



Spatial variability of some soil properties varies in oil palm (*Elaeis guineensis* Jacq.) plantations of west coastal area of India

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Abstract. Mapping spatial variability of soil properties is the key to efficient soil resource management for sustainable crop yield. Therefore, the present study was conducted to assess the spatial variability of soil properties such as acidity (pH), salinity (electrical conductivity (EC)), organic carbon, available K, available P, exchangeable Ca^{2+} , exchangeable Mg^{2+} , available S and hot water soluble B in surface (0–20 cm) and subsurface (20–40 cm) soil layers of oil palm plantations in south Goa district of Goa located in west coastal area of India. A total of 128 soil samples were collected from 64 oil palm plantations of Goa located at an approximate interval of 1–2 km and analyzed. Soil was acidic to neutral in reaction. Other soil properties varied widely in both the soil layers. Correlations between soil pH and exchangeable Ca^{2+} , between soil EC and available K, between available P and available S and between exchangeable Ca^{2+} and exchangeable Mg^{2+} in both the soil layers were found to be positive and significant ($P < 0.01$). Geostatistical analysis revealed a varied spatial distribution pattern for the measured soil properties. Best-fit models for measured soil properties were exponential, Gaussian, stable, K-Bessel and spherical with moderate to strong spatial dependency. The results revealed that site-specific fertilizer management options needed to be adopted in the oil palm plantations of the study area owing to variability in soil properties.

1 Introduction

Soil is the key part of the earth system which controls hydrological, biological, and geochemical cycles and it offers

goods, resources and services to mankind (Keesstra et al., 2012; Smith et al., 2015; Decock et al., 2015; Brevik et al., 2015; Berendse et al., 2015). Un-sustainable soil management practices lead to soil degradation, which is a worldwide topic, mainly because of loss of soil organic matter (SOM), soil erosion, changes in soil structure, degradation of the biota in the soils and soil chemical degradation (Cerda et al., 2009; Mupenzi et al., 2011; Novara et al., 2013; Mukherjee et al., 2014; Lieskovský and Kenderessy, 2014; Stanichi et al., 2015; Seutloali and Beckedahl, 2015; Novara et al., 2015). Soil degradation along with natural processes results in degradation of coastal areas, which covers more than 10 % of the earth surface area with 35, 6000 and 7517 km coast line in world and India, respectively (Misdorp, 1990; Sanil Kumar et al., 2006).

Geographical distribution maps of soil properties, obtained from soil surveys, help in correct management of soil nutrients (Brevik et al., 2016). These maps are required to understand the patterns and processes of soil spatial variability, which is the combined effect of soil physical, chemical and biological processes operating at different spatiotemporal scales combined with anthropogenic activities (Goovaerts, 1998). Geostatistical tools are useful in preparation of the maps based on limited number of samples collected from agricultural landscapes. Kriging simulation technique predicts the values at un-sampled locations by spatial correlation and reduces variance of estimation error and investigation costs (Saito et al., 2005; Pereira et al., 2015). Spatial variability of soil properties is assessed effectively by geostatistical methods (Mueller et al., 2003; Pereira et al., 2013;

Ochoa-Cueva et al., 2015) for site-specific management of nutrients through variable rate fertilizer application to avoid over and under application of nutrients (Fu et al., 2010). Information regarding variability of soil properties in soil profile is helpful to assess the contribution of subsurface soil layers to crop nutrition and potential capacity of the soil to supply nutrients during crop growth. It also helps in understanding the effect of different management practices, under a given cropping system, on the downward movement as well as recycling of nutrients to the surface layers (Behera and Shukla, 2013; Parras-Alcantara et al., 2015).

Oil palm (*Elaeis guineensis* Jacq.) is a high-oil-yielding crop compared to annual oil crops (Johnston et al., 2009; Murphy, 2009). Oil palm uses about 162, 30, 217, 38 and 36 kg of N, P, K, Mg and Ca $\text{ha}^{-1} \text{year}^{-1}$, respectively, to produce 2.5 Mg of oil $\text{ha}^{-1} \text{year}^{-1}$ (Mengel and Kirkby, 1987). Considering oil to bunch ratio of 1 : 4, 2.5 Mg oil ha^{-1} is equivalent to 10 Mg FFB $\text{ha}^{-1} \text{year}^{-1}$, but average FFB yield in well-managed plantations is much higher (Narsimha Rao et al., 2014). Nutrient content in 1 Mg of FFB obtained from Dura palms is 2.94, 0.44, 3.71, 0.77, 0.81 kg of N, P, K, Mg and Ca, respectively, whereas Mn, Fe, B, Cu and Zn content per 1 Mg of FFB is 1.51, 2.47, 2.15, 4.76 and 4.93 g, respectively (Ng and Thamboo, 1967). Calibrated soil and leaf analysis helps in effective fertilizer recommendations in most of the crops (Smith and Loneragan, 1997; McLaughlin et al., 1999). In oil palm, leaf nutrient analysis is commonly used for estimating fertilizer requirement (Fairhurst and Mutert, 1999; Corley and Tinker, 2003). The relationship between leaf analysis and palm productivity is generally evident, and an assessment of fertilizer needs can be based on such an analysis. However for a cost-effective approach, leaf analysis has to be integrated with soil analysis (Goh et al., 2003). It is therefore pertinent to assess soil nutrient status for effective and sustainable fertilizer management programme in oil palm.

Prasad et al. (2013) reported wide range in quantity of fertilizer applied indicating that oil palms were either under-fertilized or over-fertilized. Also, low cost and high availability of some fertilizers have encouraged farmers to make excessive applications with the belief that high yields would be ensured. However, this management adversely affects soil fertility, productivity, fruit quality and ground water quality. Different amount of fertilizer application to different soil types may alter soil properties. It is therefore pertinent for the farmers to economize on fertilizer adopting a strategy for site-specific and/or area-specific management based on spatial variability of soil properties to make oil palm production environmentally sustainable and economically viable. Spatial variability of soil properties in oil palm plantations have to be carefully evaluated to implement sustainable soil management practices. Thus, the present study was carried out in soils of oil palm plantations south Goa district of India with the following objectives, (i) to estimate the spatial variability of some soil properties through semivariogram anal-

