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Spatial Variability of Soil Organic Carbon and Available Nutrients under Different Topography and Land Uses in Meghalaya, India

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Authors' contributions

This work was carried out in collaboration between all authors. Author NJS designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors DLT and CG managed the analyses of the study. Author CG managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Nutrient loss from the soil is influenced by topography and crop uptake. Knowledge of spatial variability of soil properties can help in site-specific nutrient management. It was attempted to study the effect of topography and land uses on spatial variability of soil organic carbon (SOC), available nitrogen (N), available phosphorus (P) and available potassium (K) in acidic soils of the research farm of National Bureau of Plant Genetic Resource having annual crop (ginger/turmeric) with 25% slope (NBPGR 1), buckwheat-pulse, maize-fallow, perennial medicinal plants with 9% slope (NBPGR 2), Indian Council of Agricultural Research-Krishi Vigyan Kendra farm having ginger/turmeric, maize-vegetable, pulse-vegetable with 9% slope (ICAR-KVK) and ICAR-Horticulture farm having guava/mandarin with 25% slope. The SOC content was in the order of guava (2.15%) > mandarin (2.06%) > ginger/turmeric at NBPGR 1(1.98%) > maize-vegetable (1.87%) > medicinal plants (1.81%) > buckwheat-pulse (1.78%) > maize-fallow (1.76%) = pulses-vegetable (1.76%) > ginger/turmeric at ICAR-KVK (1.56%). The N was higher in buckwheat-pulse (460.35 kg/ha) followed by guava (420.85 kg/ha), maize-fallow (409.92 kg/ha), ginger/turmeric of

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ICAR-KVK (404.50 kg/ha), medicinal plants (402.2 kg/ha), pulse-vegetable (377.46 kg/ha), mandarin (366.14 kg/ha), maize-vegetable (364.68 kg/ha) and ginger/turmeric of NBPGR 1 (348.06 kg/ha). The P was in the order of maize-vegetable (52.07 kg/ha) > pulse-vegetable (40.14 kg/ha[1]) > ginger/turmeric of ICAR-KVK (35.67 kg/ha) > buckwheat-pulses (22.23 kg/ha) > mandarin (21.06 kg/ha) > guava (20.83 kg/ha) > maize-fallow (16.58 kg/ha) > ginger/turmeric of NBPGR 1 (15.71 kg/ha) > medicinal plants (13.33 kg/ha). The K was observed higher in guava (422.80 kg/ha) followed by buckwheat-pulse (330.86 kg/ha), ginger/turmeric of NBPGR 1 (192.13 kg/ha) and maize-vegetable (181.73 kg/ha). The nugget/sill ratio of P had strong to moderate and SOC, N and K had moderate to weak spatial autocorrelation in NBPGR 1 and NBPGR 2. All the nutrients in ICAR-KVK farm were found to have weak spatial correlation. Most suitable interpolation technique for SOC and K was the Radial Basis Function (RBF), ordinary kriging for N and P and gaussian model for ICAR-KVK farm. In ICAR-Horticulture farm, the exponential and pentaspherical semivariogram model best described the SOC, N, K and P, respectively. The nugget/sill ratio of P and K showed moderate spatial dependence and this was weak for SOC and N.

Keywords: Available nutrient; spatial variability; topography; land use; soil organic carbon.

1. INTRODUCTION

Since the advent of agriculture, there has been an innate interest in soil and land quality [1]. A considerable amount of nutrients from the soil is lost every year and this is influenced by topography, land use and level of erosion. The North Eastern Hill (NEH) region of India is very much prone to the soil and nutrient loss due to hilly terrain (77% hilly), very high rainfall (>2000 mm per annum), shifting cultivation and little soil and water conservation interventions. A large quantity of mineral nutrients is removed from soils due to crop uptake [2]. In this regard, an understanding of the spatial variability of soil nutrients at the field scale is important and useful for site-specific nutrient management [3]. Spatial variability of soil fertility is a function of intrinsic factors (soil forming factors and processes) and extrinsic factors (topography, land use and soil management practices) [4]. In traditional approach of soil fertility management, entire crop field is considered as homogeneous for calculating the fertilizer requirement. On the contrary, fields are actually not homogeneous and subsequently, sampling techniques to describe field variability have been recommended [5]. Application of classical statistics have some limitations for soil management studies because the variables (treatments) under investigation should be normally distributed and be spatially independent within the large experimental plots which leads to the confrontation with variability within such experimental plots. In recent years, geo-statistical techniques including non-parametric models having different algorithms and producing different interpolation errors are widely used for assessment of spatial variability of soil [6,7]. Vieira and Paz-Gonzalez [8] found spatial dependence between soil properties and crop yield components instead of having random spatial distributions, meaning that the observations are somehow related to their neighbours. Assessment of spatial dependence requires the application of geo-statistical procedures such as the analysis of scaled semivariograms using kriging [9]. Describing the spatial variability across a field has been difficult until new technologies such as Global Positioning Systems (GPS) and Geographic Information Systems (GIS) were introduced. Most of the soil variability studies have been carried out in hot-arid or semi-arid climate of India [5,10] and only a few studies have been carried out in humid subtropical climate of India [11]. Hence, this study attempts to assess the spatial variability of soil organic carbon (SOC), available nitrogen (N), available phosphorus (P) and available potassium (K) under different topography and land uses using geo-statistical techniques.

2. MATERIALS AND METHODS

2.1 Description of the Soil Sampling Sites

Four soil sampling sites were selected for the present study based on variation in slope and land use. These four sites were National Bureau of Plant Genetic Resources site 1 (NBPGR 1), NBPGR 2, Indian Council of Agricultural Research-Krishi Vigyan Kendra (ICAR-KVK) farm and ICAR-Horticulture farm located in Umiam, Ri-Bhoi district, Meghalaya (India). The average annual rainfall of the study sites was 2349 mm; mostly confined around May to November and mean daily temperature varied from 2.58°C in January to 32.58°C in August [12]. Details of the soil sampling sites have been given in Table 1.

2.2 Soil Sampling and Laboratory Analysis of Soil Sample

One composite soil sample from 10m x 10m grid was collected from each experimental site following standard procedure using Global Positioning System (GPS map 76CSX) during January to March, 2015 from a depth of 0-20 cm (Fig. 1). The soil samples were air-dried, ground and sieved using 2 mm sieve. Soil samples were sieved with 0.5 mm sieve for determination of SOC. The soil samples were analyzed for SOC [13], N [14], P [15] and K [16].

