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Assessment of spatial variability of soil properties using geostatistical approach of lateritic soil (West Bengal, India)

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ABSTRACT

Degradation of soil due to unsuitable land management practices is a chief impairment of optimum land productivity. The spatial variability of soil properties is needed for agricultural productivity, food safety and environmental modeling. The present study was conducted in lateritic soils of West Bengal, India to understand the spatial variability of soil properties using a geostatistical model. Nitrogen (N), soil pH, electrical conductivity (EC), Phosphorus (P), Potassium (K) and organic carbon (OC) were measured. Surface maps of soil properties were prepared using the semivariogram model through Kriging techniques. A positive correlation was observed between OC and N. The Quantile-quantile plots showed a normal distribution of EC, K, pH, N, and OC. The value for nugget/sill of K, N, and EC were 0.25–0.75 indicating moderate spatial autocorrelation among the variables. Phosphorus (P) was highly concentrated in the eastern part, whereas the agglomeration of higher EC was found in the north east and south west corner of the study site. The cross validation results illustrated the smoothing effect of the spatial prediction. The present study suggests that the geostatistical model can directly reveal the spatial variability of lateritic soils and will help farmers and decision makers for improving soil-water management.

Introduction

Restoration of soil must be improved for achievement of a sustainable agricultural system [1]. Accurate estimation of quantitative information on spatial variability of soils is significant for intensive agriculture, sustainable development and natural resource management [2–4]. Spatial distribution patterns of soil properties is a pervasive characteristic of natural communities of living organisms [5] and a key driver of bio-physical processes [6]. Several attempts have been made to investigate the causes of removal of soil and the temporal variation of physical characteristics of soil in the region [7–9]. However, most studies spotlight usually of the soil samples obtained from agricultural fields with special history of agricultural recuperation and remedial measure [10,11]. Spatial variability of soil properties has been studied by earlier researchers in various soils under diverse management systems worldwide [12,13]. The geographical distribution of chemical properties of soil like pH, electrical conductivity (EC), organic carbon (OC) content, nitrogen (N), Phosphorus (P), and Potassium (K) in lateritic soils of under-developed countries (like India) is weakly implicit and used for modern spatial prediction techniques [12]. Therefore, improving knowledge of the spatial distribution of soil characteristics will facilitate sustainable farming and ecological management practices by recognition of site-specific soil conservation [14].

There are a number of traditional statistical techniques available for quantifying the spatial distribution of soil properties. Geostatistics is an efficient method of study for spatial distribution of soil properties and their inconsistency [12,15]. Estimation through spatial statistical tools aids in forecasting values at unsampled sites by fascinating in the geographical association between projected and sampled points and reducing the variance of assessment error as well as execution costs [12,16]. Previous studies have applied to assess spatial association in soils and to evaluate the geographical changeability of soil characteristics [17,18]. reported that Kriging and Co-kriging are more suitable techniques in comparison to inverse distance weighting (IDW) for acquiring precise information of the geographical distribution of soil properties.

Weller et al. [19] conducted different geostatistical techniques for spatial variability of soil properties and reported the Kriging technique is better than any other technique [20]. Adopted three geostatistical techniques such as Kriging, IDW, and Radial Basis Function (RBF-

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Spline) to examine the spatial distribution of the soil pH and organic content but the results of Kriging were most suitable among other techniques.

Out of the total 8.87 m ha, West Bengal alone contributed about 2.2 m ha of soil erosion in India [21]. Soil loss is a critical concern that pretense serious intimidation to the ecological environment and human livelihood in western part of Paschim Medinipur in West Bengal (India) due to undulating topography with unsuitable land management practices [22]. Scrubland and forest have been domesticated in most of the area for feeding the population, thereby resulting in severe soil erosion and ecosystem destruction. However, excessive soil erosion in the west and southwest part of Paschim Medinipur district than the tolerance limit brought the un-sustainability of the production system and thereby accompanying ecological problems. Therefore, appraising the geographical distribution of soil properties in the lateritic upland region of Paschim Medinipur district, West Bengal in India is imperative for conniving outline for sustainable soil conservation. This study is concerned with the geographical allocation of topsoil properties like soil pH, Nitrogen (N), Phosphorus (P), Potassium (K), electrical conductivity (EC), and organic carbon (OC) using classical and geostatistical methods to understand the spatial association between soil nutrients in agriculture potential region for site-specific soil management practices.