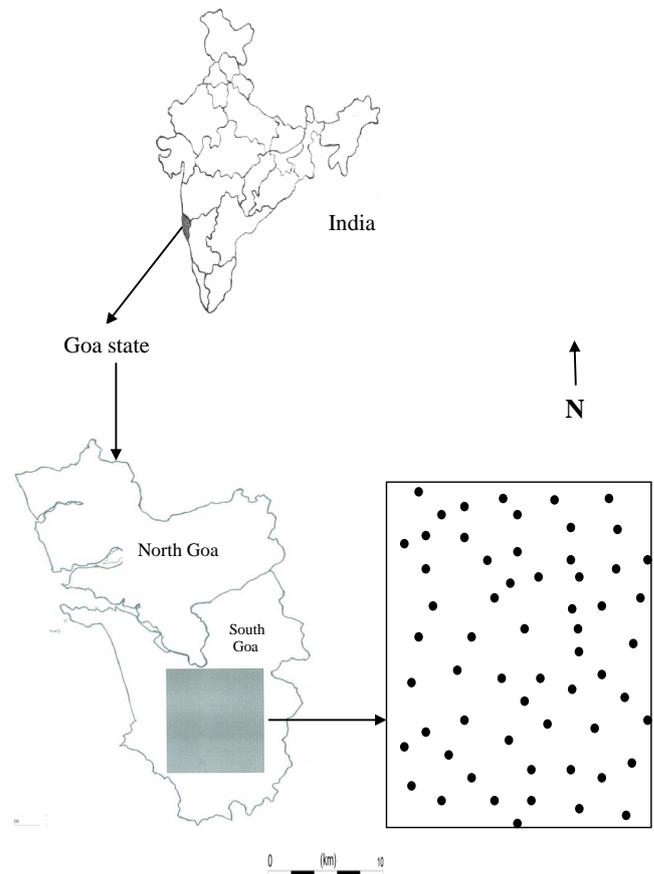


Figure 1. Spatial distribution of sampling points in south Goa district of Goa state (western India).

ysis, (ii) to assess the relationship among the estimated soil properties and (iii) to develop spatial maps for soil properties using the parameters of the best fitted semivariogram model and interpolation using ordinary kriging technique.

2 Material and methods

2.1 Study site

A survey was carried out in south Goa district of Goa state of India during 2012–2013 to find out soil and plant nutritional status in randomly selected 64 tenera oil palm plantations (with 5 to 21 years of age) (Fig. 1). Oil palm is cultivated in an area of approximately 1000 ha which is 1% of agricultural land in the state. The state lies between $15^{\circ}6.8'96''$ to $15^{\circ}41.7'26''$ N latitudes and $74^{\circ}76'60''$ to $73^{\circ}56'78''$ E longitudes with altitude ranging from 4 to 90 m a.s.l. The climate of the area is tropical monsoon type. Hot and humid climate prevails for most of the year. Annual mean rainfall (average of 30 years) is 2926 mm, concentrated from early June to late September. On average, May is the warmest month, with temperature peaks over 35°C and relative humidity of

70 %. Goa experiences short winter seasons between mid-December and February and these months are marked by mean night temperature of approximately 21 °C and a mean day temperature of around 28 °C with relative humidity of 65 %. According to Bhattacharyya et al. (2013), the main soils in the study area are Inceptisols, Ultisols, Entisols and Alfisols (classified as in Soil Survey Staff, 2014), sandy loam to silty loam texture, developed from granite, granite-gneiss, quartzite/schistose and basalt.

2.2 Soil sampling, processing and analysis

A total of 128 soil samples i.e., 64 from 0 to 20 cm (surface) and 64 from 20 to 40 cm (subsurface) depths were collected at random points inside 3 m radius from the palm during the survey to assess soil properties of oil palm plantations at an approximate interval of 1 to 2 km. Five soil samples were collected at random from each sampling location within a radius of approximately 60 cm using a hand auger. The five samples were then mixed to obtain the representative soil sample of the sampling point. The latitude, longitude, and elevation at each sampling point were recorded using a handheld global positioning system (GPS). The soil samples were dried at room temperature (25 ± 3 °C). Stone and debris from samples were removed and then ground to pass a 2 mm sieve. The processed soil samples were tested for acidity (pH), salinity (EC), organic carbon (OC) content, available K ($\text{NH}_4\text{OAc-K}$), available P (Bray's P-1) (Bray's-P), exchangeable Ca^{2+} (Exch. Ca^{2+}), exchangeable Mg^{2+} (Exch. Mg^{2+}), available S ($\text{CaCl}_2\text{-S}$) and hot water extractable B (HWB). Determination of soil pH and EC (1 : 2 soil water ratio (w/v) suspension) were carried out using pH-meter and conductivity meter (Jackson, 1973). Walkley–Black method (Walkley and Black, 1934) was followed for assessing soil OC content. $\text{NH}_4\text{OAc-K}$ was estimated after extracting soil samples with neutral 1 N ammonium acetate solution (Hanway and Heidel, 1952) followed by flame photometry estimation. Available P was extracted using Bray's P-1 reagent (Bray and Kurtz, 1945) and estimated through spectrophotometry. Exchangeable Ca^{2+} and Mg^{2+} were extracted using neutral normal ammonium acetate solution (Jones, 1998) and estimated through atomic absorption spectrometry. Available S was estimated by the turbidity method (Williams and Steinbergs, 1969). HWB content was estimated through Azomethine-H reagent (Gupta, 1967) using spectrophotometry.

2.3 Statistical and geostatistical analysis

The descriptive statistics like minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV), and skewness for soil properties were computed using the SAS 9.2 software pack (SAS, 2011). Relationship among the studied soil properties were established using Pearson's corre-

lation coefficient analysis. Significant differences were observed at $P < 0.05$.

ArcMap 10.1 (ESRI, 2012) was used to analyze the spatial structure of soil properties. Before using geostatistics, normality of data distribution was checked by Shapiro-Wilk test at 5 % (Shapiro and Wilk, 1965). Soil properties like pH and OC content in both the soil layers and $\text{CaCl}_2\text{-S}$ content in subsurface soil layers exhibited normal distribution (Table 1). While, data transformation to normal distribution was carried out for rest of the soil properties. Prior to geostatistical analyses, the data were examined for the presence of trend (by "Geostatistical analyst" of ArcGIS 10.1) and removed (by fitting to second order polynomial). According to McCormick et al. (2009), trend in the variation signals a departure from the intrinsic hypothesis in which the process is assumed to be random and it violates the assumptions on which geostatistics is based on. By removing the trend, it will be possible to more accurately model the variation because the trend will not be influencing the spatial analysis (Kerry and Oliver, 2007). The semivariogram was used to measure spatial variability of soil properties and to obtain input parameters for the kriging method of spatial interpolation (Goovaerts, 1997; Tesfahunegn et al., 2011). It is half of the expected squared difference between paired data values to the lag distance by which locations are separated. The experimental semivariograms of soil properties were derived as described below.

$$\gamma(h) = \frac{1}{2m(h)} \sum_{i=1}^{m(h)} [Z(X_i + h) - Z(X_i)]^2 \quad (1)$$

Where $\gamma(h)$ is the experimental semivariogram, h is the lag, $m(h)$ is number of sample value pairs separated by h , $Z(X_i)$, $Z(X_i + h)$ are sample values at two points at X_i and $(X_i + h)$ locations, respectively. The distance between the sample pairs is rarely equal to h in irregular sampling and h is often represented by a distance interval.