2.3 Statistical and Geo-statistical Analysis

All data were analyzed by one-way analysis of variance (ANOVA) using statistical package for social science (SPSS) software 16.0 (SPSS Inc., Chicago, IL, USA). Means were tested at a significance level of p≤0.05 using duncan's

Table 1. Description of soil sampling sites

Site	Latitude (North)	Longitude (East)	Elevation (m)	Slope (%)	Crop	Nutrient management
NBPGR 1	25°41.00' to 25°41.05'	91°54.63' to 91°54.66'	997-1032	25	Pine forest before 1980	Nil
					Ginger/turmeric during 1980-2011	500 g FYM[a] mixed with 10 gm DAP[2] & top dressing of 1-1.5 g urea per plant per year
					Fallow during 2012-14	Nil
					Turmeric in 2015	500 g FYM mixed with 10 gm DAP[b] per plant per year
NBPGR 2	25°41.03' to 25°41.12'	91°54.87' to 91°54.95'	931-977	9	Buckwheat-pulse[c] since 1980	FYM @ 500g in 2mx2m plots
					Medicinal plants[d] since 1980	Nil
					Maize-fallow since 1980	Nil
ICAR-KVK	25°41.26' to 25°41.30'	91°55.08' to 91°55.14'	931-977	9	Ginger/turmeric since 1978	FYM @ 6 t/ha and Urea:SSP:MOP @ 23:25:33 kg/ha
					Maize-vegetable[e] since 1978	FYM @ 10 t/ha and Uera:SSP:MOP @ 65:250:67 kg/ha
					Pulse[3]-vegetable since 1978	FYM @ 5 t/ha and Urea:SSP:MOP @ 45:375:70 kg/ha
					Forest before 1981	Nil
ICAR-Horticulture	25°41.38' to 25°41.44'	91°55.19' to 91°55.29'	951-1005	25	Guava since 1981	FYM @ 5 t/ha and N:P:K @ 500:200:300 gm/plant/year
					Mandarin since 1981	

[a] Farm Yard Manure, [b] Diammonium Phosphate, [c] black gram, soybean & groundnut, [d] Perilla & Coix, [e] colocasia, elephant foot yam, cabbage, cauliflower & broccoli

multiple range test (DMRT). Geostatistical analysis consisting of semivariogram calculation, cross-validation and mapping were performed using the geo-statistical analyst extension of ArcGIS 9.3.1 version [17]. Variable z of unsampled locations was estimated based on the weighted average of neighbouring measured locations and similarity & correlation of more closed points [18]. Semivariogram $\hat{\gamma}(h)$ describing the spatial variability was half of squared difference between paired data values z(uα) and z(uα+h). Graphically, it was represented by the average difference in attribute values between observations (i.e. Semivariance $\hat{\gamma}(h)$ versus distances apart i.e. Lag(h) and described in Fig. 2. The semivariance $\hat{\gamma}(h)$ was estimated using the following formula

$$\hat{\gamma}(\mathbf{h}) = \frac{1}{2N(\mathbf{h})}\sum_{\alpha=1}^{N(\mathbf{h})}\left[z(\mathbf{u}_\alpha) - z(\mathbf{u}_\alpha + \mathbf{h})\right]^2$$

where z(uα) and z(uα+h) indicated the value of the variable z at location of uα, h the lag and N(h) was the number of pairs of sample points (uα, uα+h) for property z separated by distance h. Semivariogram was computed in different directions for determining any anisotropic variation. The lag at which the semivariance became constant was known as sill (i.e. one value for a variable does not influence neighboring values). The distance at which the semivariance reached the sill was the range [19]. The semivariogram intercept on the y-axis was known as nugget which described the variation occurring at shorter distance than the minimum sampling interval. Best-fit models were selected with smallest nugget values with minimum root mean square error (RMSE). The expression of RMSE was as follows:

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

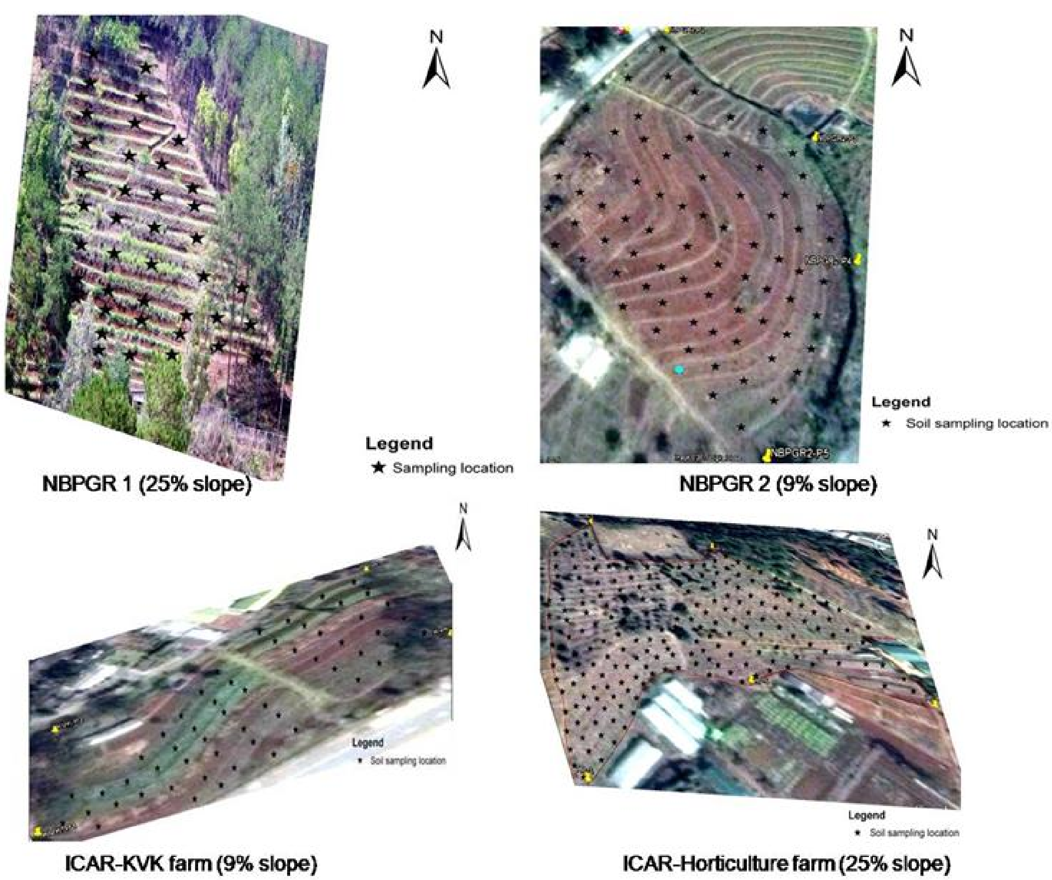

Fig. 1. Soil sampling sites in the four experimental farms (one sample from 10 m x 10 m grid)