Materials and methods

Study area

A pilot study was carried out in two mouzas (Adali and Hatia Mouza), Goaltore Farm Area of Paschim Medinipur district in West Bengal, India which is geographically extended between 22° 44′ 336” N – 22° 45′ 909” N latitude and 87° 07′ 210” E – 87° 08′ 884” E longitude measuring a total area of 45 ha (Fig. 1). Geomorphologically, the study area is undulating in nature on the upper part and the lower portion is characterized by gentle slopes. Annual average rainfall is ~1450 mm and approximately ~70% rainfall is received during June and September. The average yearly temperature is about 28.4° C in the dry season (November–February). The rainfall erosivity factors (*R*) ranges from 1200 to 1500 MJ mm ha^{-1} h^{-1} $year^{-1}$ [23]. The area is intermittently linked with rainfed cultivation practice with soil loss and less productivity of crop yield. Lateritic and younger alluvial soils are the predominant soil in the study area. Land use/land cover characteristics of the study area were classified into five types, namely grassland/scrub land (10.62%), degraded vegetation cover (2.09%), fallow land/barren land, canal and road. Most of the area in the study site is covered with fallow land/barren land stretching over 81.53%.

Soil sampling and analysis

A field survey was conducted to analyze the soil properties in the proposed farm area. A systematic random technique was used for field sampling during 6–7 April 2017 to study the soil nutrient status. 27 samples were collected from different land cover regions, namely grassland/scrub land, degraded forest and fallow land/barren land of the proposed farm area. A portable GPS was employed to collect the spatial location from each sample site. The soil samples were collected from five soil cores of undisturbed topsoil sample at depths ranges between 0 and 20 cm. Soil samples were desiccated and conceded through a 2 mm sieve for laboratory analysis textural characteristics (e.g., pH, EC, P, K, and OC). Soil texture was analysed using mechanical sieves. Soil pH was measured with pH- meter (Model: ML 962). Organic carbon concentration was determined by Walkely-Black Wet oxidation method [24]. Soil available P was measured by Spectrophotometer, ensuing wet ingestion in concentrated H_2SO_4 [25]. Potassium (K) was measured by Flame Spectrophotometer following wet digestion in HF-$HClO_4$ [26]. Nitrogen (N) was calculated using the method followed by Ref. [27].

Statistical analysis

A descriptive statistical analysis was applied to the collected data of all variables. The correlations among OC other soil properties (N, P, K, EC and soil pH) were delineated. The statistical packages for social sciences (SPSS v18.0) software was used for statistical analysis. Geographical locations of sampling points were recorded by GPS handset. Exploratory analysis of soil properties in farm areas was illustrated through trend analysis using the *Geostatistical Ánalyst* of ArcGIS v9.0 software package.

