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Spatial Variability in Soil Properties of Mango Orchards in Eastern Plateau and Hill Region of India

Mali SS, Naik SK and Bhatt BP*

Abstract

Analysis and interpretation of spatial variability of soil chemical properties is important in framing site-specific fertilizer management practices for mango orchards. This paper aims to study the spatial structure of soil variables in the mango orchards in the eastern plateau region of India. Soil samples were collected from 90 points across the mango orchards from three soil horizons (0-30, 30-60 and 60-90cm). Eleven soil properties were analysed by classical statistical and geo-statistical methods. Soil pH exhibited the lowest statistical variation (CV<15%) while it was highest (CV 68.4 to 97.8%) for the phosphorous (P) content in all the soil layers. Spherical, Gaussian and Exponential semivariogram models were developed after accounting for necessary transformations. The findings of geostatistical analysis showed that spatial structures exist in the soil variables. In surface layers, soil pH, phosphorous (P), iron (Fe), calcium (Ca) and copper, (Cu) have the strong spatial dependence with nugget-sill ratios of less than 25%. Analysis suggested that both the internal and external factors are responsible for the spatial dependence of the soil properties. The magnitude and the pattern of spatial variability in soil chemical properties have implications for variable rate fertilizer application strategies in the mango orchards of the eastern region.

Keywords

Spatial variability; Geostatistics; Semivariogram; Soil fertility; Mango orchard

Introduction

Mango (*Mangifera Indica* L.) is one of the most important commercially grown fruit crop of India. It is cultivated over 2.5 Mha area producing about 18 Mt mangoes per year [1]. Many factors play a crucial role on the yield and quality of mango crop, the most important being the fertility of the soil. Soil physical and chemical properties vary in space and time due to the combined effect of physical, chemical and biological processes, which act simultaneously with different intensities at different spatiotemporal scales. Prior knowledge about the spatial variability of the soil fertility indicators over a field can be very useful in maintaining optimum nutrient status in soil and managing other important agronomical measures. Substantial spatial variability of soil nutrient levels at the macro-scale and micro-scale often results in over or under application of fertilizers [2]. Significant relation between leaf nutrient concentrations of the mango plants and the nutrient contents in the soil highlights the need for mapping spatial variability of soil nutrients in the mango orchards [3]. Growing body of literature suggests that spatial variability in soil properties should be considered for making recommendations on variable-rate fertilizer application in mango.

The variable rate fertilizers application and site specific nutrient management can be achieved on the basis of the precisely defined spatial variability of soil nutrients. Geostatistics is one of the most popular set of statistical tools for analysing spatial variability of geocoded parameters. Geostatistics is concerned with detecting, estimating and mapping the spatial variation trends of regional variables. It provides a set of statistical tools such as fitting of a semivariogram model for the description of spatial patterns of continuous and categorical soil properties [4] and it has become an important tool in characterizing the spatial variability of soil properties [5]. This method distinguishes variation in measurement separated by known distance. Semivariogram models provide the necessary information for Kriging, which is a method for interpolating data at unsampled points [6].

Geostatistical methods have been effectively used to assess the spatial variability in soil parameters and it has become an important tool in characterizing the spatial variability of soil properties [7,8]. Houlong et al., [9] used the geostatistical approach and kriging interpolation to map the spatial variability of soil properties in the Pengshui tobacco experiment station for better management of experimental treatments to achieve reliable experimental results. Liu [10] used geostatistical method to investigate the spatial variability of soil organic matter and nutrients in paddy fields in southeast China. Behera et al. [11] analysed the spatial variability in the soil properties of the oil palm plantations in the southern India and concluded that the soil properties were influenced by intrinsic, extrinsic and both intrinsic and extrinsic factors. Conventional and geostatistical methods can be used to understand the heterogeneity of soil chemical properties and to identify factors responsible for the spatial variation of soil properties [5].

