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Spatial Variability of Soil Nutrients and Their Relationship in Semi-Arid Uplands of Southern India

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Abstract: A study was conducted to determine the spatial variability of pH, electrical conductivity, organic carbon, available macro and micronutrients in Palani block, Dindigul district representing Tamil Nadu uplands of semi-arid southern India. A total of 119 geo-referenced surface soil samples were collected based on landscape ecological units. The soils varied from very strongly acidic (pH 4.57) to strongly alkaline (pH 8.74) and were non-saline (EC<0.60dS m^{-1}). Soil pH had the lowest coefficient of variation (CV=17%), whereas, other parameters were high in CV. Experimental semi-variograms were fitted for different models like circular, spherical, exponential, gaussian and stable to map the spatial variability. Among the models, exponential model was best fitted for pH, OC, available P, Fe and Mn; circular model for available K and EC; and Gaussian model for Cu and Zn using weighted least square. The models with minimal RMSE were considered as the best cross-validation results. The Nugget-sill ratio indicated a moderate degree of spatial dependence (0.25-0.75) for EC, soil organic carbon, available P and K, and strong degree of spatial dependence (<0.25) for soil pH, available Fe, Cu, Mn and Zn. The spatial variability information on soil nutrients will help the farmers in sustainable nutrient management.

Keywords: *Spatial variability, soil fertility, semi-variogram, ordinary kriging, spatial dependence, management.*

Introduction

Soil variability is an essential criterion to assess soil nutrient status and to identify the similar management units for better fertility management (Sawant *et al.* 2018). Soils of the semi-arid tropics have limitations of nutrient losses and high soil erosion (Prabhavathi *et al*. 2013) which leads to uneven distribution of soil fertility and therefore, affects crop growth. Spatial variability of soil properties is the result of complex interactions between geology, climate, topography, land use, and management (Shi *et al*. 2007). Spatial variability of soil properties can be effectively assessed by geo-statistical methods such as kriging interpolation (Reza *et al.* 2017). The kriging interpolation technique predicts the soil properties by spatial auto-correlation and reduces variance of estimation error (Saito *et al.* 2005). Ordinary kriging is the most commonly used kriging in practice due to its better performance over other techniques (Hegde *et al.*

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2018) and it provides variability estimates of soil properties using variogram models (Pravat *et al.* 2016). The study was carried-out to assess the spatial variability of soil fertility parameters for sustainable nutrient management through geo-statistical methods.

Materials and Methods

Study area

The study was carried out in Palani block (77°18'50" to 77°37'17" E; 10°21'18" to 10°32'27" N) of Dindigul district of Tamil Nadu and covers an area of 39,960 ha. The mean annual rainfall is 760 mm and the length of growing period (LGP) ranges from 90-120 days. Major contribution of rainfall is received from North east monsoon (600 mm) than south west monsoon (200 mm). The soils of the study area belong to Alfisols (43%) and Inceptisols (30%) orders.

Soil sampling and analysis

A total of 119 geo-referenced composite soil samples were collected from surface soil layers (0-15 cm depth) based on landscape ecological units. Soil samples were processed and analyzed for pH and electrical conductivity in 1:2.5 soil: water suspension (Piper 1966). Organic carbon was estimated by Walkley and Black method (Walkley and Black 1934). The available P content of neutral and alkaline soils was estimated by Olsen method (Olsen *et al*. 1954) and for acidic soils, it was estimated by Bray method (Bray and Kurtz 1945). Available potassium was extracted using neutral normal ammonium acetate and measured with flame photometer (Jackson 1973). DTPA extractable available micronutrient (Fe, Zn, Cu and Mn) were measured in Atomic Absorption Spectrometer (Lindsay and Norvell 1978).

Statistical and geo-statistical analysis

The descriptive statistics of the soil properties *viz.,* mean, minimum, maximum, standard deviation, co-efficient of variation, skewness and kurtosis were analyzed. The relationship between the soil properties was determined using Pearson's correlation matrix in SPSS software. Spatial distribution maps of the soil properties were prepared using interpolation techniques in ArcGIS. The ordinary kriging interpolation technique was used to estimate the spatial variability of the soil properties by fitting semi-variograms which can explain the spatial structure of the soil properties (Nielsen and Wendroth 2003). The calculation of semi-variograms is expressed as,

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

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.