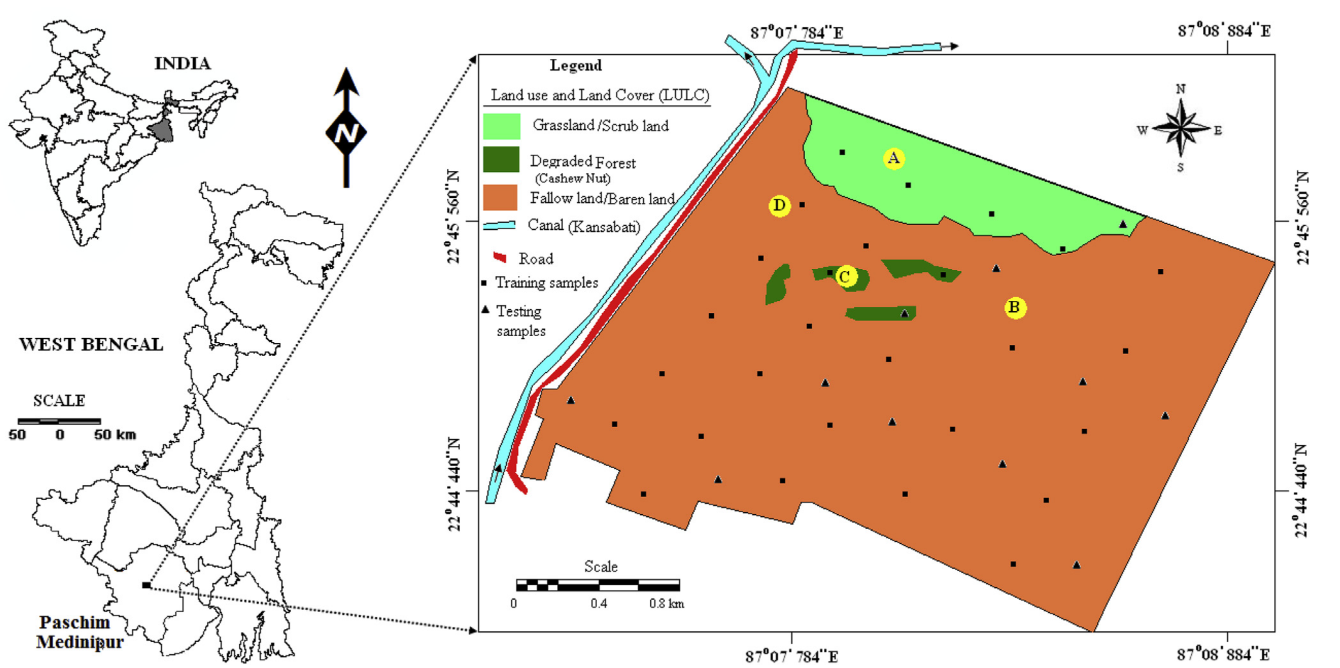

Fig. 1. Location of the study area and sampling sites.

Geostatistical analysis

Semivariogram was calculated to examine the spatial correlation within the measured data points. Geostatistical methods were employed to comprehend soil properties and its association with relief factors and land use characteristics. Spatial inconsistency is estimated as a semivariogram which portrayed the mean square variability between the two neighbouring sample locations of distance h as shown in Eq. (1):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(H)} [z(x_i + h) - z(x_i)]^2 \tag{1}$$

Where γ (h) = magnitude of the lag distance between the two samples location.

N (h) = number of observation pairs separated by distance h,
z (xi) = random variable at location x_i.

The values of semivariogram increase from minimum to maximum values demonstrating higher spatial autocorrelation at the small lag distance [28]. The soil variability data has been confirmed by a histogram analysis and Quantile-quantile (Q-Q) plots to observe the normal distribution pattern of the data variables. Presence of global trends in geographical data of soil properties was recognized by the semivariogram model through curve fitting techniques. The curve through the projected points was flat, indicating on global trend exists. While fitting the semivariogram model for the data, it was visually observed that the model should pass through the centre of the cloud of binned values and also it should pass as closely as possible to the averaged values (blue crosses). The ratio of Nugget and Sill [$C_0/(C_0+C)$] can be used to indicate the degree of spatial correlation of soil properties [29].

Predictive maps of soil properties were generated using a semivariogram model through Ordinary Kriging (OK). OK was used to transform soil samples in point location data into incessant fields of soil properties. Variograms from ArcGIS 8.1 software package were used to predict maps of soil properties. OK model is the most familiar type of Kriging and provides an accurate estimate for an area around a measure sample [8]. Finally, a cross-validation approach was conducted to evaluate the efficiency and error of the of the prediction maps for soil properties. The root-mean-square-error (RMSE) and the mean error (ME) of the model were also calculated. A value of RMSE close to zero illustrates the accuracy of prediction of the model. The following formulas were followed to calculate the RMSE and ME values:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} [Z(x_i) - Z^*(x_i)]^2} \tag{2}$$