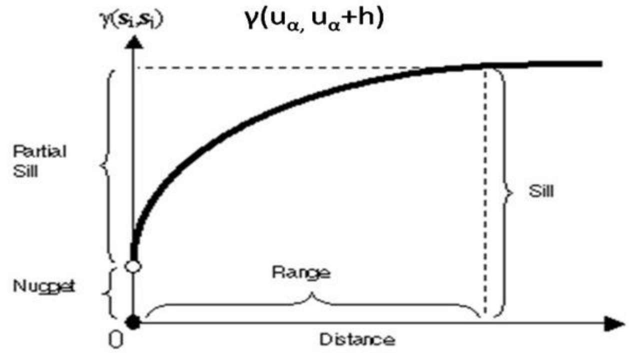

Fig. 2. Semivariogram

Semivariogram calculations were carried out while checking for possible trends in the datasets and if detected, trends were removed by fitting a polynomial surface and working with the residues. Omni-directional semivariograms were calculated and mathematical models were fitted to the experimental values. The best fit line was selected by cross-validation and once a model is chosen; its parameters (nugget effect, sill and range of spatial dependence) were determined using a least square approximation. The spatial dependence degree (SDD) was calculated as the proportion in percentage of nugget effect (C0) to the sill (C0 + C1) and classified as strong (< 25%), moderate (25-75%) and weak (> 75%) [3]. The semivariogram parameters obtained from the fitted model were used to interpolate values, at unsampled locations over the plot on a grid with an interval of 2 m using kriging. The optimal number of data points to be incorporated in the interpolation were determined by cross validation. The interpolation variance was also calculated.

3. RESULTS AND DISCUSSION

3.1 Effect of Slope and Land Uses on SOC, N, P, and K

Slope has been regarded as one of the most important topographic factors that controls the pedogenic process on a local scale [20,21]. SOC, N, P and K content in ICAR-Horticulture farm was found to be higher than that of NBPGR 1 (Table 2). The guava and mandarin plantation since 1981 with adequate nutrient management practices might have acted as natural forest and contributed to accumulation of nutrients through leaf litterfall (Table 3). Sahrawat [22] reported that forests had higher rate of N mineralization and nitrification than agricultural sites and result in greater N availability where there is less human disturbance. It was observed that the SOC was low in NBPGR 2 and ICAR-KVK farm but N, P and K were relatively high. Higher level of N, P and K in NBPGR 2 might be attributed to less nutrient uptake by the crops which were cultivated only to maintain the gene pool. Again, low level of SOC in the ICAR-KVK farm might be due to intensive tillage and fertilization which enhanced soil organic matter decomposition [23]. The buckwheat-pulses and maize-fallow sequence in NBPGR 2 and pulses-vegetable sequence in ICAR-KVK farm have also shown low SOC content. Thakuria et al. [2] also reported declining trend of SOC contents in soil of rice-legume-rice cropping system in acid soils of Assam, India. Again, optimum application of inorganic fertilizers was found to maintain or slightly increase the SOC content over the years [24]. Many authors also noted increased SOC contents on gentle and moderate slopes rather than steep slopes [25,26].

Higher N has been found in the buckwheat-pulses, maize-fallow sequence of NBPGR 2, guava orchard of ICAR-Horticulture farm and ginger/turmeric of ICAR-KVK farm. This might be attributed to low N uptake by ginger/turmeric, N supply through N fixation by buckwheat-pulses sequence and manure and fertilizer application in guava/mandarin. Lower N in ginger/turmeric of NBPGR 1, maize-vegetables and pulse-vegetables of ICAR-KVK might be due to high amount of N uptake and runoff loss in the steep slope (25%). The crop field of pulses-vegetables in ICAR- KVK farm has shown more N content.

This has been observed that mild slope (9%) stored more amount of P as compare to the steep slope (25%) (Table 2). However, higher amount of P in ICAR-Horticulture farm (25% slope) could be due to regular application of phosphatic fertilizer in the orchard (Table 1). Increase in P due to application of phosphatic fertilizer has been reported earlier also [27]. The soil of the study sites were strongly acidic (pH 4.3) and most of the added P through mineral fertilizers to these soils gradually reacted with Fe and Al compounds and transformed into relatively insoluble P compounds. Thakuria et al. [2] also reported accumulation of P in the sub soils in rice-legume-rice cropping system of acid soils of Assam, India. Lowest P was found in soil of medicinal plant of NBPGR 2. This might be due to poor nutrient management (manures/fertilizers were not applied). Similarly, higher content of K in guava/mandarin orchard soil could be attributed to the built up of soil K due to long-term application of K fertilizer (Table 1). Again, low K content in ginger/turmeric of NBPGR 1 as compared to other land use might be due to non application of K fertilizer in the crop and uptake of K from soil reserve (Table 3).

3.2 Descriptive Statistics and Spatial Variability of SOC, N, P, and K

The statistical analysis of SOC, N, P, and K indicated that the data followed a normal distribution and spatial variability. Variability of a soil property could be described by minimum, maximum, difference between median and mean, standard deviation (SD) and coefficient of variation (CV). The median value of SOC of NBPGR 1 was almost equal to the mean value in none, log and box-cox transformation. The median of soil properties was lower than the mean, which indicated that the effect of abnormal data on sampling value were not significant. The CV of SOC was found highest in the box-cox transformation, which was shown by moderate variability (29.23%). Warrick and Nielsen [28] proposed three levels of variability of soil properties based on CV; low (< 12%), medium (12-62%) and high (> 62%).

Skewness indicated departure from normality. The skewness for the normal distribution should be less than 3 and it was found to be 0.07 for the box-cox transformation. Lower values used to concentrate when skewness > 0. On the other hand, higher values used to concentrate when skewness < 0. Positive skewness indicated wider confidence limits on the variograms which made the variances less reliable. Kurtosis showed the characteristics of peak value corresponding to the average value in probability density distribution curve. The peak value of probability density distribution curve is higher than that of normal distribution when kurtosis > 0, equal to that of normal distribution when kurtosis = 0, lower than normal distribution when kurtosis < 0. Therefore, the box-cox transformation was considered for the SOC of NBPGR 1. The median of N after log transformation was found to be equivalent to mean, however, deviation of skewness from zero in case of log transformation was more as compared to none and box-cox transformation. The box-cox transformation was

Table 2. Effect of topography on SOC, N, P and K

Topological site	SOC (%)	N (kg/ha)	P (kg/ha)	K (kg/ha)
NBPGR 1 (25% slope)	2.02b	348.10c	15.71c	192.16c
NBPGR 2 (9% slope)	1.83c	435.31a	18.97b	314.62b
ICAR-KVK farm (9% slope)	1.84c	360.19bc	45.73a	277.46b
ICAR-Horticulture farm (25% slope)	2.14a	389.43b	20.96b	364.51a