Semi-variograms were fitted using different standard models *viz.* circular, spherical, exponential gaussian and stable models (Shi *et al*. 2007). Expression for different semi-variogram models used in this study is given below:

Exponential model:

$$r(h) = Co + \mathrm{C1}\left[1 - exp\left\{-\frac{h}{a}\right\}\right] for h \geq o$$

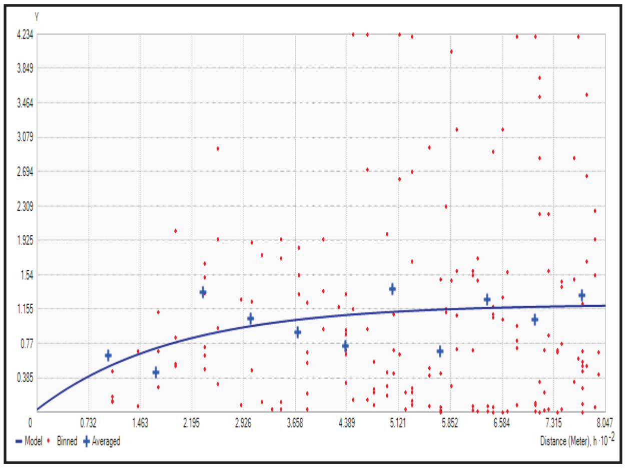
Spherical model:

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

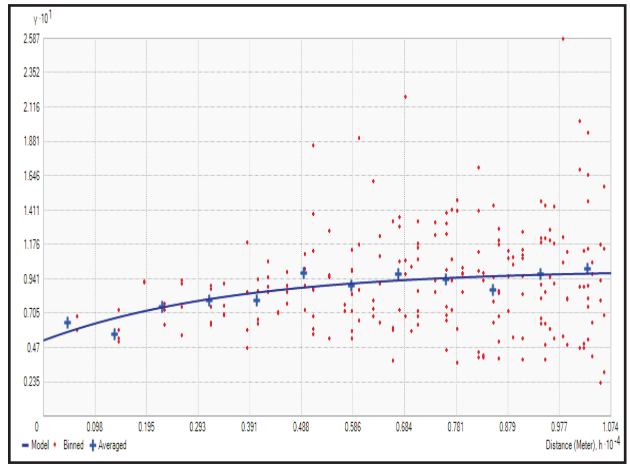
Gaussian model:

$$r(h) = Co + \mathrm{C1}\left[1 - exp\left\{-\frac{\mathrm{h2}}{\mathrm{A2o}}\right\}\right] for h \geq o$$

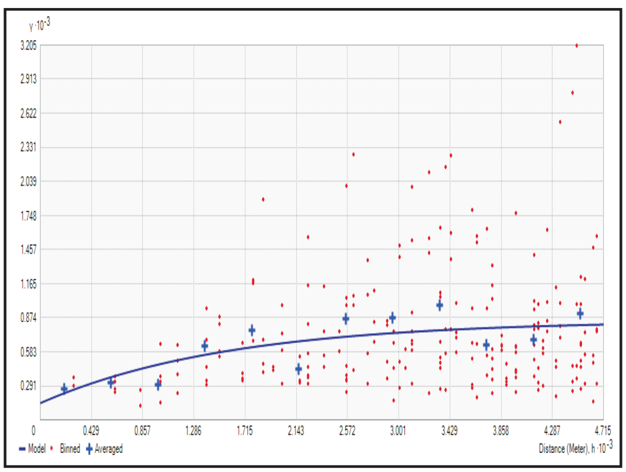
The parameters of semi-variogram like Nugget (*C0)* and Sill (*C0 + C)* were used to characterize the spatial dependency. Nugget (*C0*) explains the micro-scale variability, whereas partial sill indicates the amount of variability which could be defined by spatial correlation structure. The ratio of nugget and sill (nugget/sill) was used to define spatial dependency of the soil properties like strong spatial dependency (<0.25), moderate (0.25-0.75) and weak (>0.75) (Cambardella *et al*. 1994).