$$ME = \frac{1}{n} \sum_{i=1}^{n} [Z(x_i) - Z^*(x_i)] \tag{3}$$

Result and discussion

Descriptive statistical analysis of soil properties

The descriptive characteristics of soil properties were represented in Table 1. Soil pH had a mean of 4.63 with value of SD and CV being 0.257 and 5.30% respectively in the top soil layer. The CVs of available N is less than 15% and available P and available K exceeded 35%, which shows substantial geographical dissimilarity in the P and K properties within the study area. The mean value of EC of the study area was 32.84 µs with more than 28% CVs. The average concentrations of N, P and K at a depth of 0–20 cm were 30.48%, 2.744% and 48.22% respectively for all sampling points. Average values for all of these properties peaked at a depth between 0 and 20 cm and dropped towards the north-east part of the study area. The descriptive characteristics of soil properties imply that distribution of soil properties varies from slightly negatively skewed (skewness ≤ −0.47) to moderately positive skewed (skewness > 2.67). The median values were very near to the mean values (excluding in Silt), representing the nonappearance of outliers in the calculation of central tendency for the soil characteristics analysis. The CV indicates the overall variation of soil characteristics, varying from low to high values based on Warrick guidelines [30]. The maximum variation for CV was documented in P (67.99%), and the smallest observations recorded for clay soil (0.23%). This changeability can be attributable to the rolling nature of the relief and non-uniform management of fallow land with degraded vegetation cover, ensuing in noticeable variations in the surface soil within small distances.

Correlation analysis

A correlation matrix was calculated to understand the association between soil nutrients (Table 2). OC concentration was significantly and positively correlated with N. Subsequently, negative correlation was observed between OC and K. The value of N was strongly connected with OC concentration ($r = 0.201, p < 0.05$), but its coefficient of correlation with K was negative and very weak. Correlations of P with N, pH and EC were also weak. In addition, K, pH and EC had significant positive correlations with each other. The difference in OC concentration was instigated by natural circulation of organic matter. Consequently, soil nitrogen level is influenced by accumulation of OC through soil micro-organisms. Different concentrations of P and K can be caused by different effects of organic matter, different pH values, and mineral composition. To the depth of 0–20 cm, the strong positive correlation between soil OC concentration and topographic attribute reveals that OC concentration decreases at higher elevation. The coefficient of correlation between OC and elevation was strong and positive ($r = 0.516$, $p < 0.05$).

Geostatistical analysis

The results of autocorrelation functions portrayed variation in geographical variation of soil properties. The significant confidence interval of the autocorrelation was estimated though 95% cumulative

Table 1
Descriptive statistics of soil properties in goaltore farm area (n = 27).

Descriptive Statistics	Sand (%)	Silt (%)	Clay (%)	N (ppm)	P (ppm)	K (ppm)	Soil pH	Organic Carbon (%)	EC (µs)
Min	10.48	7.7	8.87	23.8	1.4	25	4.63	0.16	14.3
Max	75.45	50.39	53.20	40.6	8.6	77.5	5.51	0.43	54.8
Mean	40.84	21.98	35.52	30.48	2.74	48.22	4.89	0.29	32.84
Median	39.58	24.18	35.23	29.4	2.3	42.5	4.86	0.29	31.7
SD	11.22	6.89	8.83	4.02	1.56	15.23	0.26	0.06	9.10
CV (%)	0.26	0.25	0.23	13.682	67.99	35.84	5.30	22.39	28.71
Skew	0.64	0.56	−0.47	0.75	2.67	0.58	0.61	−0.047	0.55
Kurt	0.59	4.28	0.15	0.40	7.70	−0.67	−0.14	−0.06	1.14

Table 2
Correlation matrix among the variables.