Spatial variability of soil physical and chemical properties under different crops and management practices have been analysed by different researchers across the world. Although such studies provide information on the soil variability at the experimental sites, the variability at larger spatial scale, such as district, is not well characterised. Information on variation of soil properties under mango orchards is seriously lacking. Assessment of spatial variability of soil properties is important in fertility management of mango orchards in East India Plateau. The objective of this study was to evaluate the spatial variability of soil chemical attributes and principal soil fertility traits in the mango plantations using traditional statistics and geostatistics at district scale to provide information for better soil fertility management in mango orchards of the eastern plateau and hill region of India.

Materials and Methods

Study area

The study was carried out during 2012 and 2013 in the Gumla and Simdega districts located in the south-western part of the Jharkhand

***Corresponding author:** Mali SS, ICAR-Research Complex for eastern Region, Research Centre Ranchi-834010, Jharkhand, India, Tel: +91-8092-55-6024; E-mail: santosh.icar@gmail.com

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state to assess the fertility status of the soils in the mango orchards. The study districts lies between 22^0 19' 40" N to 23^0 36' 43" N latitude and 84^0 00' 21" E to 85^0 05' 09" E longitude with average mean sea level of 300 and 424 m. The climate of the Gumla and Simdega districts is tropical monsoon type and receives an average annual rainfall of about 1100 and 1397 mm respectively. Soils of the region are characterised with red laterite, red and yellow with texture ranging from loamy to sandy loam having slightly acidic reaction.

Soil sampling and laboratory analysis

A field survey was undertaken to collect the soil samples from different mango orchards located in the study area. The age of the mango orchards varied from 6 to 18 years. A total of 90 soil samples were collected from the study orchards at various soil profile depths. Mango trees have very well spread, deep, and extensive root system and the widespreading feeder roots also extend many anchor roots to deeper depths. To represent the entire root zone more precisely, the soil samples were collected from0-30, 30-60 and 60-90 cm depth profiles. Each sample was formed from the four samples collected within 1.5 to 2 m radius of the four different trees and mixed well to form one representative sample of an orchard. The geographic coordinates (latitude, longitude and elevation) of every sampling point were recorded with a handheld global positioning system (GPS) (Oregon 550, Garmin Ltd, Kansas, USA).The soil samples were placed into plastic bags then air-dried, ground to pass through a 2-mm sieve and analysed for soil physicochemical properties.

The samples were analyzed for soil acidity (pH), organic carbon (OC), available nitrogen (N), available phosphorous (P), available potassium (K), exchangeable calcium (Ca) and magnesium (Mg), DTPA-extractable iron (Fe), DTPA-extractable manganese (Mn), DTPA-extractable copper, DTPA-extractable zinc. Determination of soil pH was done based on 1:2.5 soil water ratio (w/v) suspension using pH meter following half an hour equilibrium [12]. The soil organic carbon content was determined by Walkley and Black method [13]. The following methods were used to determine available nutrient contents: the method of Subbiah and Asija [14] for N, that of Bray and Curtz [15] for P, and the flame photometric method [12] for K. the exchangeable Ca and Mg was determined by Versenate method [16]. DTPA-extractable Fe, Mn, Cu and Zn were measured with an atomic absorption spectrophotometer by following the method of Lindsay and Norvel [17].

Descriptive statistics

Data were subjected to descriptive analysis. The minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV), skewness and kurtosis for soil properties were computed. Skewness is the most common statistic parameter to identify a normal distribution that is confirmed with skewness values varying form – 1 to + 1. Criterion established by Warrick [18] was used to classify the parameter variability on the basis of variation coefficient values as low: <15%, moderate: from 15% to 50%, and high: >50%.

Geostatistical analysis

Exploratory Spatial Data Analysis (ESDA) was carried out to assess and correct the trend, periodicity and extreme values present in the datasets pertaining to soil properties. The ArcGIS10.0 was used for performing the ESDA.