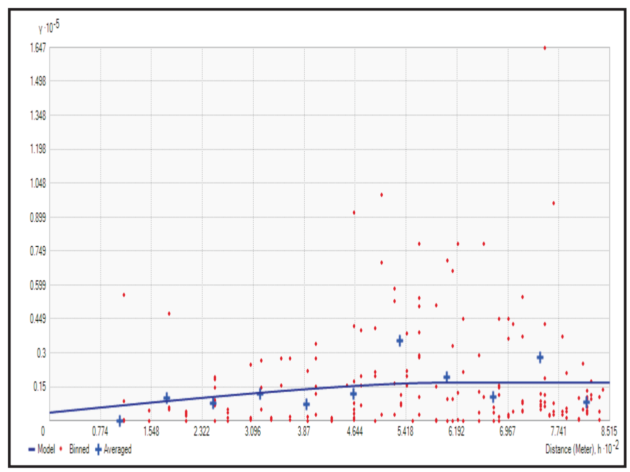
(a) pH- Exponential



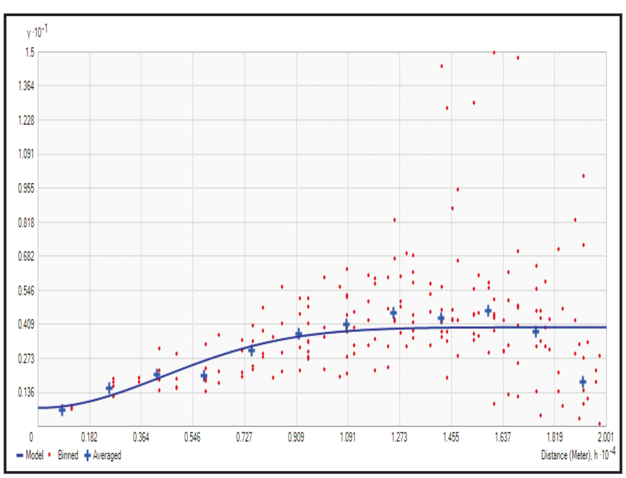
(b) OC-Exponential



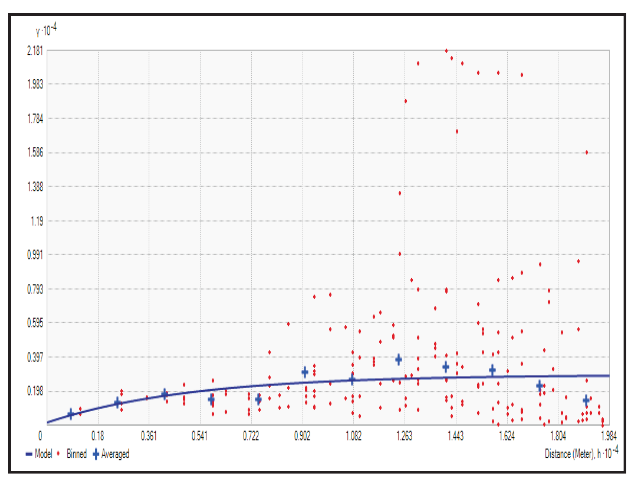
(c) Available P-Exponential



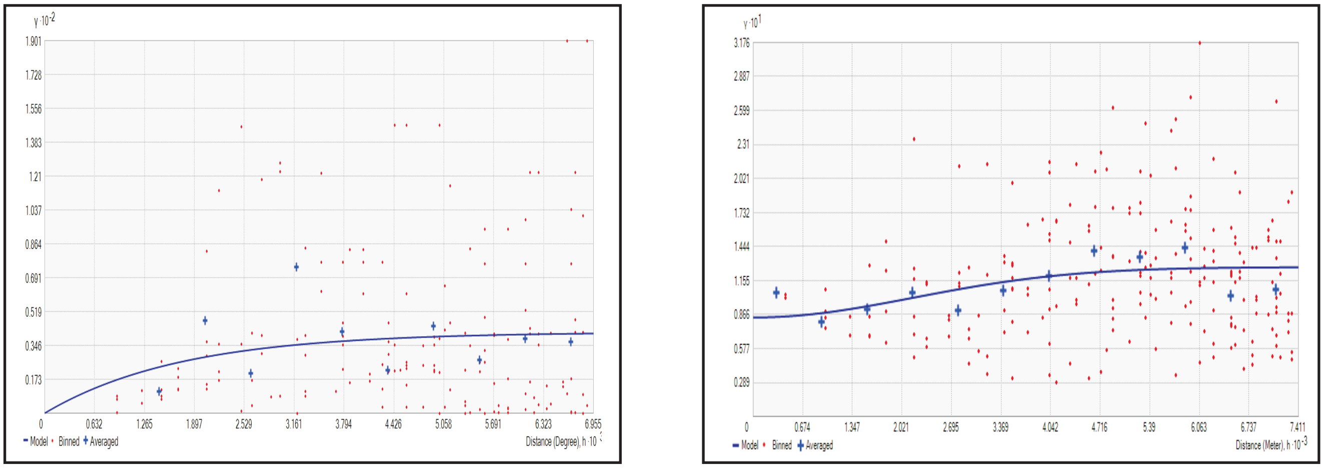
(d) Available K-circular



(e) Copper-Gaussian



(f) Fe-exponential



(g) Mn-exponential (h) Zn-Gaussian

Fig. 1 (a-h): Semi-variograms of best fitted theoretical models based on RMSE

Cross validation

The performance of the interpolation technique used to prepare spatial variability maps was evaluated by cross validation technique. The uncertainty estimates like Root mean square error (RMSE), Mean standardized error (MSE), Root mean square standardized error (RMSSE) and Average standardized error (ASE) were used to evaluate the performance. Smaller RMSE and MSE values indicate minimal errors and bias. The models with minimal RMSE were considered as best fit models.

Best-fitted models with minimum root mean square error (RMSE) were selected for each soil nutrients:

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

$$MSE = 1\frac{1}{n}\sum_{i=1}^{n}\frac{ME}{\sigma^2(xi)}$$

$$RMSSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{ME}{\sigma^2(xi)}\right)^2}$$

$$ASE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\sigma^2(xi)}$$

Where, z (xi) is the observed value, $\hat{z}$ (xi) is the predicted value, N is the number of values in dataset and σ^2 is the kriging variance for location xi.

Results and Discussion

Descriptive statistics of the soil properties and their relationship