	N	P	K	pH	OC	EC
N	0					
P	0.045077	0				
K	−0.00498	−0.18378	0			
pH	−0.29095	0.00799	0.101976	0		
OC	0.201077	−0.27346	0.195177	−0.0354	0	
EC	0.113927	0.102371	0.35282	0.368164	−0.1320	0

probability for a standardized normal distribution [31,32]. The Quantile–quantile (Q-Q) plot showed that N, P, K, pH, and EC exhibited a normal distribution between the actual and predictive value (Fig. 2). The scatter plots between the observed and predicted values were illustrated in Fig. 3. Table 3 represents the key parameters of semivariogram models. The best fitting models of semivariogram for N, P, K, pH, and EC are portrayed in Fig. 4. Their optimal theoretical model is considered as an exponential curve. The R^2 values were calculated to measure the goodness of fit [33]. The coefficient of determination (R^2) of all variables, except for P, K, and EC were greater than 0.5, indicating a good fit (Table 3). Nitrogen (N) had a moderate fit, with R^2 values of 0.48. The residual sum square (RSS) were all approximate near to 0, but the theoretical model for pH and OC weakly fitted with R^2 values of 0.43 and 0.41 respectively. This result indicates that theoretical models of N, P, K and EC are better to imitate the geographical distribution characteristics of such soil properties, whereas the investigational data series of P, OC and pH represent strong the spatial associations.

The information derived through semivariograms determines the continuation of different spatial characteristics for soil properties