Table 3. Effect of land use on SOC, N, P and K

Land use	SOC (%)	N (kg/ha)	P (kg/ha)	K (kg/ha)
Guava orchard of ICAR-Horticulture farm	2.15a	420.85ab	20.83cd	422.80a
Mandarin orchard of ICAR-Horticulture farm	2.06a	366.14bcd	21.06cd	321.35c
Ginger/turmeric of NBPGR 1	1.98ab	348.06d	15.71de	192.13d
Buckwheat-pulses of NBPGR 2	1.78c	460.35a	22.23c	330.86bc
Ginger/turmeric of ICAR-KVK	1.56d	404.50abc	35.67b	399.39ab
Maize-vegetables of ICAR-KVK	1.87bc	364.68bcd	52.07a	181.73d
Pulse-vegetables of ICAR-KVK	1.76c	377.46b	40.14b	354.00abc
Medicinal plants (*Perilla*, *Coix*) of NBPGR 2	1.81bc	402.21bc	13.33f	305.36c
Maize-fallow of NBPGR 2	1.76c	409.92ab	16.58de	289.77c

considered for N in NBPGR 1. The median of P was found to be smaller than the mean value in all the transformations including none transformation. Box-cox transfprmation had higher CV skewness deviation from zero as compared to log transformation. Log transformation was considered for normal distribution for spatial variability analysis of P in NBPGR 1. Similarly, box-cox transformation was also considered for spatial variability analysis of K due to comparatively smaller median and slightly higher CV than other transformations. The skewness was nearer to zero (-0.33) in box-cox transformation. The spatial variability analysis of SOC and N in NBPGR 2 was carried out using the box-cox transformation because of higher CV (41.09% and 15.57%, respectively), comparatively lower median values and skewness nearer to 0 (-0.61 and -0.91, respectively). However, log transformation was considered for P and K due to lower median value than the mean and skewness near to 0 (0.15 and -0.05, respectively). The spatial variability analysis of SOC, N, P and K of ICAR-KVK farm was carried out using box-cox, none, box-cox and log transformation, respectively. The box-cox transformation was considered for spatial variability of SOC analysis because of higher CV (24.24%) and skewness nearer to zero (-0.98). Again, spatial variability analysis of N was performed using none transformation, which has medium CV (19.78%) and 0.22 skewness. Spatial variability analysis of P was performed with box-cox transformation with medium CV (33.02%) and skewness nearer to zero (0.01). The log transformation for K was considered because of normal distribution of data having CV (7.89%) and skewness (0.01). In case of ICAR-Horticulture farm, spatial variability analysis of SOC, N and K were performed by box-cox, however, P was analyzed by log transformation based on mean, median, CV and skewness.

Table 4. Descriptive statistics of various soil parameters for NBPGR 1

Soil parameter	Transfor-mation	Min.	Max.	Mean	S.D	CV	Skewness	Kurtosis	Median
SOC (%)	None	1.32	2.74	2.02	0.30	14.74	0.07	3.19	2.01
	Log	0.28	1.01	0.69	0.15	21.85	- 0.41	3.39	0.70
	Box-Cox	0.32	1.74	1.02	0.30	29.23	0.07	3.19	1.01
N (kg/ha)	None	188.16	501.76	348.10	76.4	21.23	- 0.16	2.46	351.23
	Log	5.24	6.22	5.83	0.24	4.05	- 0.69	3.08	5.86
	Box-Cox	187.16	500.76	347.10	76.37	22.00	- 0.16	2.46	350.23
P (kg/ha)	None	10.50	23.90	15.09	4.74	31.44	0.74	1.90	13.95
	Log	2.35	3.17	2.71	0.28	10.47	0.55	1.82	2.64
	Box-Cox	9.50	22.90	14.09	4.74	33.67	0.74	1.90	12.95
K (kg/ha)	None	153.44	224.00	192.16	15.66	8.15	- 0.33	2.76	193.20
	Log	5.03	5.41	5.26	0.08	1.58	- 0.54	3.03	5.26
	Box-Cox	152.44	223.00	191.60	15.66	8.17	- 0.33	2.76	192.20

Table 5. Descriptive statistics of various soil parameters for NBPGR 2

Soil parameter	Transfor-mation	Min.	Max.	Mean	S.D	C.V	Skewness	Kurtosis	Median
SOC (%)	None	0.90	2.63	1.83	0.34	18.61	- 0.61	3.50	1.90
	Log	- 0.10	0.97	0.58	0.21	35.70	- 1.23	4.46	0.64
	Box-Cox	- 0.10	1.63	0.83	0.34	41.09	- 0.61	3.50	0.90
N (Kg/ha)	None	188.16	489.57	404.36	62.80	15.53	- 0.91	3.50	414.20
	Log	5.24	6.19	5.99	0.17	2.91	- 1.07	6.21	6.03
	Box-Cox	187.16	488.57	403.36	62.80	15.57	- 0.91	3.50	413.13
P (Kg/ha)	None	8.89	39.84	19.03	6.91	36.34	0.88	3.38	17.77
	Log	2.18	3.68	2.88	0.35	12.19	0.15	2.36	2.60
	Box-Cox	7.89	38.84	18.03	6.92	38.36	0.88	3.38	12.45
K (Kg/ha)	None	158.37	520.80	315.24	80.49	25.53	0.56	2.81	301.73
	Log	5.06	6.26	5.72	0.25	4.45	- 0.05	2.80	5.71
	Box-Cox	157.37	519.80	314.24	80.49	25.61	0.56	2.81	300.73