Semivariogram parameters like nugget/sill ratio and range were obtained for soil properties. The nugget/sill ratio was used to classify the spatial dependence of variables (Oliver and Webster, 2014). Ratio values less than or equal to 0.25, between 0.25 and 0.75, more than 0.75 were considered strongly, moderately and weakly spatially dependent, respectively (Behera et al., 2011). Best-fit semivariogram models were selected by cross-validation technique. Mean square error (MSE) was estimated to predict the accuracy of models (Utset et al., 2000).

$$\text{MSE} = \frac{\sum_{i=1}^n [z(x_i, y_i) - z \cdot (x_i, y_i)]^2}{n} \quad (2)$$

Goodness-of-prediction criterium G is one of the methods used for accuracies of interpolated maps (Agterberg, 1984; Tesfahunegn et al., 2011). Accuracies of interpolated maps of studied soil properties were checked by G values. According to Parfitt et al. (2009), positive G values indicate that the map

Table 1. Soil properties of surface (0–20 cm) and subsurface (20–40 cm) layers ($n = 64$ at each case).

Variable	Soil layer	Mean \pm SD	CV (%)	Minimum	Maximum	Skewness	Distribution
pH	Surface	5.35 \pm 0.45	8.64	4.25	6.77	0.18	Normal
	Subsurface	5.28 \pm 0.46	8.63	4.53	6.52	0.65	Normal
EC	Surface	0.13 \pm 0.17	125	0.05	1.06	4.06	Transformed
	Subsurface	0.08 \pm 0.06	75.3	0.03	0.41	3.02	Transformed
OC	Surface	19.8 \pm 8.77	44.4	5.07	48.4	0.83	Normal
	Subsurface	13.2 \pm 7.33	55.5	1.95	31.2	0.75	Normal
NH ₄ OAc-K	Surface	270 \pm 29.9	88.7	58.1	1167	1.80	Transformed
	Subsurface	199 \pm 165	82.8	16.1	856	2.16	Transformed
Bray's-P	Surface	24.7 \pm 3.39	127	0.86	141	2.14	Transformed
	Subsurface	9.78 \pm 13.2	135	0.90	42.3	2.52	Transformed
Exch. Ca ²⁺	Surface	914 \pm 588	64.3	200	2997	1.56	Transformed
	Subsurface	795 \pm 724	91.1	194	5177	3.89	Transformed
Exch. Mg ²⁺	Surface	203 \pm 141	69.3	36.0	744	1.75	Transformed
	Subsurface	225 \pm 156	69.4	24.0	720	1.27	Transformed
CaCl ₂ -S	Surface	23.2 \pm 16.4	70.7	3.00	87.7	1.60	Transformed
	Subsurface	16.3 \pm 10.1	62.0	1.50	43.5	0.93	Normal
HWB	Surface	0.70 \pm 0.38	54.7	0.09	2.10	1.43	Transformed
	Subsurface	0.64 \pm 0.44	68.6	0.04	2.56	1.70	Transformed

SD – standard deviation; CV – coefficient of variation; EC – electrical conductivity, dS m^{-1} ; OC – organic carbon, g kg^{-1} ; NH₄OAc-K, mg kg^{-1} ; Bray's-P, mg kg^{-1} ; exch. Ca²⁺, mg kg^{-1} ; exch. Mg²⁺, mg kg^{-1} ; CaCl₂-S, mg kg^{-1} ; HWB, mg kg^{-1} .

obtained by interpolating data from the samples is more accurate than a catchment average. Negative and close to zero G values indicate that the catchment-scale average predicts the values at unsampled locations as accurately as or even better than the sampling estimates. Ordinary kriging interpolation was carried out to develop spatial distribution maps for soil properties.

3 Results and discussion

3.1 Descriptive statistics of soil properties

The descriptive statistics revealed considerable variability of soil properties in both surface and subsurface soil layers of oil palm plantations (Table 1). The mean values of soil properties were 5.35, 0.13 dS m^{-1} , 19.8 g kg^{-1} , 270 mg kg^{-1} , 24.7 mg kg^{-1} , 914 mg kg^{-1} , 203 mg kg^{-1} , 23.2 mg kg^{-1} and 0.70 mg kg^{-1} for pH, EC, OC, NH₄OAc-K, Bray's-P, exchangeable Ca²⁺, exchangeable Mg²⁺, CaCl₂-S and HWB, respectively, in surface soil layers. Whereas the mean values were 5.28, 0.08 dS m^{-1} , 13.2 g kg^{-1} , 199 mg kg^{-1} , 9.78 mg kg^{-1} , 795 mg kg^{-1} , 225 mg kg^{-1} , 16.3 mg kg^{-1} and 0.64 mg kg^{-1} for pH, EC, OC, NH₄OAc-K, Bray's-P, exchangeable Ca²⁺, exchangeable Mg²⁺, CaCl₂-S and HWB, respectively, in subsurface soil layers. The values of CV for soil properties ranged from 8.63 to 135%. The values of CV for soil pH in both the soil layers revealed their low variability ($\text{CV} < 25\%$). The rest of the soil properties exhibited moderate ($\text{CV} 25\text{--}75\%$) variability except salinity, NH₄OAc-K and Bray's-P in both the soil layers and ex-

changeable Ca²⁺ in subsurface soil layers, which had high ($\text{CV} > 75\%$) variability. Low CV values for soil pH was due to transformed measurement of hydrogen ion concentration. Skewness values of 0.18 to 3.89 for different soil properties revealed that some soil properties were not normally distributed. This variation and non-normal distribution of soil properties in the studied areas may be due to adoption of different soil management practices including variation in fertilizer application and other crop management practices (Teshahunegn et al., 2011; Srinivasarao et al., 2014; Ferreira et al., 2015).

The mean values of soil pH were acidic in both surface (5.35) and subsurface (5.28) soil layers (Table 1). The acidic nature of soil in the studied area may be due to acidic parent material and prevailing rainfall pattern. The values of soil EC indicate the non-saline nature of soils. Soil OC contents varied widely in both surface and subsurface soil layers. Principal reason for variation in soil OC content may be due to adoption of different cultural practices including addition of crop biomass to the soils. Surface soil layers had slightly higher OC content (mean value 19.8 g kg^{-1}) than OC content in subsurface soil layers (mean value 13.2 g kg^{-1}). Surface soil layers had higher NH₄OAc-K, Bray's-P, CaCl₂-S and HWB content compared to that in subsurface soil layers (Table 1). The content of these nutrients varied greatly among the soils because of heterogeneity in fertilizer application in the area. The mean values of exchangeable Ca²⁺ were 914 and 795 mg kg^{-1} for surface and subsurface soil layers, respectively, whereas surface soil layers were having 203 and 225 mg kg^{-1} of mean exchangeable Mg²⁺ content,

Table 2. Pearson's correlation coefficients between soil properties at the surface (0–20 cm) and subsurface (20–40 cm) layers. Only significant coefficients are shown (*, $p < 0.05$; **, $p < 0.01$) ($n = 64$).