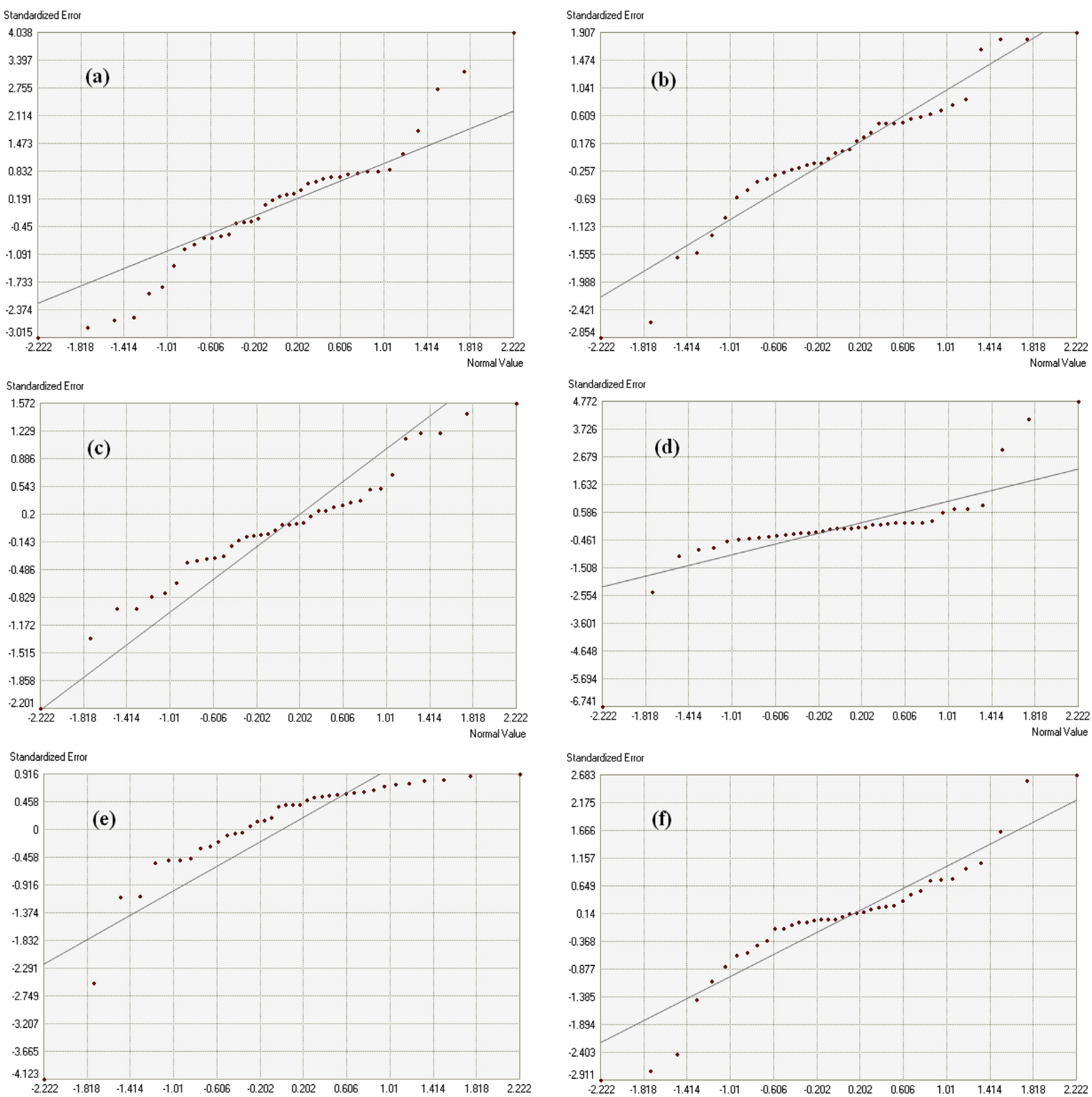

Fig. 2. Q-Q Plots for soil properties; (a) K, (b)pH, (c) N (d) OC, (e)P (f) EC.