Variance of the difference between two values is assumed to depend only on the distance h between the two points, and not on the location x. Spatial patterns were usually described using the experimental semivariogram $\gamma(h)$, which measures the average dissimilarity between data separated by distance h. The semivariance as a function of both the magnitude of the lag distance was computed using [6,19];

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

Where, $\gamma(h,\alpha)$= semivariance as a function of both the magnitude of the lag distance or separation vector (h) and its direction (α); N(h,α) = number of observation pairs separated bydistance h and direction α used in each summation; $Z(x_i)$= random variable at location x_i.A semivariogram consists of three basic parameters that describe the spatial structure as: $\gamma(h) = C_0 + C$. $C0+ C$ is the sill (total variance), which is the lag distance between measurements at which one value for a variable does not influence neighbouring values. C_0 is the combination of random errors and sources of variation at distances smaller than the shortest sampling interval [20]. C is the structural variance, which is the constant semivariance value where the curve was stabilized. The range is the distance over which soil property is spatially related. The nugget ratio ($C0/(C0 + C)$; nugget-sill) represents the parameters that characterize the spatial structure of a property [21]. Several semivariogram functions (Spherical, Gaussian, Exponential, Linear, Linear to sill etc.) were evaluated to choose the best fit with the data. The best fit semivariogram model was selected on the basis of coefficient of determination (R^2) and the residual sum of squares (RSS). Semivariance calculation and semivariogram function model fitting were performed using the geostatistical software GS+ for Windows. Semivariogram, differences in nugget/sill ratio and range were examined for various soil properties.

Results and Discussion

Descriptive statistics

The data were analysed using classical statistical methods to understand the characteristics of the general soil properties prior to the investigation on the spatial structure (Table 1). The concentrations of soil properties (pH, OC, N, P, K, Ca, Mg, Fe, Mn, Zn, Cu) were described by minimum, maximum, mean, median, standard deviation (SD), coefficient of variation (CV), skewness and kurtosis of data distribution in the study area (Table 1). The summary statistics of soil properties suggested that all the soil properties exhibited considerable variability across the study region. The soil pH varied from 4.08 to 7.78 depending on the soil layer. The surface profile (0-30 cm) showed dominantly acidic reaction with pH varying from 4.08 to 6.61 with mean value of 5.15 ± 0.61. The pH also varied with depth with mean pH increasing from 5.15 in surface layer to 5.56 at subsurface layers. The values of CV for soil pH in all the soil layers revealed their moderate variability and these values were less compared to CV values of other measured soil properties. The CV values in the range of 10 to 100 are considered in the class of 'moderate variability' [22]. Low CV values for soil pH was due to transformed measurement of hydrogen ion concentration. Behera et al. [11] also reported the lower CV values of 17.1 and 19.5 for the pH of surface and subsurface soils of oil palm plantations in the southern plateau of India. Houlong et al. [9] observed lowest CV in case of soil pH as compared to other soil properties recorded in tobacco plantations of southern china.

The organic carbon content in the surface soil layers varied from 0.21 to 0.91% across the study region. The mean organic carbon content decreased with increasing soil depth. The mean value of

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Table 1: Descriptive statistics* for selected soil properties of surface layers (n=90).