Layer		pH	EC	OC	Bray's-P	Exch. Ca ²⁺
Surface	NH ₄ OAc-K		0.45**			
	Bray's-P					
	Exch. Ca ²⁺	0.67**		0.26*		
	Exch. Mg ²⁺					0.37**
	CaCl ₂ -S		0.31*		0.44**	
	HWB			0.30*		
Subsurface	NH ₄ OAc-K		0.48**			
	Bray's-P		0.32*			
	Exch. Ca ²⁺	0.42**				
	Exch. Mg ²⁺					0.33**
	CaCl ₂ -S				0.36**	

EC – electrical conductivity, dS m⁻¹; OC – organic carbon, g kg⁻¹; NH₄OAc-K, mg kg⁻¹; Bray's-P, mg kg⁻¹; exch. Ca²⁺, mg kg⁻¹; exch. Mg²⁺, mg kg⁻¹; CaCl₂-S, mg kg⁻¹; HWB, mg kg⁻¹.

respectively. Other studies reported similar results highlighting different distribution pattern of soil properties, primary, secondary and micronutrients under different soil-crop management situations (Franzlubbers and Hons, 1996; Sharma et al., 2005; Behera and Shukla, 2013).

3.2 Relationship among soil properties

The exchangeable Ca²⁺ content increased significantly with soil pH (Table 2). Behera and Shukla (2015) also recorded a positive and significant relationship of soil pH and soil OC with K, exchangeable Ca²⁺ and exchangeable Mg²⁺ content in some cropped acid soils of India. Soil OC content in surface layers was positively and significantly correlated with exchangeable Ca²⁺ and HWB ($P < 0.05$). Most of the soil properties which influence nutrient storage and availability to plants are influenced by SOM type and content (Foth and Turk, 1972). Increased soil EC content led to higher NH₄OAc-K in both soil layers ($P < 0.01$), and higher CaCl₂-S in surface layer and Bray's-P in subsurface layer ($P < 0.05$). Soil EC does not directly affect plant growth but has been used as an indirect indicator of the amount of nutrients available for plant uptake and salinity levels (Corwin and Lesch, 2005). EC has been used as a surrogate measure of salt concentration, organic matter, cation-exchange capacity, soil texture, soil thickness, nutrients, water-holding capacity, and drainage conditions. In site-specific management and high-intensity soil surveys, EC is used to partition units of management, differentiate soil types, and predict soil fertility and crop yields (Corwin and Lesch, 2005).

3.3 Spatial structure and distribution of soil properties

The best-fitted semivariograms for studied soil properties are depicted in Fig. 2, whereas their parameters are given in Table 3. The best fit models were exponential, Gaussian, sta-

ble, exponential, K-Bessel and circular for different soil layers. The value of nugget varied widely for soil properties. It was highest for exchangeable Ca²⁺ and the lowest for soil pH. A higher nugget value indicates that the selected sampling distance could not capture well the spatial dependence, whereas lower nugget value reveals low spatial variability within small distances. Our findings are in line with the observations made by Tesfahunegn et al. (2011).

The nugget/sill ratio values ranged from 0.00 to 0.70 with strong (for surface pH, subsurface EC, and both surface and subsurface exchangeable Ca²⁺) to moderate (for rest soil properties) spatial dependency for the soil properties. Moderate to strong spatial dependence of soil properties are ascribed to intrinsic factors (such as mineralogy) as well as extrinsic factors including fertilization and other crop management practices (Cambardella et al., 1994). The range of the semivariogram is the maximum distance over which the soil properties of two samples are related. This can be an effective criterion for the evaluation of sampling design and the mapping of soil properties (Utset et al., 2000; Zhang et al., 2015). The range values of soil properties ranged from 878 to 4244 m (Table 3). Samples separated by distances lower than the range are spatially related, whereas those separated by a distance greater than the range are considered not to be spatially related. The soil sampling distance in the range of 1 to 2 km in this study was close with models range value. Level of similarity or disturbance of soil condition can be assessed by spatial dependency. A large range indicates that the value of measured soil property is influenced more by natural and anthropogenic factors over great distances than properties having smaller ranges (Lopez-Granados et al., 2002). Thus, a range value of about 4244 for CaCl₂-S in the study region indicates that the measured values can be influenced over great distances comparison with other soil properties having smaller ranges. This is in agreement with the find-