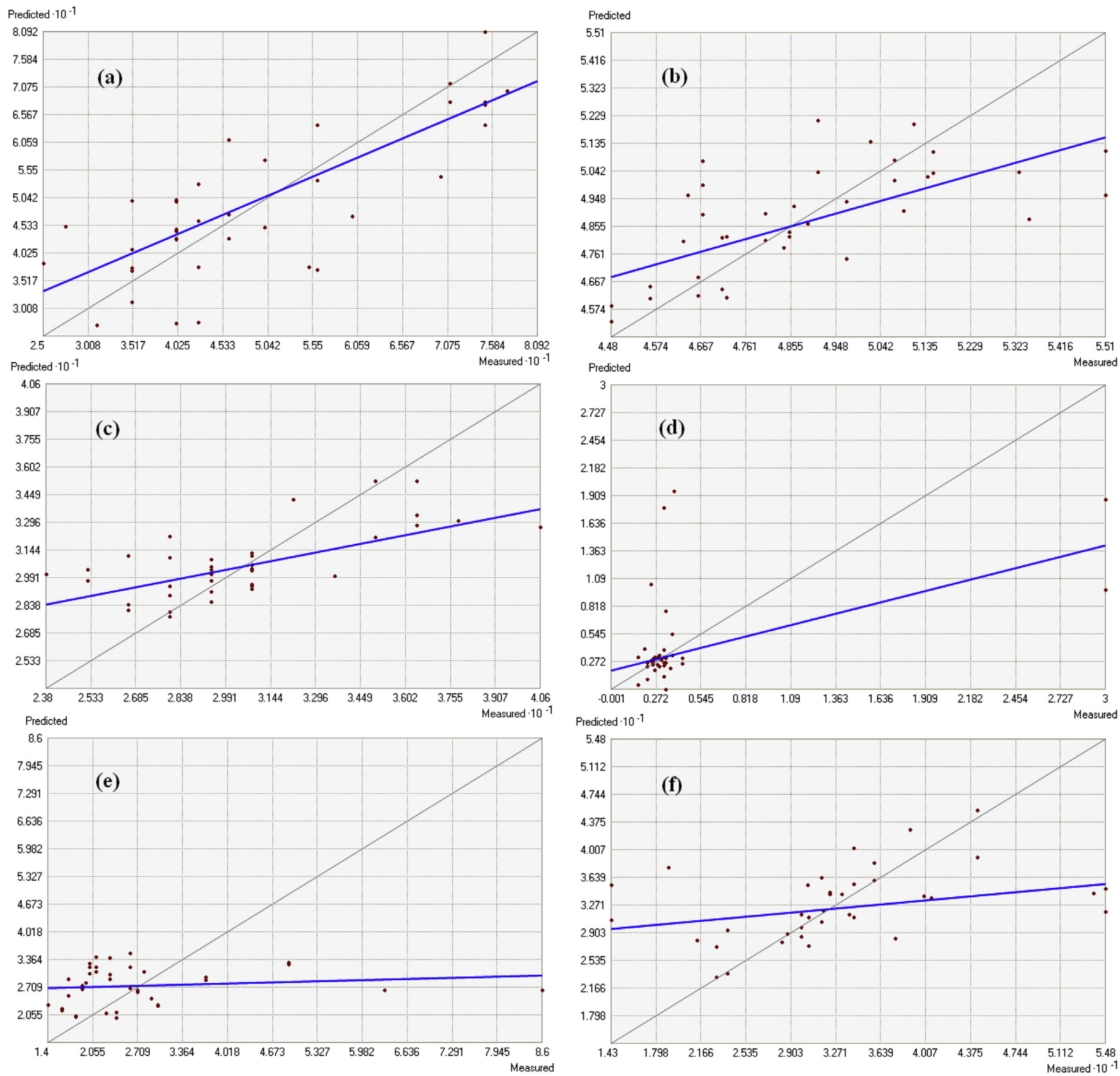

Fig. 3. Observed and predicted values of variables for validation of the results by semivariogram model; (a) K, (b)pH, (c) N (d) OC, (e)P (f) EC.

Table 3
Summary of semivariogram parameters of best-fitted theoretical model to predict soil properties and cross-validation statistics.

Soil property	Model	Nugget (C_0)	Sill (C_0 + C)	Range (m)	Nugget/Sill	R^2	RSS	ME	RMSE
N (ppm)	Exponential	0.15	1.10	1.076	0.14	0.48	0.002	0.09	0.20
P (ppm)	Exponential	0.001	0.97	1.335	0.10	0.63	0.008	0.02	0.16
K (ppm)	Exponential	0.001	1.08	1.210	9.26	0.53	0.001	0.03	0.21
pH	Exponential	0.25	0.98	1.418	0.25	0.43	0.0009	0.05	0.14
Organic Carbon (%)	Exponential	0.66	1.00	1.254	0.66	0.41	0.001	0.03	0.23
EC (µs)	Exponential	0.76	1.10	1.371	0.69	0.52	0.005	0.04	0.22

R^2 = coefficient of determination, RSS = residual sum square, ME = mean error, RMSE = root mean square error.

(Table 3). C_0 is the nugget variance; C is the structural variance, and Sill (C_0 + C) represents the degree of spatial variability, which are affected by both structural and stochastic factors (Fig. 4). The Nugget/Sill higher ratio indicates that the spatial variability is primarily caused by stochastic factors, such as fertilization, farming measures, cropping systems and other human activities. The lower ratio suggests that structural factors, such as climate, parent material, topography, soil properties and other natural factors, play a significant role in spatial variability [34]. The values of < 0.25, 0.25–0.75, and > 0.75 show strong, moderate and weak spatial autocorrelation in soil properties, respectively. With regard to OC and EC, the values for nugget/sill ratio are all more than 0.25 but less than 0.75, indicating moderate spatial