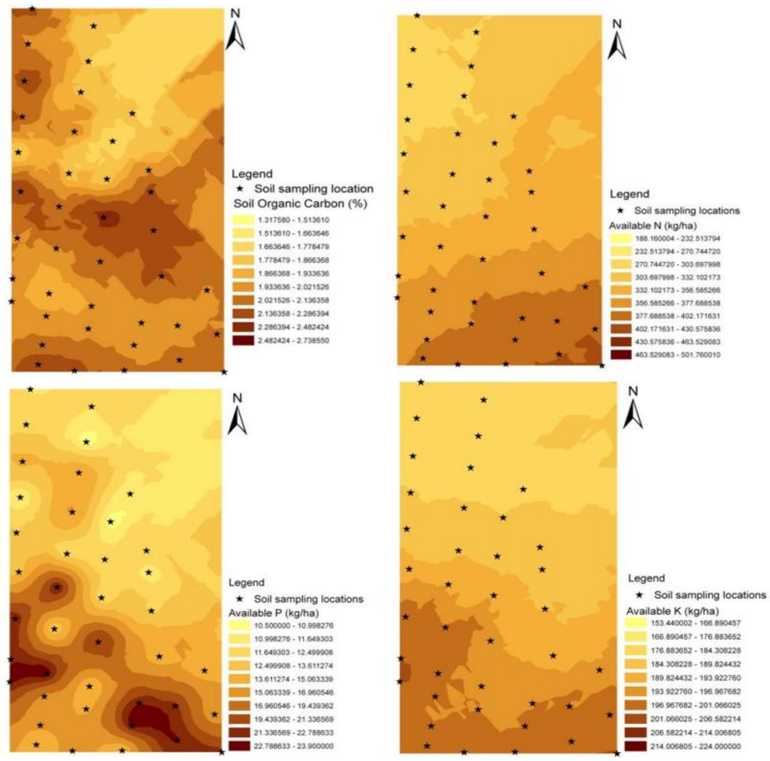

Fig. 3. Spatial variability of SOC, N, P and K in NBPGR 1

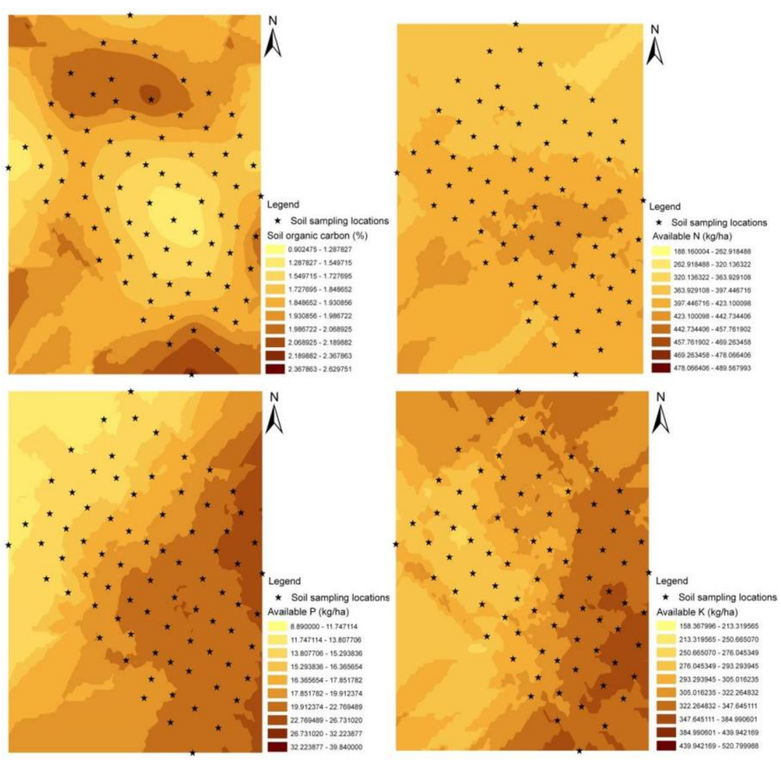

Fig. 4. Spatial variability of SOC, N, P and K in NPBGR 2

Table 6. Descriptive statistics of various soil parameters for ICRA-KVK farm

Soil parameter	Transfor-mation	Min.	Max.	Mean	S.D	C.V	Skewness	Kurtosis	Median
SOC (%)	None	1.09	2.18	1.84	0.42	22.87	- 0.98	4.77	1.86
	Log	0.02	0.78	0.60	0.12	19.94	- 1.58	7.32	0.62
	Box-Cox	0.09	1.18	0.84	0.20	24.24	- 0.98	4.77	0.86
N (Kg/ha)	None	187.16	500.76	359.19	71.07	19.78	- 0.22	3.30	375.32
	Log	5.24	6.22	5.86	0.21	3.65	- 0.93	4.16	5.93
	Box-Cox	188.16	501.76	360.19	71.07	19.73	- 0.22	3.30	376.32
P (Kg/ha)	None	6.11	78.85	45.73	14.76	32.28	0.01	2.83	43.94
	Log	1.81	4.37	3.76	0.41	10.83	- 2.00	10.57	3.78
	Box-Cox	5.11	77.85	44.73	14.76	33.02	0.01	2.83	42.94
K (Kg/ha)	None	106.40	504.00	265.85	112.69	42.39	0.43	1.84	229.60
	Log	4.67	6.22	5.49	0.43	7.89	0.01	1.69	5.44
	Box-Cox	105.40	503..00	264.85	112.69	42.55	0.43	1.84	228.60

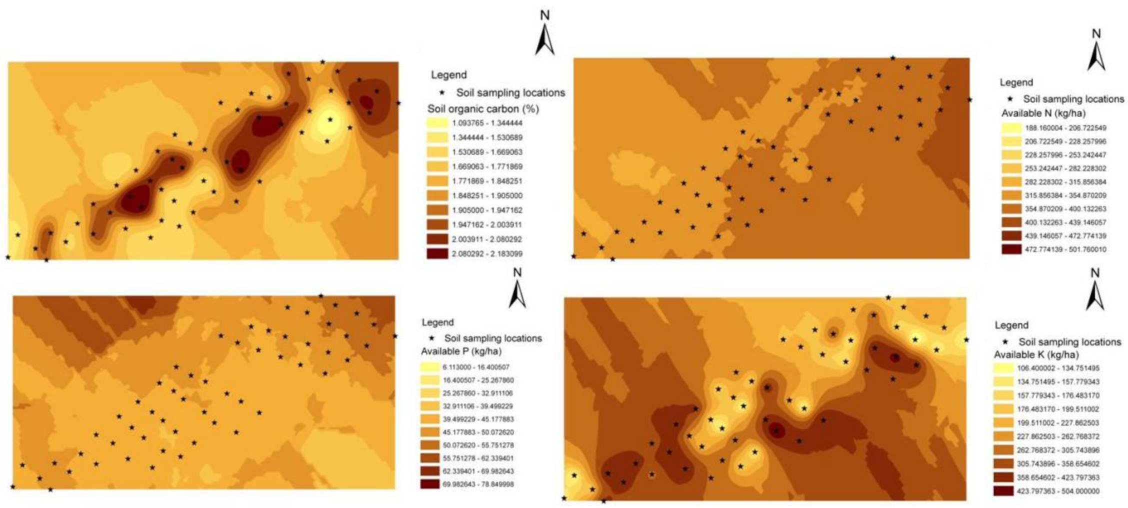

Fig. 5. Spatial variability of SOC, N, P and K in ICAR-KVK farm

Table 7. Descriptive statistics of various soil parameters for ICAR-Horticulture farm

Soil parameter	Transfor-mation	Min.	Max.	Mean	S.D.	C.V	Skewness	Kurtosis	Median
SOC (%)	None	1.38	3.06	2.14	0.27	12.58	- 0.19	3.52	2.15
	Log	0.32	1.12	0.75	0.13	17.35	- 0.66	3.88	0.77
	Box-Cox	0.38	2.06	1.14	0.27	23.63	- 0.19	3.52	1.15
N (Kg/ha)	None	125.44	652.29	389.43	93.75	24.07	0.11	2.99	376.32
	Log	4.83	6.48	5.93	0.26	4.38	- 0.89	5.22	5.93
	Box-Cox	124.44	651.29	388.43	93.75	24.14	0.11	2.99	375.32
P (Kg/ha)	None	8.99	66.19	20.96	8.44	40.25	2.07	9.57	19.39
	Log	2.20	4.19	2.98	0.35	11.73	0.52	3.65	2.96
	Box-Cox	7.99	65.19	19.96	8.44	42.27	2.07	9.57	18.39
K (Kg/ha)	None	109.76	499.74	335.41	106.47	31.74	- 0.29	1.98	341.04
	Log	4.68	6.21	5.75	0.37	6.39	- 0.84	2.84	5.83
	Box-Cox	108.76	498.74	334.41	106.47	31.84	- 0.29	1.98	340.04