The descriptive statistics indicated considerable variability in soil properties (Table 1). The mean values of EC, OC, available P, K, Cu, Fe, Mn and Zn are 0.15 dS m^{-1}, 0.47%, 28.8 kg ha^{-1}, 208 kg ha^{-1}, 1.46 mg kg^{-1}, 19.7 mg kg^{-1}, 9.0 mg kg^{-1} and 0.4 mg kg^{-1}, respectively. The possible reason for variable nutrients could be pedogenic process, parent material, fertilizers use, land use types, and management (Shukla *et al.* 2016). The co-efficient of variation for soil properties ranged from 17 and 126%. The order of CV is Fe>Cu>Mn>EC>P>Zn>K>OC>pH. The co-efficient of variation for the macro and micronutrients is high owing to significant of variability in the soil. The skewness of the soil properties varied from 0.02 to 2.46 which show asymmetrical distribution of the soil properties due to different soil fertility and crop management activities (Behera *et al.* 2016). Pearson linear correlation matrix expresses that OC has significantly positive relationship with the available nutrient contents (Table 2).

Table 1. Descriptive statistics of the soil properties

Soil Properties	Minimum	Maximum	Mean	SD	CV %	Skewness	Kurtosis
pH	4.57	8.74	-	-	16.65	0.02	-1.12
EC (dSm^{-1})	0.025	0.587	0.15	0.12	79.61	1.54	2.34
OC (%)	0.03	1.43	0.47	0.27	56.64	1.07	1.12
P (kg ha^{-1})	4	90	28.78	20.52	71.31	1.00	0.28
K (kg ha^{-1})	37	474	208.0	133.6	64.20	1.66	4.31
Cu (mg kg^{-1})	0.18	7.1	1.46	1.58	107.9	1.79	2.31
Fe (mg kg^{-1})	0.84	135.3	19.74	24.91	126.2	2.46	6.55
Mn (mg kg^{-1})	1.58	30.82	9.02	6.21	68.86	1.06	0.83
Zn (mg kg^{-1})	0.08	1.56	0.40	0.33	80.14	1.85	2.98

Table 2. Correlation coefficients among soil properties and their level of significance

