiving higher level of phosphorus and sulphur containing fertilizers. Kurtosis and skewness of P_2O_5, K_2O and S are positive. The mean concentration of Cu, Fe, Mn, Zn and B are 1.67, 19.6, 21.4, 0.58 and 0.55 mg kg^{-1} soil, respectively. Kurtosis and skewness of micronutrients are positive. The standard deviation of microntrients follows the order of Mn<Fe<Cu<Zn and coefficient of variation is in the order of Zn<Fe<Cu<Mn. The variability observed in the DTPA extractable micronutrient concentrations might be due to variation in soil parent material, rainfall and soil management (Li *et al.* 2008).

Spatial distribution of soil nutrients

The maps generated for some nutrients for the Berambadi watershed have been generated by using kriging method under GIS and classified into different

Fig. 2. Spatial distribution map of soil properties and nutrients in of area

classes (Fig. 2). The results indicated, available phosphorus content of the soil was medium and covered maximum area of about 1526 ha (57 %) followed by an area of 622 ha (23%) is low. The soil analysis revealed that available potassium is high (>330 kg ha^{-1}) in about 1608 ha (61%) and medium (140-330 kg ha^{-1}) in an area of 1048 ha (39%) in the watershed. Available boron content is medium (0.5-1.0 mg kg^{-1}) in an area of about 1338 ha (50%) and low (<0.5 mg kg^{-1}) in an area of about 1244 ha (47%). The data showed low (<0.5 mg kg^{-1}) available zinc in an area of about 1515 ha (57%), marginal (0.5-0.75 mg kg^{-1}) in about 542 ha (20%), adequate (0.75-1.50 mg kg^{-1}) in an area of 488 ha (18%) and high (>1.50 mg kg^{-1}) in an area of about 110 ha (4%) and thus there is need to apply zinc containing fertilizers to maitain the soil zinc content.

Correlation between soil pH, organic C and soil properties

Interrelationship between the soil nutrients offers a better understanding of the soil system (Table 2). Soil organic carbon showed a significant ($P < 0.01$) and positive effect on availability of Cu and Mn contents. The concentrations of Zn, Cu, Mn and Fe in soil increased with SOC as revealed by the significant and positive correlation coefficient. The SOC improve soil structure and supply soluble chelating agents and reduces oxidation and precipitation of cations, thus resulting in increased concentrations of Zn, Cu, Mn and Fe (White and Zasoski 1999). The correlation between soil organic carbon and available P was significantly ($P < 0.05$) negative. Soil reaction is another soil property which influences availability of plant nutrients. A positive and significant relationship was found between soil pH and available P, K, S and B and a negative and significant relationship with Fe. In our study, the concentrations of Zn, Cu, Mn and Fe got reduced with the increase in soil pH, which was in agreement with the observations of Lindsay (1979) who reported that by each unit increase of soil pH in the range from 4 to 9, the solubility of Fe in soil decreases by 1000 fold compared with100-fold decrease for Mn, Cu and Zn.

Correlation coefficient between major and micro nutrients

Phosphorus had significant and positive relationship between K and S (Table 2). Crops respond to higher K levels and helps to uptake and availability of other nutrients. Potassium showed significant positive relation between S and B. Amongst available nutrients, a positive significant relationship was found between S x B, Cu x Fe, Cu x Mn, Cu x Zn and Fe x Mn. correlation between S x Zn and Mn x Zn were significant negative interaction.

Table 2. Pearson's correlation coefficients among soil properties and their level of significance.

	pH	EC	OC	P	K	S	B	Cu	Fe	Mn	Zn
PH	1.00										
EC	0.26**	1.00									
OC	-0.07	0.12**	1.00								
P	0.27**	0.08	-0.10*	1.00							
K	0.41**	0.27**	0.03	0.44**	1.00						
S	0.17**	0.19**	0.09	0.26**	0.16**	1.00					
B	0.17**	0.09	0.008	0.10*	0.11*	0.17**	1.00				
Cu	0.11*	-0.02	0.12**	0.08	0.24**	0.003	0.02	1.00			
Fe	-0.17**	-0.13**	0.02	0.03	-0.05	-0.05	-0.04	0.12**	1.00		
Mn	-0.10*	-0.15**	0.13**	-0.03	0.01	0.15**	0.07	0.17**	0.45**	1.00	
Zn	-0.09*	-0.01	-0.002	0.04	0.10*	-0.15**	-0.11*	0.37**	0.11*	-0.36**	1.00

Notes: *Correlation is significant at $P < 0.05$ level (two-tailed); **correlation is significant at $P < 0.01$ level (two-tailed).