Theoretically, nugget should be zero at lag distance zero. The nugget value of SOC, P and K was low, however it was around 4 for N at NBPGR 1. Lower nugget values indicated that the sampling interval was proper to reflect the variance [29]. Negligible nugget effect indicated better spatial continuity at close distance between sample points. Higher nugget value indicated higher small scale spatial variability. The range expressed distance could be interpreted as a diameter of the zone of influence of SOC, N, P and K of two sampling points. At a distance less than the range, SOC, N, P and K of two sampling points were more alike. The higher range was for much larger sampling interval of 1-2 km in a relatively larger area [30]. When the semivariance did not change significantly with increasing lag distance, the plateau reached, called sill which reflected the magnitude of random variation [27]. The nugget/sill ratio was a criterion for classifying the spatial dependency of soil properties. Nugget/sill ratio < 0.25 indicated strong spatial dependence of variance, ratio between 0.25-0.75 indicated moderate spatial dependence and ratio > 0.75 indicated weak spatial dependence [31]. Again, spatial dependency was considered as weak if the best-fit semivariogram model had RMSE < 0.5 [28]. Most reliable surface was predicted with mean, RMSE and RMSS. The mean error should be closed to 0, RMSE should be as small as possible and RMSS should be close to 1.

Soils of NBPGR 1 were found to have high SOC (1.6-2.7%), medium N (232.5-463.5 kg/ha), low P (<16.9 kg/ha) and medium K (153.4-206.6 kg/ha) (Fig. 3). Spatial dependency of SOC, N and K in NBPGR 1 was found to be moderate which could be due to application of small amount of FYM without mineral K fertilizers. Strong spatial dependency in case of P could be due to intrinsic factors (parent material etc.) and addition of small amount of P might not contribute to this. Zhang and McGrath [32] and Chai et al. [33] also reported the strong spatial dependency of soil properties with intrinsic factors and weak spatial dependency with extrinsic factors. The variations of SOC were correlated to land uses and higher amount of SOC was observed at sites nearer to the mandarin plantation and grassland of NBPGR 1. Again, higher amount of N, P and K content were found towards foot-slope and toe-slope (south-west direction).

The nugget effect on SOC, N, P and K in NBPGR 2 also followed similar trend as NBPGR 1. Soils of NBPGR 2 were found to have high SOC (1.55-1.99%), medium N (263-443 kg/ha), low P (11.7-26.7 kg/ha) and medium K (213-440 kg/ha) (Fig. 4). The variability scale for N was narrow. The nugget/sill ratio for SOC & P had moderate spatial autocorrelation and N & K had weak spatial relationship. The RMSS of SOC, N, P & K were 0.97-1.03 which indicated that the predicted surfaces were reliable. SOC, N, P and K content was found to increase towards toe-slope of the NBPGR 2. This might be due to accumulation of water soluble fractions of SOC, N, P and K in the toe-sole. This was also evident from higher moisture content in the toe-sole. The range of influence of SOC, N, P and K was 5m, 9m, 17m and 16m, respectively. This indicated that the variability of SOC and N was less compared to the variability of P and K in NBPGR 2. The pattern of SOC, N, P and K distribution in NBPGR 2 was similar to the NBPGR 1 in spite of

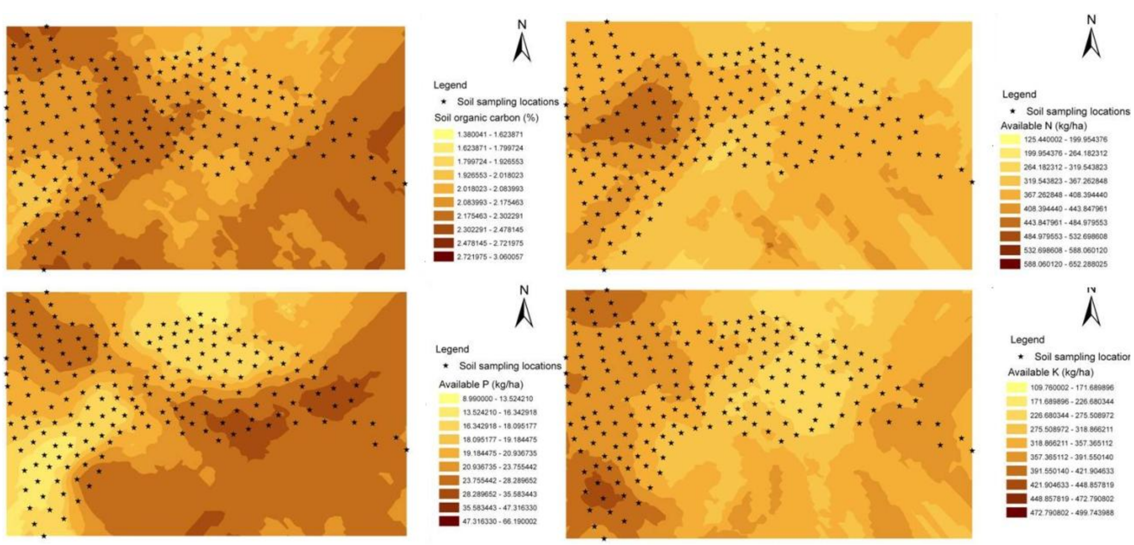

Fig. 6. Spatial variability of SOC, N, P and K in ICAR-Horticulture farm

Table 8. Comparative evaluation of different geostatistical methods and models for NBPGR 1