Soil Properties	Soil Layer (cm)	Min	Max	Mean	Med	SD	CV (%)	Skew.	Kurt.
pH	0-30	4.08	6.61	5.15	5.17	0.61	11.84	0.54	0.62
	30-60	4.37	7.78	5.46	5.47	0.73	13.47	1.49	1.34
	60-90	4.29	7.65	5.56	5.56	0.77	13.90	0.76	1.55
OC, %	0-30	0.26	0.91	0.51	0.49	0.20	38.87	0.47	-0.87
	30-60	0.13	0.84	0.40	0.36	0.19	46.00	0.49	-0.47
	60-90	0.02	0.72	0.31	0.28	0.14	45.47	0.73	1.81
N, kg/ha	0-30	87.8	175.6	126.4	125.4	19.96	15.80	0.30	0.75
	30-60	75.2	138.0	111.3	112.9	17.71	15.91	-0.65	-0.15
	60-90	37.6	138.0	101.3	100.4	26.02	25.69	-0.67	0.28
P, kg/ha	0-30	0.16	14.57	4.80	4.29	3.29	68.47	1.44	2.91
	30-60	0.16	16.66	3.83	2.92	3.29	85.99	2.52	8.44
	60-90	0.16	14.10	3.02	2.53	2.96	97.83	2.40	7.36
K, kg/ha	0-30	173.6	380.8	270.5	266.6	65.90	24.37	0.23	-1.22
	30-60	159.0	369.6	241.8	225.1	64.07	26.49	0.40	-1.10
	60-90	144.5	336.0	225.0	208.3	59.05	26.24	0.40	-1.14
Ca, g/kg	0-30	414.0	1320.0	725.8	620.0	272.1	37.49	0.56	-0.93
	30-60	600.0	1566.0	953.1	928.0	238.4	25.02	0.71	0.18
	60-90	488.0	1448.0	975.4	936.0	243.9	25.01	0.22	-0.60
Mg, g/kg	0-30	164.4	648.0	331.6	296.4	138.9	41.92	0.83	-0.31
	30-60	159.6	796.8	382.9	362.4	136.8	35.71	0.99	2.00
	60-90	220.8	654.0	395.1	387.6	102.5	25.95	0.61	0.52
Fe, g/kg	0-30	8.04	29.40	16.26	15.24	5.54	34.10	0.95	0.29
	30-60	5.21	22.76	10.59	9.30	5.25	49.61	1.37	0.95
	60-90	3.84	19.56	9.76	8.07	4.62	47.38	0.93	-0.05
Mn, g/kg	0-30	12.98	24.18	19.15	18.99	2.72	14.20	-0.10	0.84
	30-60	2.31	23.84	16.50	17.72	5.09	30.83	-1.30	1.72
	60-90	3.44	23.56	15.16	15.51	4.51	29.74	-0.78	1.17
Zn, g/kg	0-30	0.22	0.71	0.39	0.37	0.12	31.57	0.79	0.02
	30-60	0.22	0.43	0.31	0.29	0.05	17.59	0.35	-0.58
	60-90	0.15	0.57	0.30	0.30	0.10	31.32	0.81	0.91
Cu, g/kg	0-30	0.41	1.55	0.96	0.93	0.32	33.53	-0.03	-0.89
	30-60	0.36	1.51	0.82	0.75	0.31	38.19	0.64	-0.35
	60-90	0.05	1.38	0.77	0.71	0.30	38.45	0.31	0.71

*Min-minimum, Max-maximum, mean, SD-standard deviation, CV-coefficient of variation, Skew-skewness, Kurt- kurtosis.

the total N content is classed as 'low' and it further decreased with increasing depth. Coefficient of variation (CV) of available N at sub-surface layer is higher (25.7%) than at top-layer (15.8 %), meanwhile all the CV of available N in the soil could be classified as moderate variability. Available N content in the top layer was about 24.7% higher than the sub-surface layer (60-90 cm). This is probably due to the higher organic residues deposited on the soil surface than the sub surface soil. Highest spatial variation was observed in case of available P content of the soil. The variability of available P in deeper layer (CV = 97.8%) was higher than surface layer (CV=68.5 %). This condition is probably due to difference of soil pH and total organic carbon between the layers. Mean K content in the top layers was about 270.5 kg ha^{-1} which decreased to 225.0 kg ha^{-1}at the sub soil layer. The spatial variation in K content in all the studied soil profile was classed as 'moderate' (CV=24.4 to 26.5%). This variability is the result of the irregular cropping system and non-uniform management practices.

The secondary macronutrient (Ca and Mg) and micronutrient (Mn, Fe, Zn, Cu) content in all the soil layers was situated in the 'moderate variability' class except for the Mn content in the top layer. The CV of these parameters varied in a narrow range of 14.2 to 49.6 %. Among the secondary macronutrient and micronutrient, the Mg showed highest variation in the surface soil layer (CV=41.9%). Concentration of Ca was higher (>725 g kg^{-1}) in the soil layers. With the increasing depth, the concentration of Ca and Mg increased while that of Fe, Mn, Zn and Cu decreased.