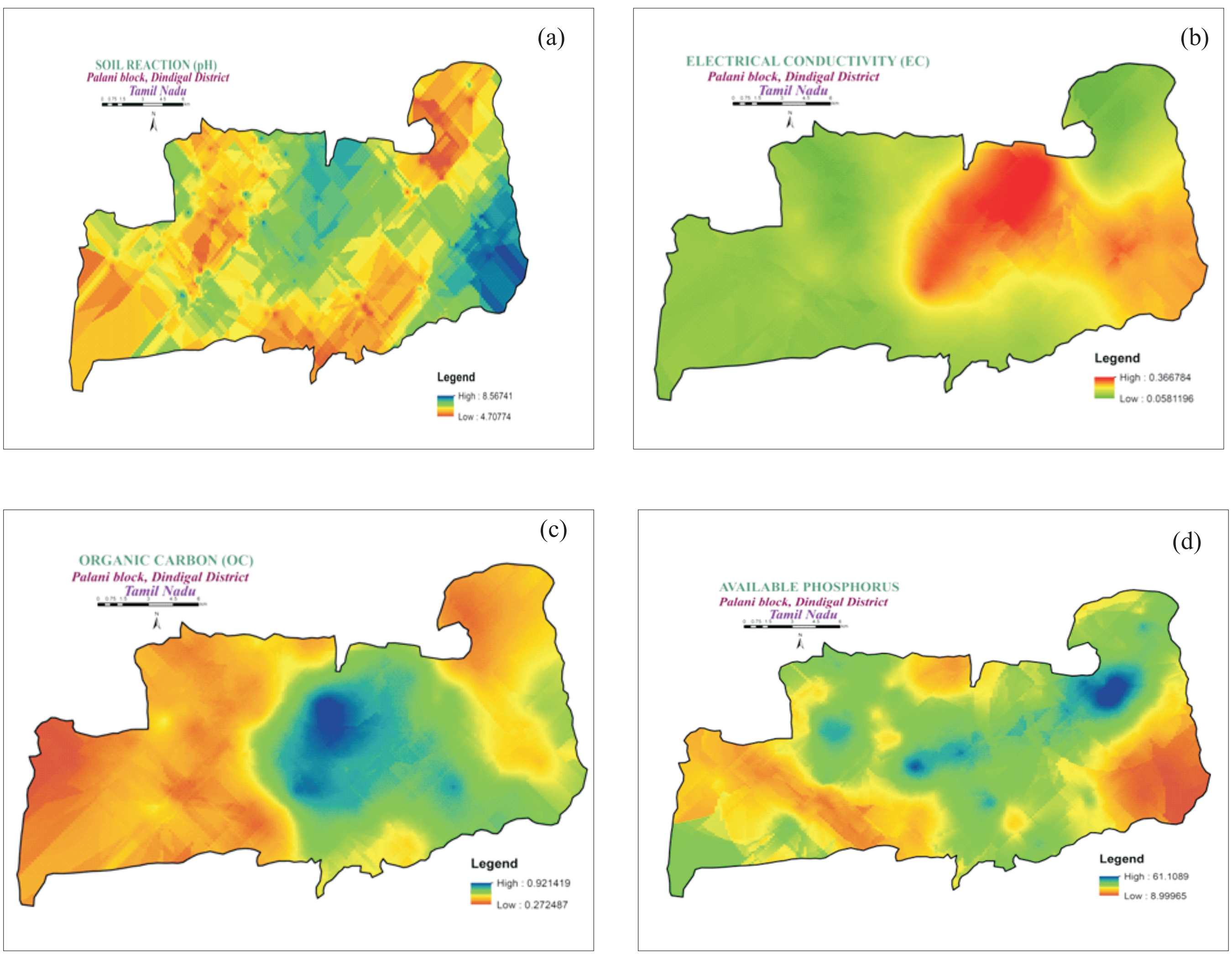
	pH	**EC**	**OC**	**P**	**K**	**Cu**	**Fe**	**Mn**	**Zn**
pH	1								
EC	.623**	1							
OC	.377**	.676**	1						
P	-.537**	-.165	.060	1					
K	.481**	.389**	.194*	-.215*	1				
Cu	.096	.487**	.706**	.071	-.114	1			
Fe	-.524**	-.134	.158	.279**	-.414**	.506**	1		
Mn	-.673**	-.385**	-.180	.448**	-.269**	.013	.338**	1	
Zn	.129	.284**	.474**	.128	.183*	.428**	.084	.094	1

The pearson correlation matrix revealed a significant positive relationship between pH and OC (r=0.38, p<0.01). Except available P, Fe and Mn, soil available nutrients showed highly significant positive relationship with OC. The soil pH had significantly negative relationship with available P (r=-0.54), Fe (r=-0.52) and Mn (r=-0.67) but available phosphorus had positive correlation with manganese (r=0.45) at 1% significance.