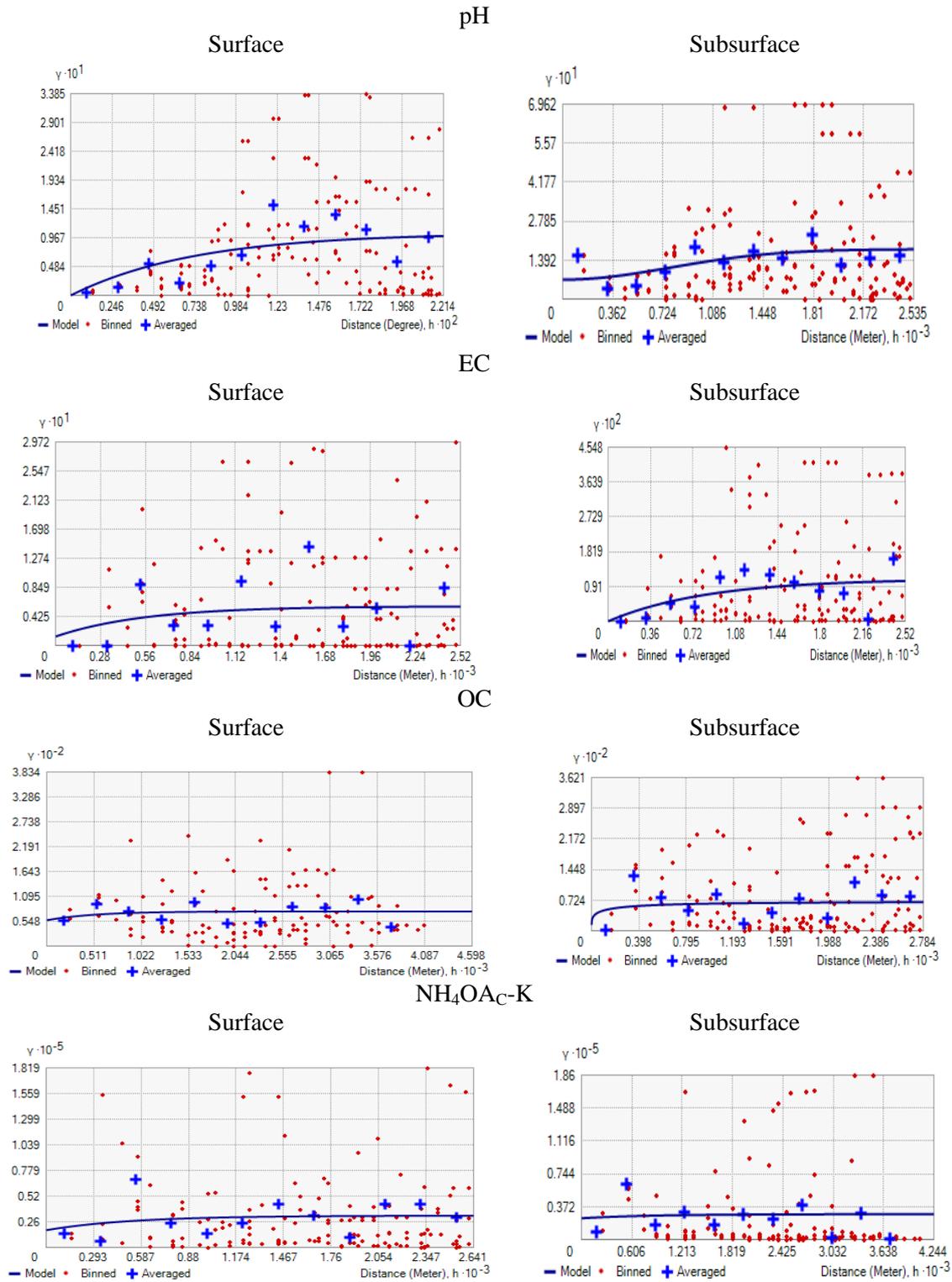


Figure 2.

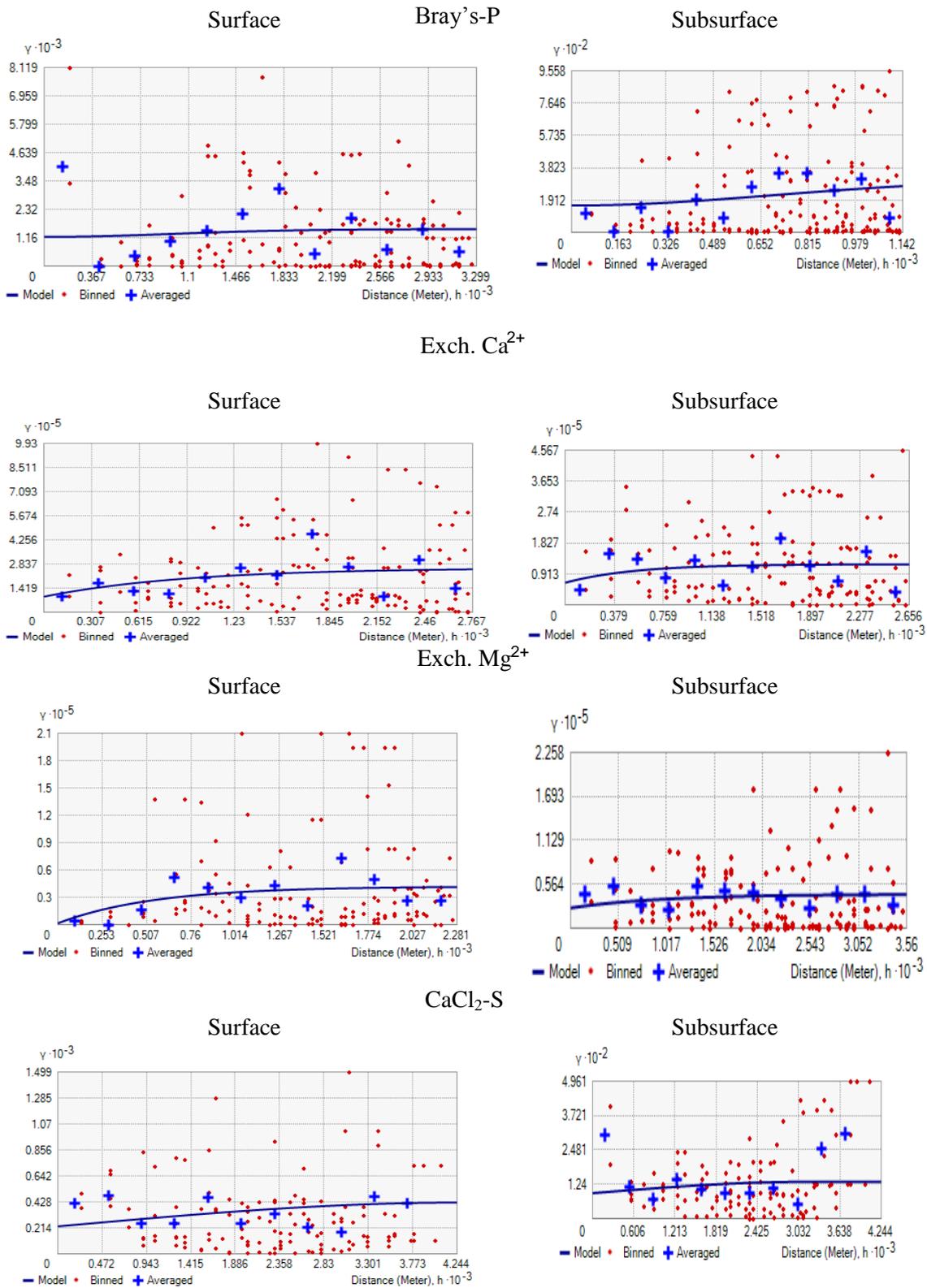


Figure 2.

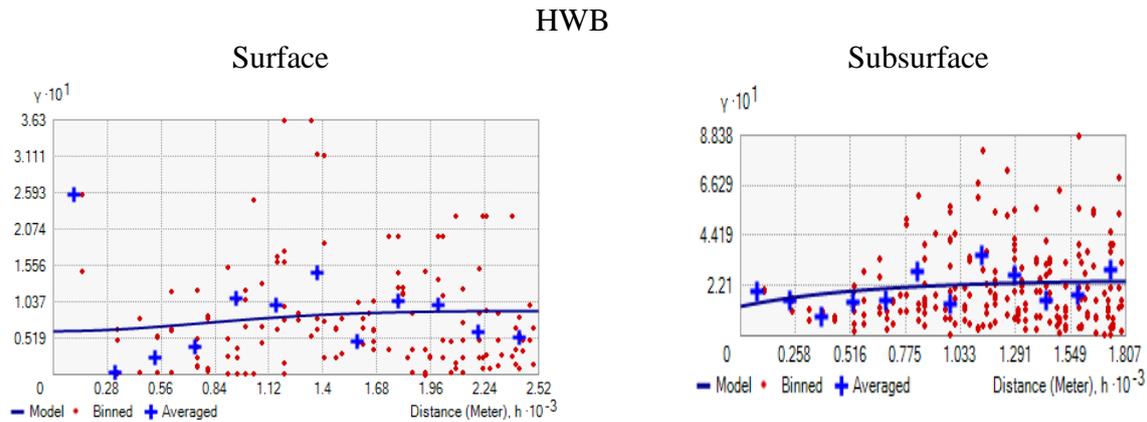


Figure 2. Semivariograms of soil properties in surface (0–20 cm) and subsurface (20–40 cm) soil layers.