The descriptive statistics of soil properties suggested that all variable distributions were only slightly skewed, and their medians values were close to their mean values, identifying a normal distribution of soil variables. The values for skewness and kurtosis between -2 and +2 are considered acceptable in order to prove normal univariate distribution [23]. Highly skewed properties indicated that these properties had a local distribution, the high values were recorded for these properties at some points, but most of the values of these properties were low [24]. The principal reason for some soil properties having non-normally distributions may be related with soil management practices [25]. The kurtosis values ranged from -1.22 to 8.44. The skewness and kurtosis values for available P data series was very high and also there was significant difference in the mean and medium values observed at all soil layers. The probability distributions of P concentration data at all the soil layers are positively skewed and have sharp peaks. The calculation of variation function should generally be in accordance with the normal distribution.

Therefore logarithmically transformed P concentration data were used in the geostatistical analysis of variation function.

Geostatistical Analysis

Knowledge about the spatial variability of soil properties is very useful in optimizing and determining the fertilizer application recommendations in mango orchards. Appropriate use of nutrients can contribute to enhance crop quantity and quality, while being environmentally sustainable [26]. The inherent limitation of predicting the soil properties at the un-sampled sites precludes the use of classical statistics in variability assessment of soil properties. Geostatistical analysis however permits examination and understanding of spatial dependency of a soil property [27].

The results of geostatistical analysis (Table 2) indicated different spatial distribution models for the soil properties. The geostatistical analysis indicated different spatial distribution models and spatial dependence levels for the soil properties. In most of the parameters, spherical variogram model was found to be ideal fitting model. Apart from spherical model, the Gaussian and Exponential models were also fitted well in case of some soil properties. In particular, the Zn had exponential best fit model at all soil layers. Among the major nutrient contents (N, P K) only N had the Gaussian best fit model for the surface layer (0-30) and K had an Exponential best fit model for the deeper soil layer. In selecting the best fit model, the prediction accuracy of the semivariogram model was also taken into consideration. The plots between observed and predicted values at the sampled location and the values of coefficient of determination (R^2) were considered in selecting the best fit model. The sample plot between observed and predicted values for Cu is shown in Figure 1. Several researchers [9,11,28] have reported spherical model as the best fit for soil parameters like N, P, K, OC, Fe, Cu, Mn and Zn.

The nugget to sill ratio is used to define spatial dependence of soil properties. If the ratio is <0.25, there is strong spatial dependence; if the ratio is 0.25 to 0.75, there is moderate spatially dependence; and if the ratio is >0.75, spatial dependence is weak. Strong spatial dependence of soil properties can be attributed to intrinsic factors such as soil properties and mineralogy, whereas, weak spatial dependence is due to extrinsic factors such as anthropogenic activities. Moderate spatial dependence is owing to both intrinsic and extrinsic factors [11]. As shown in Table 2, the ratio values indicated the presence of strong to weak spatial dependence for all soil parameters (values between

Table 2: Semivariogram parameters of soil properties at different layers.