Spatial variability and distribution of the soil properties

Spatial distribution of pH, EC, OC and available macro and micronutrients using interpolation method has been depicted in fig. 2 a-i. Kriging technique helps to derive the continuous spatial data from point observations. The central part of the study area showed medium to high range of OC content. The high OC concentration of the surface soils are mainly influenced by land use, climate, parent material and topography (Pravat *et al.* 2016). Available phosphorus showed less availability in south east part of the area where the pH recorded high. This could be due to the fixation of the phosphorus by calcium at alkaline pH. Available potassium is high in central and southern part of the study area. The variability in available K might be due to erosion of top soil and fertilizer management (Srinivasarao *et al.* 2014). The major reason for micronutrients deficiency is due to inappropriate application of high analysis fertilizers and meager quantity of application of micronutrients (Vasu *et al.* 2017).

Different models like circular, spherical, exponential, gaussian, and stable were used to study the variability of soil properties by fitting semi-variograms having minimum RMSE. The analysis of isotropic variogram showed different parameters (Nugget and Sill) of semi-variograms for pH, EC, OC, available macro and micronutrients (Table 3). The best fitted model obtained from semi-variogram analysis was exponential for pH, OC, available P, Fe and Mn, Gaussian model for available Cu and Zn and Circular



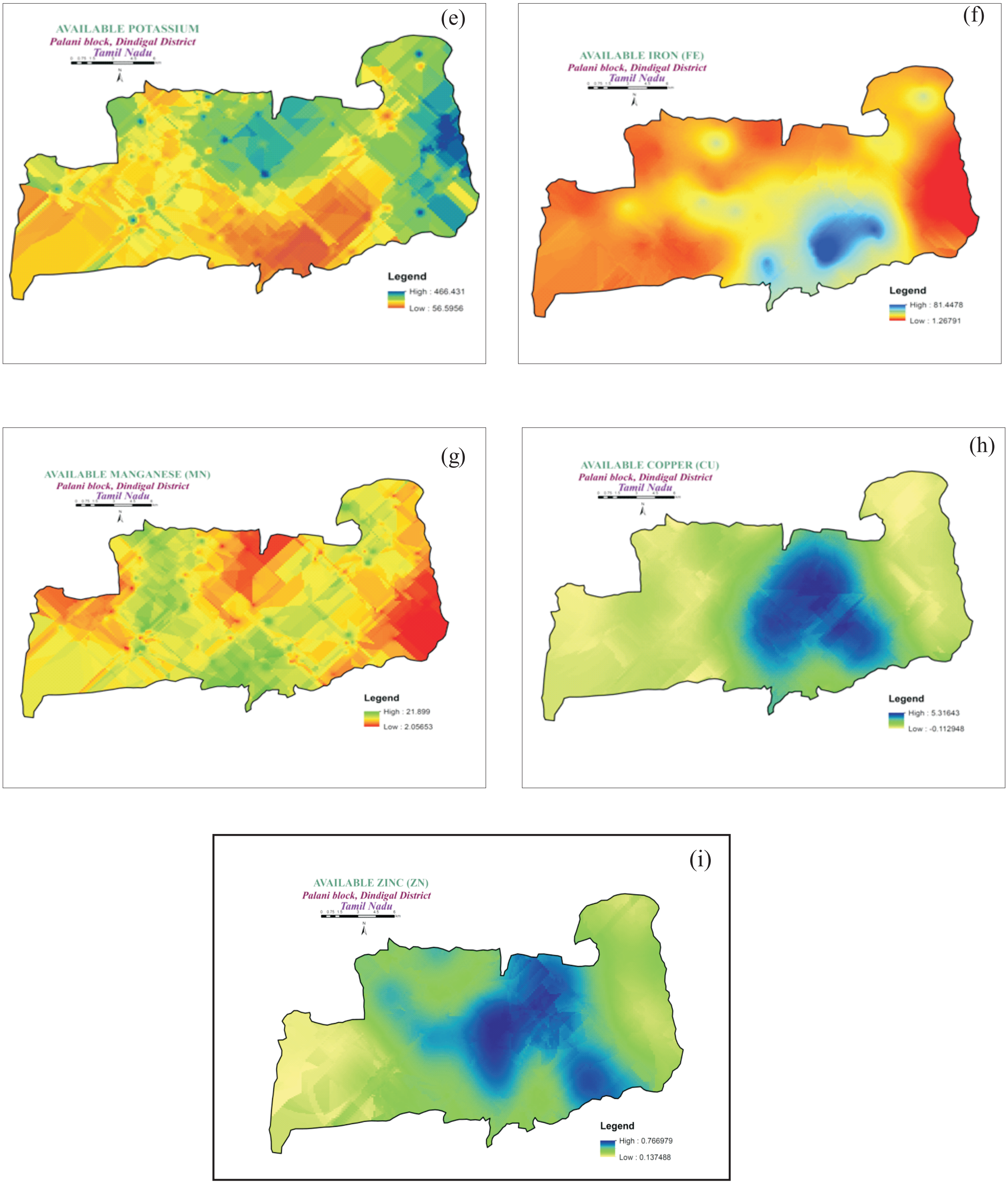


Fig. 2 (a-i): Spatial variability maps of soil pH, EC, OC, macro and micronutrients using geo-statistical interpolation techniques