Table 3. Semivariogram parameters of soil properties of studied areas.

Variable	Soil layer	Model	Nugget	Sill	Nugget: sill ratio	Spatial class	Range (m)	Obs. vs. est.	MSE	G (%)
pH	Surface	Exponential	0.00	10	0.00	Strong	2367	0.915	0.61	54
	Subsurface	Gaussian	0.06	0.18	0.33	Moderate	1892	0.888	0.52	53
EC	Surface	Stable*	0.02	0.06	0.33	Moderate	1656	0.892	0.00	48
	Subsurface	Exponential*	0.00	0.01	0.00	Strong	2519	0.953	0.00	43
OC	Surface	K-Bessel	44.1	93.61	0.47	Moderate	1579	0.961	1.56	35
	Subsurface	Stable	14.36	69.4	0.21	Strong	1579	0.943	1.89	51
NH ₄ OAc-K	Surface	Exponential*	17 546	32 272	0.54	Moderate	1697	0.912	31.3	55
	Subsurface	Exponential*	17 568	35 786	0.49	Moderate	1697	0.855	22.6	47
Bray's-P	Surface	Gaussian*	1193	1708	0.70	Moderate	2401	0.981	22.9	48
	Subsurface	K-Bessel*	159.43	323	0.49	Moderate	878	0.915	22.6	39
Exch. Ca ²⁺	Surface	Exponential*	91 642	260 984	0.35	Strong	2767	0.935	123.4	23
	Subsurface	Exponential*	65 328	120 128	0.54	Strong	1589	0.971	165.2	24
Exch. Mg ²⁺	Surface	Exponential*	1574	41 995	0.04	Moderate	1656	0.852	54.3	38
	Subsurface	Exponential*	26 151	43 836	0.60	Moderate	2905	0.984	42.1	51
CaCl ₂ -S	Surface	Spherical*	234	410	0.57	Moderate	4244	0.912	0.04	38
	Subsurface	Spherical	92.2	133.4	0.69	Moderate	3141	0.955	0.03	40
HWB	Surface	Gaussian*	0.06	0.09	0.67	Moderate	1888	0.963	0.02	60
	Subsurface	Exponential*	0.13	0.24	0.54	Moderate	1807	0.961	0.02	58

* Transformation for normal distribution.

EC – electrical conductivity, dS m⁻¹; OC – organic carbon, g kg⁻¹; NH₄OAc-K, mg kg⁻¹; Bray's-P, mg kg⁻¹; exch. Ca²⁺, mg kg⁻¹; exch. Mg²⁺, mg kg⁻¹; CaCl₂-S, mg kg⁻¹; HWB, mg kg⁻¹; MSE-mean square error; G – goodness-of-prediction criterium.

ings of Foroughifar et al. (2013) who reported range values of 1600 to 7364 m for different soil properties of northwest Iran. Several studies also reported different range values of 2.5 to 9.1 km for DTPA extractable Zn (Behera et al., 2011), 3.30 to 28 km for DTPA extractable Cu (Behera et al., 2012), and 0.7 to 66 km for DTPA extractable Mn and 2.7 to 5.2 km for DTPA extractable Fe (Behera and Shukla, 2014) in some acid soils of India. According to Kerry and Oliver (2004), the sampling interval should be less than half the semivariogram range. It is therefore recommended that for ensuing studies aimed at characterizing spatial dependency of soil properties in similar areas, soil sampling should be done at distances shorter than the range found in this study.

Cross-validation technique was used to identify the most accurate predictions for soil properties with the lowest MSE values (Table 3). Lowest MSE values indicate that kriging predictions of soil properties are closer to measured values. The accuracy of kriged interpolation maps of soil properties was also measured by the *G* values (Table 3) which varied from 23 (for exchangeable Ca²⁺ in surface layer) to 60% (for HWB in surface layer). This is in consistent with the observations made by Mueller et al. (2003) and Tesfahunegn et al. (2011). The *G* values for the soil properties reveal the prediction capacity of the data sets using kriging from the sample points as compared to average values of the area. Greater than zero *G* values indicate that kriging is more accurate than

the average value of the area. For example, the G value of 54 % for soil surface pH indicates that the kriged pH map is 54 % more accurate than those achieved using average value of the area. Thus, the use of kriging interpolation technique was appropriate for developing maps of soil properties.

Spatial distribution maps (Fig. 3) of different soil properties revealed that oil palm plantations of the area could be divided into homogenous small zones depending upon the different nutrient ranges. Distribution map of pH in surface soil layers revealed almost all the area having pH of 5.00 to 6.00. Low pH values occurred in southern and south-eastern parts. In subsurface soil layers, low pH of < 5.00 occurred in south-eastern part whereas relatively higher pH prevailed in north-western part. According to Dessai (2011), areas having low pH values compared to other areas may be due to acidic parent material from which the soil developed and different soil management practices. Soil EC had irregular distribution pattern whereas relatively low values of EC were recorded in north-western parts of both the soil layers. This may be due to sandy loam soil texture and the presence of low OC in north-western part (Bhattacharyya et al., 2013). Higher EC values in other parts of surveyed area probably due to silt loam soil texture with high water table (Pal et al., 2014). Higher amount of soil OC was found to be distributed in the southern and south-eastern parts in surface as well as subsurface soil layers. This may be ascribed to prevalence of higher slope and low rate of SOM mineralization in south-eastern parts compared to other areas. Lower amounts of $\text{NH}_4\text{OAc-K}$ were recorded in western parts in both the soil layers. Higher amount of Bray's-P was found to be distributed in most parts in surface soil layers whereas low amount of Bray's-P occurred in south-western part. Bray's-P distribution was irregular in subsurface soil layers. Build up of P in surface layers may be due to continuous P addition and their fixation in soil which is acidic in nature. Exchangeable Ca^{2+} exhibited irregular distribution pattern in both the soil layers. In surface as well as subsurface soil layers, lower amount of exchangeable Mg^{2+} was found to be distributed in southern parts as compared to that in northern parts. Irregular distribution pattern of $\text{CaCl}_2\text{-S}$ was recorded in surface soil layers whereas low values of $\text{CaCl}_2\text{-S}$ were observed in southern part of the study area. Higher amount of HWB was found to be distributed in central part in contrast to low values in north-western and south-eastern part in surface soil layers. Distribution pattern of HWB was irregular in subsurface soil layers. The different distribution variability of the soil properties in oil palm plantations of this area is predominantly due to climate and landscape along with farm practices including application of different quantities of nutrients through fertilizers (Behera et al., 2016). The kriged distribution maps for different soil properties providing quantitative information about soil properties in both the soil layers is of great use for plantation staff, farm managers, extension officers and farmers. This will help in visualizing soil fertility status for planning appropriate strategies for efficient

site specific soil nutrient management and variable-rate fertilizer application technology. It leads for obtaining optimum output and oil palm yield which can provide environmentally sustainable maximum return to farmers with optimum input utilization combined with best management practices (Fu et al., 2010; Behera et al., 2012). The areas with low and medium nutrient status require more amount of fertilizer application as compared to areas having high nutrient status. For example, exchangeable Mg^{2+} status is low in southern part of the area compared to northern part.