Soil Property	Soil Layer (cm)	Parameters of Semi Variogram					
		Model	Nugget	Sill	Range (m)	Nugget/sill ratio	Spatial Class
pH	0-30	Spherical	0.04	0.40	1430	0.10	Strong
	30-60	Spherical	0.00	0.59	2530	0.00	Strong
	60-90	Spherical	0.01	0.66	2090	0.02	Strong
OC, g/kg	0-30	Spherical	0.03	0.06	21890	0.50	Moderate
	30-60	Spherical	0.03	0.06	21890	0.50	Moderate
	60-90	Spherical	0.02	0.03	21890	0.67	Moderate
N, kg/ha	0-30	Gaussian	302.4	604.9	6160	0.50	Moderate
	30-60	Spherical	285.8	295.8	6490	0.97	weak
	60-90	Spherical	61.00	689.0	1650	0.09	Strong
P, kg/ha	0-30	Spherical	1.84	7.65	4730	0.24	Strong
	30-60	Spherical	0.01	11.69	1210	0.00	Strong
	60-90	Spherical	0.01	11.44	1210	0.00	Strong
K, kg/ha	0-30	Spherical	3190	8063	16170	0.40	Moderate
	30-60	Spherical	2900	8095	19800	0.36	Moderate
	60-90	Exponential	2960	7292	14190	0.41	Moderate
Ca	0-30	Spherical	7200	85700	1210	0.08	Strong
	30-60	Spherical	18800	54000	1100	0.35	Moderate
	60-90	Exponential	47900	95810	19360	0.50	Moderate
Mg	0-30	Spherical	17827	15325	6490	1.16	weak
	30-60	Spherical	7950	19300	2750	0.41	Moderate
	60-90	Spherical	100.00	9440	660	0.01	Strong
Fe	0-30	Exponential	15.00	78.50	12870	0.19	Strong
	30-60	Spherical	19.96	39.90	11000	0.50	Moderate
	60-90	Exponential	0.01	24.41	660	0.00	Strong
Mn	0-30	Spherical	2.03	7.86	1430	0.26	Moderate
	30-60	Spherical	2.27	29.39	2750	0.08	Strong
	60-90	Spherical	0.01	23.87	2750	0.00	Strong
Zn	0-30	Exponential	0.01	0.03	21890	0.33	Moderate
	30-60	Exponential	0.00	0.01	14630	0.00	Strong
	60-90	Exponential	0.01	0.02	21890	0.50	Moderate
Cu	0-30	Spherical	0.00	0.12	1210	0.00	Strong
	30-60	Spherical	0.00	0.10	1210	0.00	Strong
	60-90	Spherical	0.00	0.10	1210	0.00	Strong

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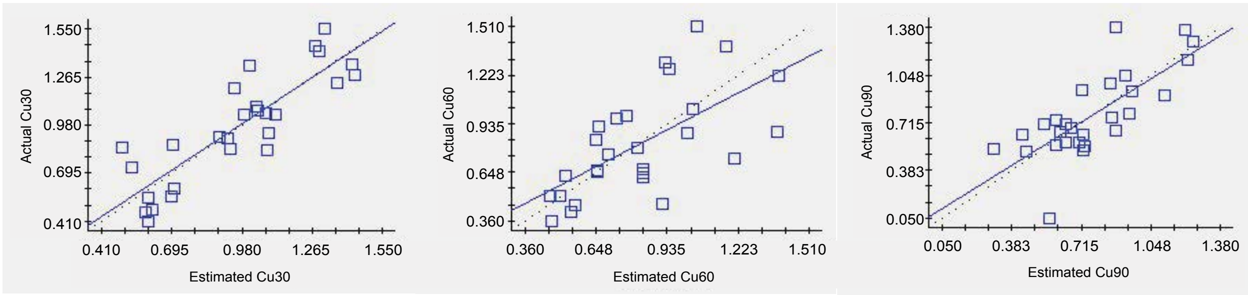

(a) (b) (c)

Figure 1: Observed and estimated copper (Cu) concentration at (a) 0-30 cm, (b) 30-60 cm and (c) 60-90 cm soil depths at sampled locations.

0 and 1.16). Stronger spatial dependence observed in case of pH, P and Cu (low nugget to sill ratio) and indicated that the soil properties might be affected by the internal factors. Total N content in the sub-surface layer and concentration of Mg in the surface layer showed weak spatial dependence. The rest of variables were in moderate spatial dependence with the nugget-sill, are between 0.25 and 0.75, illustrating that the soil variables might be affected by internal and external factors, such as cultivation and fertilization. Wang et al. [14] found that most of the soil properties in the studied area were classed as moderately spatially dependent. Liu et al. [10] reported the nugget-sill ratios of Zn and Cu were less than 0.50.

Range is the distance at which the semivariogram levels off and beyond which the semivariance is constant [29]. Knowledge of the range of influence for various soil properties allows for the construction of independent data sets that can be used for classical statistical analysis. A smaller range indicates that observed values of the soil variable are influenced by other values of this variable over lesser distances than soil variables which have larger ranges [30]. In the present mango orchards, the range for soil properties varied from 660 (deep layer Fe) to 21890 m (Surface layer Zn). In surface layer, the range for pH, P, Ca, Mn, Cu was about 1430, 4730, 1210, 1430 and 1210 m. Low range for these variables indicated that these values are influenced by the neighbouring values at lesser distance than other variables. The smaller range suggested that smaller sampling intervals are needed pH, P, Ca, Mn, Cu. In particular, OC, K and Zn showed consistently higher range values at all the sampling depths.