Table 3. Geo-statistical parameters of the fitted semi-variogram models for soil properties

Nutrient	Model	RMSE	MSE	RMSSE	ASE	Nugget (C)	Partial sill (C_0)	Sill $(C+C_0)$	Nugget/sill $(C_0/C+C_0)$	Spatial dependence
pH	Exponential	0.9766	0.0054	0.8745	1.123	0.1476	1.0096	1.1572	0.1275	Strong
EC	Circular	0.1085	0.00734	1.0888	0.099	0.0072	0.0093	0.0165	0.4345	Moderate
OC	Exponential	0.2599	0.005	1.074	0.241	0.0405	0.0507	0.0912	0.4441	Moderate
P	Exponential	19.19	-0.0072	0.9905	19.43	232.47	207.55	440.02	0.5283	Moderate
K	Circular	112.87	-0.0152	0.898	125.8	4541.3	10005	14546	0.3122	Moderate
Cu	Gaussian	1.12	0.0038	1.316	0.839	0.5618	3.1062	3.668	0.1532	Strong
Fe	Exponential	21.75	0.0093	1.175	18.66	206.7	659.06	865.7	0.2387	Strong
Mn	Exponential	6.054	-0.0057	0.9073	6.71	0	41.39	41.39	0	Strong
Zn	Gaussian	0.335	0.0036	1.063	0.316	0.5618	3.106	3.668	0.1532	Strong

model for EC and available K. Nugget variance is caused by sampling and experimental errors. The nuggets for available P (232.5) and K (4541) are very high (nugget effect) which might be due to the lack of optimal distance sampling (too sparse sampling) (Hegde *et al*. 2018). Some properties like manganese (Mn) shows zero nugget effect which indicates the smooth continuity of the soil properties over the distance and neighboring points. The ratio between nugget and sill showed spatial dependency of various soil properties. The soil pH, available Fe, Cu, Mn and Zn were strongly spatial dependent (N/S<0.25) whereas, the organic carbon, electrical conductivity (EC), available P and K were moderately dependent (N/S~0.25-0.75). Soil parameters which are strongly spatial dependent (<0.25) are influenced by parent material, climate, relief and other soil forming factors (Vasu *et al*. 2017). Moderately spatial dependent soil properties were influenced by anthropogenic activities and natural process of soil formation (Wang *et al*. 2013). For accurate prediction of soil properties, systematic sampling and increased sample size are the primary criteria than random sampling (Wang and Qi1998).

Conclusions

The assessment of soil variability using geo-statistical analysis showed that except pH, other soil properties varied highly in the study area. Among the models, exponential model was best fitted for pH, OC, available P, Fe and Mn, Circular model for available K and EC and Gaussian model for Cu and Zn using. The soil pH and micronutrients showed strong spatial dependency whereas; OC, EC, available P and K are moderately spatial dependent. The variability of moderately spatial dependent soil properties such as EC, OC, Available P and K can be better managed by soil fertility and land use management. The assessment of variability and spatial dependency will help to identify the soil units which require fertility and crop management practices for sustainable crop production.

References

Behera, S.K., Suresh, K., Rao, B.N., Mathur, R.K., Shukla, A.K., Manorama, K. and Prakash, C. (2016). Spatial variability of some soil properties in west coastal area of India having oil palm (*Elaeis guineensis* Jacq.) plantations. *Solid Earth* **7**, 979–993.

Bray, R.H. and Kurtz, L.T. (1945). Determination of total, organic and available forms of phosphorus in soils. *Soil Science* **59**, 39-45.

Cambardella, C.A., Moorman, T.B., Novak, J.M., Parkin, T.B., Karlen, D.L., Turco, R.F. and Konopka, A.E. (1994). Field scale variability of soil properties in central Iowa soils. *Soil Science Society of America Journal* **58**, 1501–1511.