Soil parameter	Geostatistical method	Model	Nugget (m)	Sill (m)	Nugget/ Sill	Range (m)	Mean	RMSE	RMSS
SOC (%)	IDW	Optimization power-2					-0.02	0.32	
	RBF						-0.01	0.33	
	Kriging	Circular	0.65	0.89	0.73	1	-0.01	0.33	1.05
		Spherical	0.58	0.89	0.65	1	-0.01	0.03	1.05
		Tetra spherical	0.52	0.89	0.58	1	-0.00	0.33	1.04
		Pentaspherical	0.47	0.89	0.53	1	-0.01	0.33	1.04
		Exponential	0.70	0.89	0.79	1	-0.01	0.33	1.04
		Gaussian	0.73	0.89	0.82	1	-0.01	0.33	1.05
N (Kg/ha)	IDW	Optimization power-2					-0.13	74.07	
	RBF						-0.65	74.81	
	Kriging	Circular	4.09	7.53	0.54	8	-0.39	70.56	1.00
		Spherical	4.00	7.24	0.55	8	-0.34	70.79	1.00
		Tetra spherical	3.94	7.04	0.56	8	-0.32	71.01	1.01
		Pentaspherical	3.88	6.90	0.56	8	-0.30	71.21	1.01
		Exponential	3.47	7.03	0.49	8	-0.33	72.15	1.02
		Gaussian	4.54	7.71	0.59	8	-0.37	69.35	0.98
P (Kg/ha)	IDW	Optimization power-2					0.15	3.80	
	RBF						0.05	3.89	
	Kriging	Circular	0.00	0.6	0.00	0.1	0.11	3.66	0.93
		Spherical	0.00	0.6	0.00	0.1	0.11	3.68	0.94
		Tetra spherical	0.00	0.6	0.00	0.1	0.09	3.65	0.93
		Pentaspherical	0.00	0.6	0.00	0.1	0.09	3.63	0.92
		Exponential	0.00	0.6	0.00	0.1	0.06	3.75	0.94
		Gaussian	0.00	0.6	0.00	0.1	0.10	3.70	0.94
K (Kg/ha)	IDW	Optimization power-2					-0.33	15.39	
	RBF						-0.26	15.49	
	Kriging	Circular	0.16	0.32	0.48	7	-0.19	14.98	1.06
		Spherical	0.15	0.31	0.49	8	-0.18	15.00	1.06
		Tetras pherical	0.15	0.30	0.49	8	-0.17	15.03	1.06
		Pentaspherical	0.15	0.30	0.50	8	-0.17	15.05	1.07
		Exponential	0.13	0.30	0.43	8	-0.21	15.19	1.07
		Gaussian	0.16	0.32	0.50	8	-0.16	14.85	1.05

variation in slope. SOC content was more in the toe-slope of medicinal plant growing areas of NBPGR 2. This could be due to accumulation of plant litters in the toe-slope by surface runoff.

In ICAR-KVK farm, N had higher nugget value than SOC, P and K. The nugget/sill ratio showed weak spatial autocorrelation for all the soil variables. It might be attributed to regular uniform soil tillage and agronomic management practices. Though ICAR-KVK farm and NBPGR 2 had same slope (9%), the range of SOC and N influence zone in ICAR-KVK farm was 2-2.5 and 1-1.5 times higher than NBPGR 2, respectively. On the other hand, influence zone of P was 5-6 times lower than the NBPGR 2. The range of available K influence zone was slightly less than NBPGR 2. It might be due to influence of uniform extrinsic factors (uniform tillage and crop management practices) on SOC, N and K and influence of intrinsic factor (strongly acidic reaction) on P. The RMSS of all the soil variables were nearer to 1 which indicated reliability of spatial map generated for ICAR-KVK farm. The localized effect of SOC with non uniform addition of FYM was observed. SOC, N, P and K content in the soil was found in the range of 1.09-2.18%, 228-400 kg/ha, 16.4-39.5 kg/ha and 106-504 kg/ha respectively (Fig. 5).

The nugget of the soil variables for ICAR-Horticulture farm was very small and nugget/sill ratio of SOC and N indicated weak spatial dependency, however, P and K had moderate spatial dependence. Zone of influence for SOC and P was similar. The range for N was less which indicated higher spatial variation. On the other hand lower spatial variation was observed for K. The RMSS of the variables were nearer to 1 indicating reliable surface variability prediction. Soils of the ICAR-Horticulture farm were found to be high in SOC (1.79-2.47%), medium in N (200-444 kg/ha), low in P (8.9-28.29 kg/ha) and medium in K (110-392 kg/ha) (Fig. 6). The spatial variability map showed higher amount of SOC in the entire farm which might be due to decomposition of leaf litters. Again, P was found to be higher in the shoulder as well as toe-slope (guava orchard) lower in back slope and foot slope (mandarin orchard). This may be attributed to differences in crop and nutrient management in guava and mandarin. N and K also showed similar trend of spatial variability.

Table 9. Comparative evaluation of different geostatistical methods and models for NBPGR 2

Soil parameter	Geostatistical method	Model	Nugget (m)	Sill (m)	Nugget/ Sill	Major range (m)	Mean	RMSE	RMSS
SOC (%)	IDW	Optimization power-2					-0.01	0.32	
	RBF						-0.00	0.32	
	Kriging	Circular	0.07	0.12	0.58	4.8	0.00	0.32	1.01
		Spherical	0.07	0.12	0.58	5.3	0.00	0.32	1.01
		Tetra spherical	0.07	0.12	0.57	6.0	0.00	0.32	1.01
		Pentaspherical	0.07	0.12	0.57	6.4	0.00	0.32	1.01
		Exponential	0.06	0.12	0.48	6.2	0.00	0.32	1.001
		Gaussian	0.08	0.12	0.65	5.0	0.00	0.33	1.01
N (kg/ha)	IDW	Optimization power-2					1.66	68.08	
	RBF						0.96	71.70	
	Kriging	Circular	3.69	4.02	0.92	8.1	0.86	64.51	1.02
		Spherical	3.69	4.02	0.92	9	0.90	64.53	1.01
		Tetra spherical	3.69	4.02	0.92	9.8	0.84	64.54	1.01
		Pentaspherical	3.69	4.02	0.92	11	0.83	64.55	1.01
		Exponential	3.71	4.04	0.92	13	0.84	64.52	1.01
		Gaussian	3.75	4.03	0.93	8.4	0.87	64.42	1.01
P (kg/ha)	IDW	Optimization power-2					0.08	6.33	
	RBF						0.03	6.49	
	Kriging	Circular	0.08	0.18	0.42	17	0.02	6.26	0.99
		Spherical	0.08	0.17	0.44	17	0.02	6.26	1.01
		Tetra spherical	0.07	0.16	0.46	17	0.03	6.26	1.02
		Pentaspherical	0.07	0.16	0.47	17	0.03	6.27	1.02
		Exponential	0.06	0.16	0.41	17	0.05	6.30	1.03
		Gaussian	0.09	0.19	0.48	17	-0.01	6.25	1.00
K (kg/ha)	IDW	Optimization power-2					0.51	87.52	
	RBF						0.51	87.52	
	Kriging	Circular	0.07	0.07	1.00	16	1.51	82.69	1.00
		Spherical	0.07	0.07	1.00	16	1.51	82.69	1.00
		Tetra spherical	0.07	0.07	1.00	16	1.51	82.69	1.00
		Pentaspherical	0.07	0.07	1.00	16	1.51	82.69	1.00
		Exponential	0.07	0.07	1.00	16	1.51	82.69	1.00
		Gaussian	0.07	0.07	1.00	16	1.51	82.69	1.00

Table 10. Comparative evaluation of different geostatistical methods and models for ICAR-KVK farm