Semivariogram analysis of soil properties

Semivariogram parameters (nugget, sill, and range) for each soil properties with best fitted model were identified based on minimum root-mean-square error (RMSE). The parameters for the models fitted to the semivariograms are shown in table 3. C_0 is the nugget value, which is caused by experimental error and other artificial factors; C_1 is the partial sill value, which is caused by climate, parent material, topography, soil type and other natural factors; C_0+C_1 is the sill value, which presents the total variation of the system.

Analysis of the isotropic variogram indicated that the pH, EC, OC, K_2O, B, Cu and Fe content of semivariograms were well described by exponential model, with the distance of spatial dependence being 2387, 616, 1962, 2185, 2661, 9196 and 2291 m, respectively, while the S and Mn semivariograms were best fitted by spherical model with the range of 3581 and 2279 m; P_2O_5 and Zn semivariograms were described by Gaussian model with range value of 1020 and 440 m, respectively (Table 3). Samples separated by distances lower than the range are spatially related, whereas, those separated by a distance greater than the range are considered not to be spatially related. A large range indicates the value of measured soil property to be influenced by natural and anthropogenic factors over great distances than properties having smaller ranges (Lopez-Granados *et al.* 2002). The different range values for soil properties is might be due to combined effect of parent material, climate and adoption of different land managements. The different models for the soil properties is attributed to inherent soil properties (such as soil pH, EC, SOC and soil mineralogy) as well as management factors including fertilization and cropping sequences. The spatial distribution of soil nutrients is affected by both structural and random factors. There is strong spatial correlation in soil nutrients when they are greatly affected by natural factors such as climate, parent material, topography, soil type and so on. While random factors such as fertilization, tillage measure, cropping system and other anthropogenic factors can weaken spatial correlation of soil nutrients (Chien *et al.* 1997).

The nugget-sill ratios of pH and zinc are 21% and 0.1%, respectively, which shows that there is a strong spatial dependence among them. They are mainly affected by climate, parent material, topography, soil type and other natural factors. The nugget-sill ratios of electrical conductivity, organic carbon, available phosphorus, potassium, sulphur, boron, DTPA

Table 3. Geostatistical parameters of the fitted semivariogram models for soil properties

Soil nutrients	Model	Nugget (C_0)	Partial Sill (C_1)	Sill ($C_0 + C_1$)	Range (m)	Nugget/Sill	Spatial Dependence	RMSE
pH	Exponential	0.30	1.12	1.42	2387	0.21	Strong	0.80
EC	Exponential	0.01	0.02	0.03	616	0.33	Moderate	0.17
OC	Exponential	0.03	0.04	0.08	1962	0.43	Moderate	0.22
P_2O_5	Gaussian	1602	649	2251	1020	0.71	Moderate	41.1
K_2O	Exponential	28,234	25,430	53664	2185	0.53	Moderate	191.7
S	Spherical	29.3	11.7	41.0	3581	0.71	Moderate	5.56
B	Exponential	0.08	0.06	0.14	2661	0.61	Moderate	0.32
Cu	Exponential	0.70	1.34	2.04	9196	0.34	Moderate	1.03
Fe	Exponential	144.1	80.8	226.9	2291	0.64	Moderate	13.4
Mn	Spherical	79.7	160.8	240.5	2279	0.33	Moderate	10.9
Zn	Gaussian	0.004	0.43	0.43	440	0.001	Strong	0.59

extractable cupper, iron and manganese were 33%, 43%, 71%, 53%, 71%, 61%, 34%, 64% and 33%, respectively, which shows that the spatial dependence was observed to be moderate, which means the spatial variances among them are influenced by both structural and random factors (Chien *et al.* 1997).

In semivariogram analysis Root Mean Square Error is one of the important parameter and RMSE is frequently used to measure the difference between values predicted by a model and the value sactually observed from the environment that is being modelled. RMSE is a measure of accuracy to compare forecasting errors of different models for a particular data. RMSE of soil pH, EC and OC were 0.80, 0.17 and 0.22, respectively. The RMSE for P_2O_5, K_2O, S and B showed 41.1, 191.7, 5.56 and 0.32, respectively. The RMSE values for DTPA-Cu, Fe, Mn and Zn showed 1.03, 13.4, 10.9 and 0.59, respectively. The highest root mean square error (RMSE) value was noticed in potassium (191.7) and the lowest was observed in electrical conductivity (0.17).

Conclusion

Our investigations on the spatial distribution of soil nutrients in Berambadi watershed in the semi-arid tropics indicated that the highest coefficient of variation was noticed in P_2O_5 compared to other soil nutrients. Ordinary kriging was applied for spatial interpolation of soil nutrients of the area. The study showed high spatial variability with moderate spatial dependence for most of the soil parameters (EC, OC, P, K, S, B, Cu, Fe and Zn) and strong spatial dependence for pH and Zn. Exponential and guassian model performed well in describing the spatial distribution of soil nutrients. In watershed, B and Zn deficiency was observed and call for suitable interventions.

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