Hegde, R., Niranjan, K.V., Bardhan, G., Bhaskar, B.P. and Singh, S.K. (2018). Assessment of spatial variability of soil properties in Gopalapur micro-watershed, Gundlupet taluka, Chamarajanagar district, Karnataka, India. *Current Journal of Applied Science and Technology* **26,** 1-16.

Jackson, M.L. (1973). 'Soil chemical analysis'. pp. 498. (Prentice Hall of India Pvt. Ltd, New Delhi).

Lindsay, W.L. and Norvell, W.A. (1978). Development of a DTPA soil test for zinc, iron, manganese and copper. *Soil Science Society of American Journal* **42,** 421–428.

Nielsen, D.R. and Wendroth, O. (2003). Spatial and temporal statistics-sampling field soils and their vegetation. Catena-Verlag publisher, Germany. pp.398.

Olsen, S.R., Cole, C.V., Watanabe, F.S. and Dean, L.A. (1954). Estimation of available phosphorus in soils by extraction with sodium bicarbonate. Circular of United States Department of Agriculture. pp. 939. (Washington: D.C.).

Piper, C.S. (1966). 'Soil and plant analysis: A laboratory manual of methods for the examination of soils and the determination of the inorganic constituents of plants'. (Hans Publishers, Bombay, India).

Prabhavathi, M., Patil, S.L. and Raizada, A. (2013). Assessment of soil fertility status for sustainable crop production in a watershed of Semi-arid tropics in Southern India. *Indian Journal of Soil Conservation* **41**, 151-157.

Pravat, K.S., Bhunia,G.S. and Ramkrishna, M. (2016). Spatial analysis of soil properties using GIS based geo-statistics models. *Modeling Earth System and Environment* **2,** 107. https://doi.org/10.1007/s40808-016-0160-4

Reza, S.K., Nayak, D.C., Mukhopadhyay, S., Chattopadhyay, T. and Singh, S.K. (2017). Characterizing spatial variability of soil properties in alluvial soils of India using geo-statistics and geographical information system. *Archives of Agronomy and Soil Science* **63,** 1489-1498.

Saito, H., McKenna, A., Zimmerman, D.A. and Coburn, T. (2005). Geo-statistical interpolation of object counts collected from multiple strips transects: Ordinary kriging versus finite domain kriging. *Stochastic Environment Research Risk Assessment* **19**, 71–85.

Sawant, S.S., Nagaraju, M.S.S., Rajeev Srivastava., Jagdish Prasad., Nasre, R.A., and Mohekar, D.S. (2018). Mapping of spatial variability in soil properties for site- specific nutrient management of Nagpur Mandarin in Central India. *Indian Journal of Horticulture* **75**, 209-217.

Shi, J., Wang, H., Xu, J., Wu, J., Liu, X., Zhu, H. and Yu, C. (2007). Spatial distribution of heavy metals in soils: A case study of Changxing China. *Environmental Geology* **52,** 1-10.

Shukla, A.K., Behera, S.K., Lenka, N.K., Tiwari, P.K., Malik, R.S., Sinha, N.K., Singh, V.K., Patra, A.K. and Chaudhary, S.K. (2016). Spatial variability of soil micronutrients in the intensively cultivated Trans-Gangetic Plains of India. *Soil and Tillage Research* **163,** 282–289.

Srinivasarao, C., Venkateswarlu, B., Lal, R., Singh, A.K., Kundu, S., Vittal, K.P.R., Patel, J.J. and Patel, M.M. (2014). Long-term manuring and fertilizer effects on depletion of soil organic carbon stocks under pearl millet-cluster bean-castor rotation in Western India. *Land Degradation and Development* **25,** 173–183.

Vasu, D., Singh, S.K., Sahu, N., Tiwary, P., Chandran, P., Duraisami, V.P., Ramamurthy, V., Lalitha, M. and Kalaiselvi, B. (2017). Assessment of spatial variability of soil properties using geospatial techniques for farm level nutrient management. *Soil Tillage and Research* **169,** 25-34.

Walkley, A. and Black, I.A. (1934). An examination of the Degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. *Soil Science* **37**, 29–38.

Wang, K., Zhang, C. and Li, W. (2013). Predictive mapping of soil total nitrogen at a regional scale: A comparison between geographically weighted regression and cokriging. *Applied Geography* **42,** 73–85.

Wang, X.J. and Qi, F. (1998). The effects of sampling design on spatial structure analysis of contaminated soil. *The Science of the Total Environment* **224,** 29-41.