Soil parameter	Geostatistical method	Model	Nugget (m)	Sill (m)	Nugget/ Sill	Range (m)	Mean	RMSE	RMSS
SOC (%)	IDW	Optimization power-2					0.01	0.02	
	RBF						0.01	0.15	
	Kriging	Circular	0.39	0.44	0.89	14	0.01	0.21	1.01
		Spherical	0.39	0.42	0.90	14	0.01	0.21	1.01
		Tetra spherical	0.39	0.43	0.91	14	0.01	0.21	1.01
		Pentaspherical	0.39	0.42	0.92	14	0.01	0.21	1.01
		Exponential	0.39	0.42	0.92	14	0.01	0.21	1.01
		Gaussian	0.39	0.44	0.88	14	0.01	0.21	1.02
N (kg/ha)	IDW	Optimization power-2					-0.51	74.43	
	RBF						-0.32	76.71	
	Kriging	Circular	4.66	5.54	0.84	14	-0.00	71.43	1.00
		Spherical	4.66	5.44	0.86	14	-0.01	71.45	1.00
		Tetra spherical	4.66	5.37	0.87	14	-0.01	71.46	1.00
		Pentaspherical	4.67	5.33	0.88	14	-0.01	71.47	1.00
		Exponential	4.63	5.33	0.87	14	-0.01	71.59	1.00
		Gaussian	4.75	5.62	0.85	14	-0.01	71.22	1.00
P (kg/ha)	IDW	Optimization power-2					-0.31	16.3	
	RBF						0.04	16.63	
	Kriging	Circular	2.07	2.19	0.95	3	-0.32	14.89	0.98
		Spherical	2.07	2.19	0.95	3	-0.28	14.95	0.99
		Tetra spherical	2.08	2.19	0.95	3	-0.27	14.91	0.98
		Pentaspherical	2.08	2.19	0.95	4.7	-0.28	14.95	0.99
		Exponential	2.08	2.18	0.95	2	-0.36	15.38	0.99
		Gaussian	2.11	2.18	0.97	3	-0.32	14.77	0.97
K (kg/ha)	IDW	Optimization power-2					-1.40	102.6	
	RBF						0.10	102.3	
	Kriging	Circular	0.17	0.22	0.77	14	2.30	110.2	0.88
		Spherical	0.17	0.22	0.77	14	2.27	110.1	0.89
		Tetra spherical	0.17	0.21	0.81	14	2.24	110	0.89
		Pentaspherical	0.17	0.21	0.81	14	2.23	109.9	0.89
		Exponential	0.16	0.21	0.76	14	1.98	109.2	0.89
		Gaussian	0.17	0.22	0.78	14	2.74	111.1	0.88

Table 11. Comparative evaluation of different geostatistical methods and models for ICAR Horticulture farm

Soil parameter	Geostatistical Method	Model	Nugget (m)	Sill (m)	Nugget/ Sill	Major (m)	Mean	RMSE	RMSS
SOC (%)	IDW	Optimization power-2					-0.00	0.26	
	RBF						-0.00	0.27	
	Kriging	Circular	0.07	0.07	0.91	9	0.00	0.26	0.97
		Spherical	0.07	0.07	0.91	9	0.00	0.26	0.97
		Tetra spherical	0.07	0.07	0.91	10	0.00	0.26	0.97
		Pentaspherical	0.07	0.07	0.91	10	0.00	0.26	0.97
		Exponential	0.07	0.07	0.89	10	0.00	0.26	0.97
		Gaussian	0.07	0.07	0.93	8	0.00	0.26	0.97

Soil parameter	Geostatistical Method	Model	Nugget (m)	Sill (m)	Nugget/ Sill	Major (m)	Mean	RMSE	RMSS
N (kg/ha)	IDW	Optimization power-2					1.68	92.82	
	RBF						0.59	93.30	
	Kriging	Circular	0.08	0.88	0.92	4	0.88	91.90	0.97
		Spherical	0.80	0.88	0.90	4	0.86	91.82	0.97
		Tetra spherical	0.78	0.88	0.89	4	0.84	91.76	0.97
		Pentaspherical	0.77	0.87	0.88	4	0.82	91.72	0.97
		Exponential	0.80	0.88	0.90	4	0.90	91.95	0.97
		Gaussian	0.83	0.88	0.94	4	0.88	91.90	0.97
P (kg/ha)	IDW	Optimization power-2					-0.00	7.69	
	RBF						0.02	7.63	
	Kriging	Circular	0.09	0.13	0.71	7	0.05	7.65	1.04
		Spherical	0.09	0.13	0.70	8	0.05	7.65	1.04
		Tetra spherical	0.09	0.13	0.70	9	0.05	7.65	1.04
		Pentaspherical	0.09	0.13	0.70	10	0.05	7.64	1.04
		Exponential	0.08	0.13	0.61	8	0.03	7.60	1.04
		Gaussian	0.10	0.13	0.75	7	0.06	7.68	1.05
K (kg/ha)	IDW	Optimization power-2					-2.14	100.00	
	RBF						-0.83	100.20	
	Kriging	Circular	0.78	13.12	0.61	13	0.43	99.29	1.04
		Spherical	0.79	13.14	0.60	15	0.43	99.27	1.05
		Tetra spherical	0.79	13.15	0.60	16	0.42	99.25	1.05
		Pentaspherical	0.79	13.16	0.60	18	0.42	99.25	1.05
		Exponential	0.76	13.95	0.54	23	0.32	99.13	1.05
		Gaussian	0.87	13.42	0.65	14	0.61	99.69	1.03

4. CONCLUSION

This study has shown that soils of all the four sites were high in SOC, low to medium in N and K and low in P. The status of N, P and K suggested need for fertilizers use on the basis of soil test values. Geo-statistical methods and models were found to be useful in generating spatial variability maps which could be used for site specific nutrient management. Land use had a greater role in influencing nutrient status of soil and this was evident from higher nutrient content in ICAR-Horticulture farm compared to NBPGR 1 in spite of having same slope (25%). However gentle slope (9%) was found to have lower SOC content and higher N, P and K compared to moderately steep slope (25%). Plantation crops (guava, mandarin) and long duration crops (ginger/turmeric) increased the SOC during 35 years of prolonged cultivation. On the other hand, intensive cropping with short duration crops (maize-vegetable, pulse-vegetable sequence) depleted SOC during 35 years of cultivation. However, mineral nutrients (N, P and K) were found to be medium to high in the intensive cropping sites. The nugget/sill ratio demonstrated strong to moderate spatial auto-correlation for P and moderate to weak spatial auto correlation for SOC, N and K in moderately steep slopes (25%). Again, RBF was found to be best interpolation technique for SOC and K whereas ordinary kriging gaussian model was suitable for N and P in gentle slopes (9%). The best described semivariograms for SOC, N, P, and K in moderately steep slopes (25%) were exponential, pentaspherical, exponential and exponential model, respectively. This study has demonstrated that geo-statistical methods on a large scale could be used for evaluation of spatial variability of soil properties in diverse topography and land uses in acidic soils of north-eastern India. The soil chemical properties used to have spatial dependence and understanding such interaction could provide new insights into soil behavior for the better land management.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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