In present study, N exhibited moderate spatial dependence in surface soils (0-30 cm), weak spatial dependence in sub-surface layer (30-60 cm) and strong spatial dependence at deeper layers. Spatial dependence of K was classed as 'moderate' at all depths implying the impact of both the intrinsic and extrinsic factors on its spatial variability. This phenomenon might be explained by high mobility of K in sandy loam soils with low cation exchange capacity, which can accentuate leaching effects of strong rains characterising the study districts. Exchangeable K exhibited three spatial patterns: strong dependence at topsoil (0-0.05 m depth), moderate from 0.05 to 0.2 m depth, and no spatial correlation in the lower layer (0.2 –0.3 m). The Mg concentration in the surface horizon showed weak spatial dependence as the nugget-sill ratio was more than 0.75 indicating comparatively lesser influence of the Mg concentration at neighbouring points.

The presented results suggested that there is considerable spatial variability in the soil properties across the mango orchards of the eastern plateau region. While planning the field experiments in the farmers' field, it is necessary to obtain coincident soil conditions and avoid the test errors from the inconsistent soil properties [31]. Results obtained under this study can be used to facilitate the procedure of the preparation for field experiment in the mango plantation areas of the eastern plateau region.

Conclusion

The classic statistical analysis revealed a considerable statistical and spatial variability of pH, OC, N, P, K, Ca, Mg, Fe, Mn, Zn and Cu among soil horizons and across the mango orchards of the eastern plateau region. Then mean values of pH, Ca and Mg increased while that for OC, N, P, K, Fe, Mn, Zn and Cu decreased with increasing soil depth. The findings of geostatistical analysis showed that spatial structures exist in the soil variables. Apart from surface horizon (0-30 cm), a strong to moderate spatial dependence was observed for subsoil and deeper soil horizons. Higher range values for some of the soil parameters implied that the soil chemical properties had spatial dependence over larger distances. This study demonstrated that the variability of soil chemical properties was associated to the management practices (fertilizer, residue management etc.) and local conditions (topography, climate etc.). It is concluded that the orchard specific fertility management recommendations needs to be considered over the general fertilizer recommendations for entire region.

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References

1. NHB (2013) Indian Horticulture Database. National Horticulture Board. Ministry of agriculture, Government of India.
2. Ferguson RB, Hergert GW, Schepers JS, Gotway CA, Cahoon JE, et al. (2002) Site-specific nitrogen management of irrigated maize: Yield and soil residual nitrate effects. Soil Sci Soc Am J 66: 544-53.
3. Madi APLM, Boeger MRT, Bruno CP (2015) Distribution of Cu, Fe, Mn, and Zn in two mangroves of southern brazil. Braz Arch Biol Tech 58: 970-976.
4. Goovaerts P (1999) Geostatistics in soil science: state-of-the-art and perspectives. Geoderma 89: 1-45.
5. Lic J, Li Y, Jian MA, Lian Lian FAN, Wang Q (2010) Spatial heterogeneity of soil chemical properties between haloxylon persicum and haloxylon ammodendron populations. J Arid Land 2: 257-265.