4 Conclusions

Geostatistical analysis is the key for studying the spatial variability of soil properties for sustainable soil resource management. The mean values of soil properties in surface and subsurface layers of study area were 5.35 and 5.28 (pH), 0.13 and 0.08 dS m^{-1} (EC), 19.8 and 13.2 g kg^{-1} (OC), 270 and 199 mg kg^{-1} ($\text{NH}_4\text{OAc-K}$), 24.7 and 9.78 mg kg^{-1} (Bray's-P), 914 and 795 mg kg^{-1} (exchangeable Ca^{2+}), 203 and 225 mg kg^{-1} (exchangeable Mg^{2+}), 23.2 and 16.3 mg kg^{-1} ($\text{CaCl}_2\text{-S}$) and 0.70 and 0.64 mg kg^{-1} (HWB), respectively. Studied soil properties had large variability in spatial distribution pattern in both surface and subsurface soil layers of oil palm plantations. Positive and significant correlations were recorded between soil pH and exchangeable Ca^{2+} , soil EC and $\text{NH}_4\text{OAc-K}$, Bray's-P and $\text{CaCl}_2\text{-S}$ and exchangeable Ca^{2+} and exchangeable Mg^{2+} in both the soil layers. Best-fit models of studied soil properties were exponential, Gaussian, stable, K-Bessel and spherical with moderate to strong spatial dependency. The prediction maps generated by geostatistical analysis are useful for site-specific soil nutrient management in oil palm plantations of the area by delineating management zones and adoption of variable fertilizer application strategies.

5 Data availability

The data are available in data bank of ICAR-Indian Institute of Oil Palm Research, Pedavegi, West Godavari, Andhra Pradesh, India (<http://www.dopr.gov.in>).

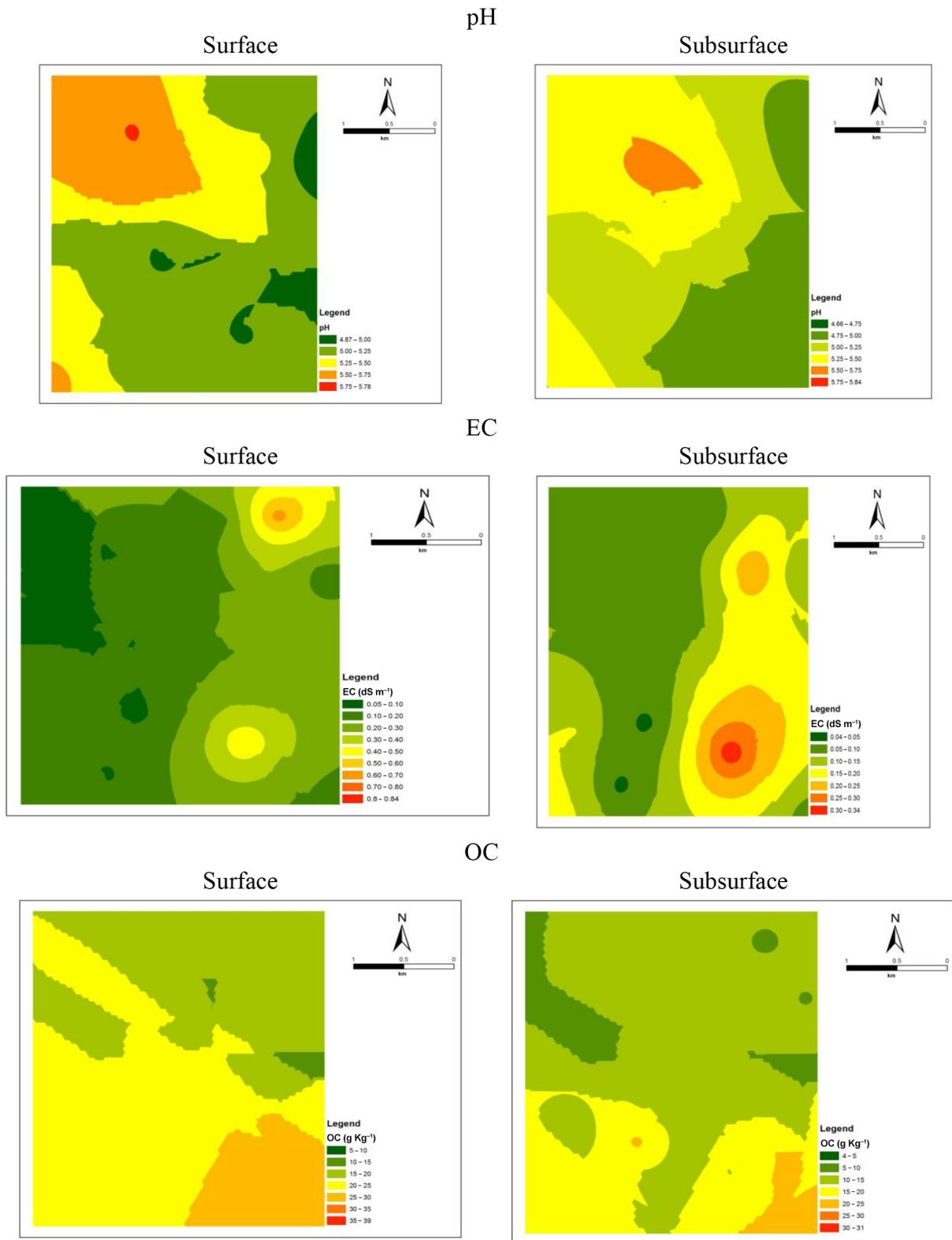


Figure 3.

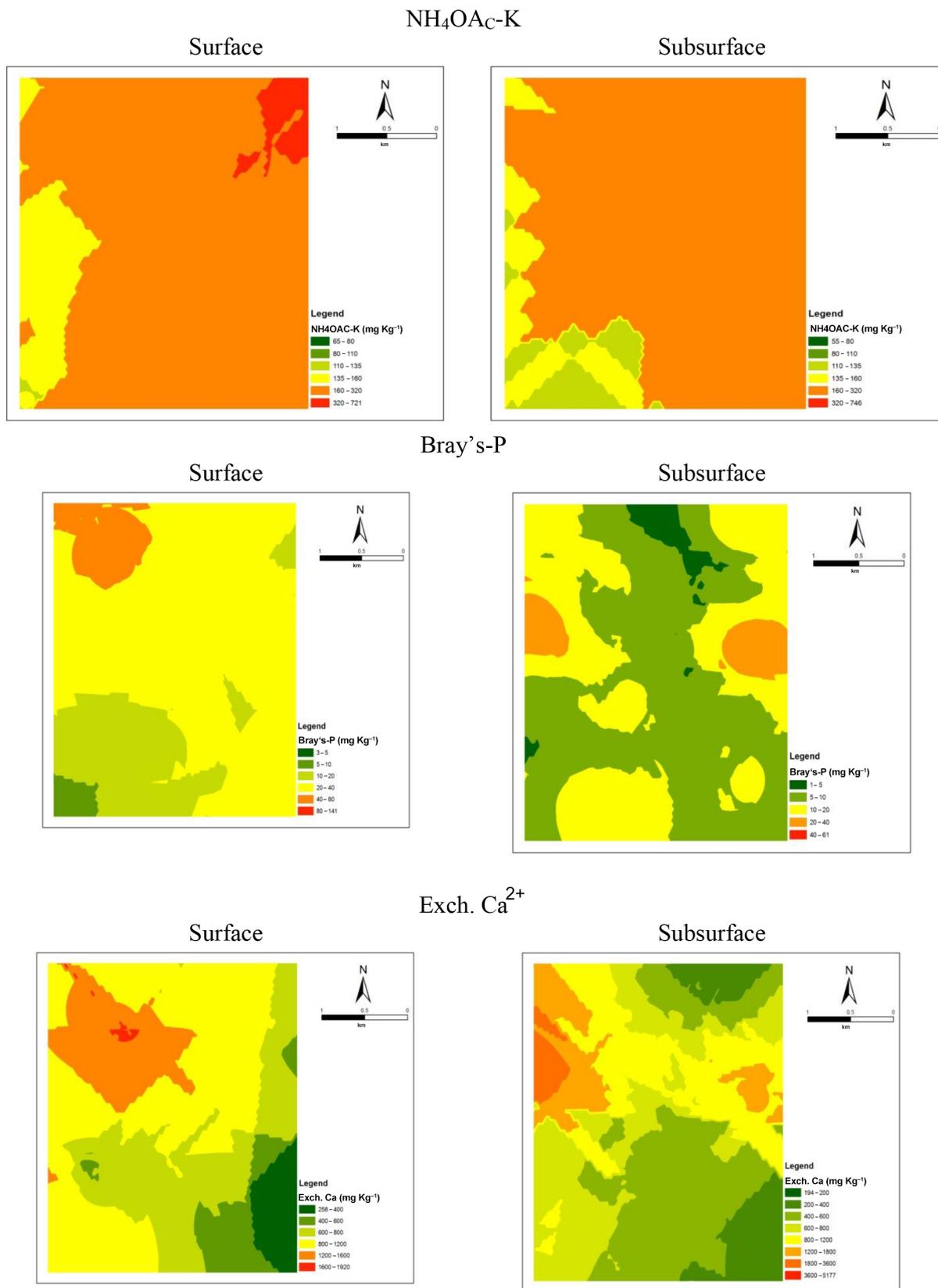


Figure 3.

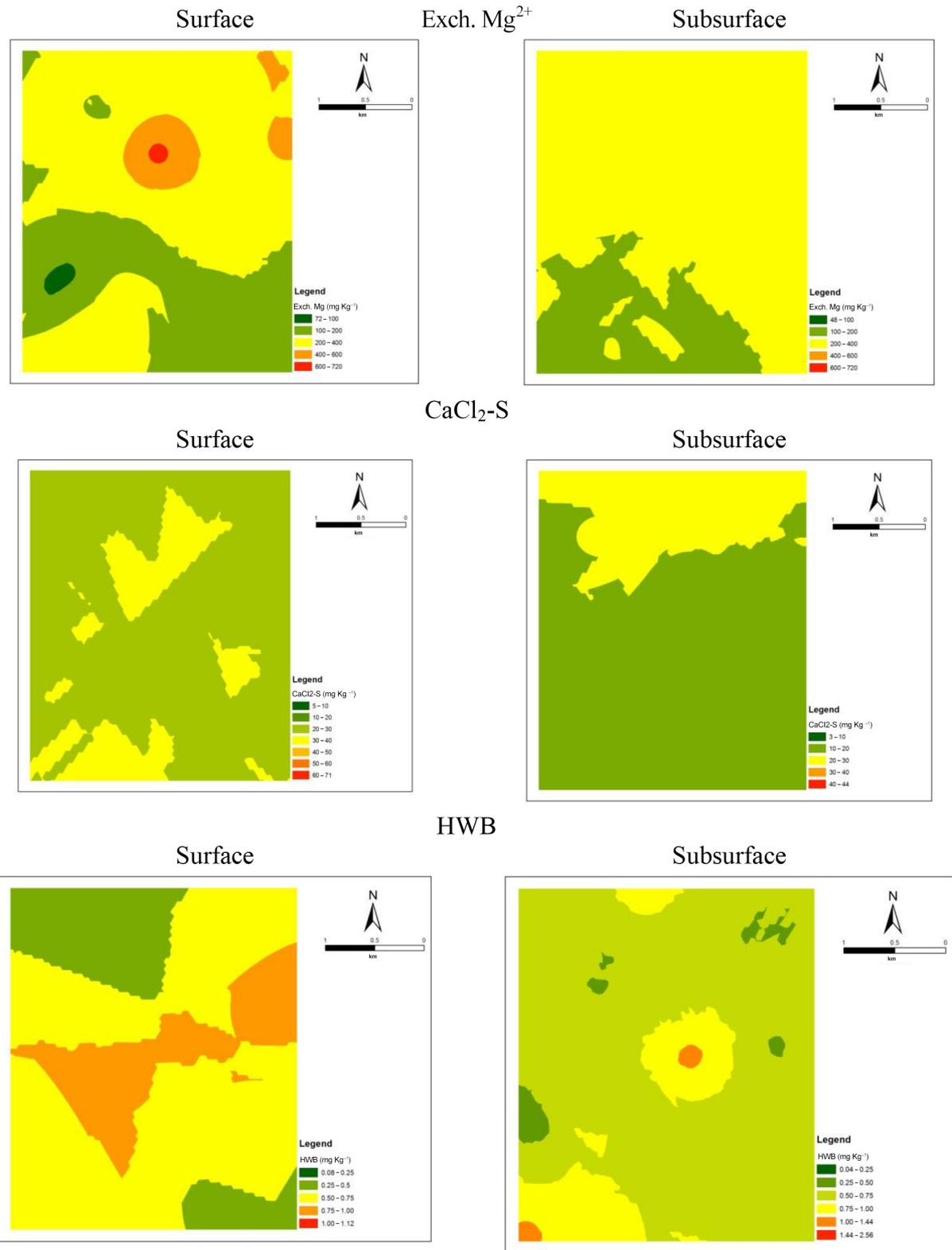


Figure 3. Kriged interpolation maps of soil properties in surface (0–20 cm) and subsurface (20–40 cm) soil layers.

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