doi: 10.5958/2229-4473.2016.00070.7

6. Lopez-Granados F, Jurado-Exposito M, Atenciano S, Garcia-Ferrer A, Sanchez de la Orden M, et al. (2002) Spatial variability of agricultural soil parameters in southern Spain. Plant and Soil 246: 97-105.
7. Wang DD, Shi XZ, Lu XX (2010) Response of soil organic carbon spatial variability to the expansion of scale in the uplands of northeast china. Geoderma. 154: 302-310.
8. Weindorf DC, Zhu Y (2010) Spatial variability of soil properties at capulin volcano, New Mexico, USA: Implications for sampling strategy. Pedosphere 20: 185-197.
9. Houlong J, Hongfeng W, Li N, Xu A, Yang C, et al. (2014) Evaluation of spatial variability of soil propertises in a long-term experimental tobacco station in southwest china. J of Agric Sci Tech 4: 723-735.
10. Liu XM, Zhao KL, Xu J M, Zhanh M, Si B, et al. (2008) Spatial variability of soil organic matter and nutrients in paddy fields at various scales in southeast China. Environ Geol 53: 1139-1147.
11. Behera SK, Rao BN, Suresh K, Manorama K, Ramachandrudu K, et al. (2015) Distribution variability of soil properties of oil palm (elaeis guineensis) plantations in southern plateau of india. Ind J Agri Sci 85: 1170-1174.
12. Jackson ML (1973) Soil chemical analysis. Prentice Hall of India Pvt. Ltd, New Delhi, India.
13. Walkley A, Black IA (1934) An examination of the degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. Soil Sci 37: 29-38.
14. Subbiah BV, Asija GL (1956) A rapid procedure for the determination of available nitrogen in soils. Cur Sci 25: 259-260.
15. Bray RH, Kurtz LT (1945) Determination of total, organic, and available forms of phosphorus in soils. Soil Sci 59: 39-45.
16. Hesse PR (1971) A textbook of soil chemical analysis. John Murray Publishers Ltd, London, United Kingdom.
17. Lindsay WL, Norvell A (1978) Development of DTPA soil test for zinc, iron, manganese and copper. Soil Sci Soc Am J 42: 421-428.
18. Warrick AW (1998) Spatial variability. in environmental soil physics, Academic Press, 655-675.
19. Deutsch CV, Journel AG (1992) GSLIB geostatistical software library and user's guide. New York, Oxford University Press, USA.
20. Goovaerts P (1998) Geostatistical tools for characterizing the spatial variability of microbiological and physicochemical soil properties. Biol Fertil Soils 27: 315-334.
21. Kravchenko A N (2003) Influence of spatial structure on accuracy of interpolation methods. Soil Sci Soc Am J 67: 1564-1571.
22. Nielsen DR, Bouma J (1985) Soil spatial variability. Wagenigen, The Netherlands.
23. George D, Mallery M (2010) SPSS for windows step by step: A simple guide and reference, 17.0 update (10th edtn) Boston, Pearson, USA.
24. Grego CR, Vieira SR, Lourencao AL (2006) Spatial distribution of pseudaletia sequax franclemlont in triticale under no-till management. Scientia Agricola 63: 321-327
25. Tesfahunegn GB, Tamene L, Vlek PLG (2011) Catchment-scale spatial variability of soil properties and implications on site-specific soil management in northern ethiopia. Soil Till Res 117: 124-139.
26. Miransari M, Mackenzie AF (2010) Wheat (triticum aestivum L.) grain N uptake as affected by soil total and mineral N, for the determination of optimum N fertilizer rates for wheat production. Comm in Soil Sci Plant Anal 41: 1644-1653.
27. Liu X, Herbert SJ, Hashemi AM, Zhang X, Ding G (2006) Effects of agricultural management on soil organic matter and carbon transformation – a review. Plant. Soil and Environ 52: 531-536.
28. Gargouri K, Sarbeji M, Barone E (2014) Assessment of soil fertility variation in an olive rchard and its influence on olive tree nutrition. Italy.
29. Webster R and Oliver M A (2001) Geostatistics for environmental scientists. John Wiley Chichester, England.
30. Samper FJ, Carrera J (1996) GeoestadÍStica: Aplicaciones a la HidrologiA SubterraNea.(2nd edtn), Barcelona, Spain.
31. Panagopoulos T, Jesus J, Antunes MDC, Beltrao J (2006) Analysis of spatial interpolation for optimizing management of a salinized field cultivated with lettuce. European J Agron 24: 1-10

Author Affiliations

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ICAR-Research Complex for eastern Region, Research Centre Ranchi, Jharkhand, India