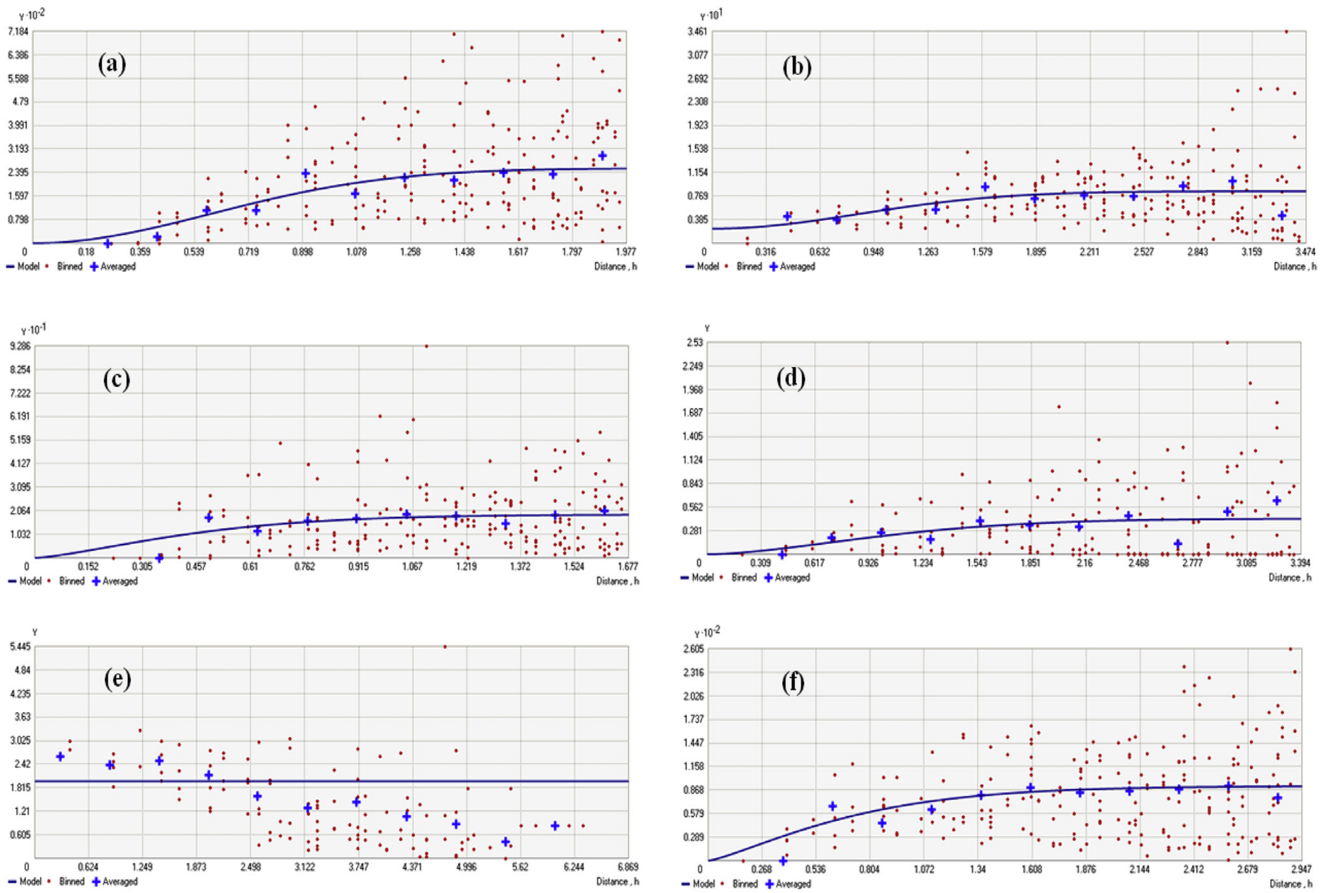

Fig. 4. Semivariograms with fitted models for soil properties (a) K, (b)pH, (c) N (d) OC, (e)P (f) EC.

autocorrelation. While the ratio values for N, P, and pH are less than 0.25, they indicate very strong spatial autocorrelation. As such, the K value indicates very weak spatial autocorrelation. Therefore, stronger spatial correlation of soil N, P, and pH can be accredited to structural characteristics, whereas a moderate degree of spatial correlation of OC, and EC are mostly a result of random factors. Consequently, fertilization, irrigation, and other management behaviours could decrease the heterogeneity of a soil characteristic and reduce its spatial correlation.

Spatial interpolations of soil properties

Fig. 5 shows the spatial variability of soil properties like N, K, P, EC, OC and pH using Ordinary Kriging (OK) interpolation methods. OK was used to switch soil samples into continuous fields of soil characteristics. Interpolated spatial variability maps indicate soils high in K are found in south-east parts of the study area (Fig. 5a). Concentration of N was observed in the central and eastern parts. The value of P is highly concentrated in the eastern part, whereas the agglomeration of higher EC is in the northeast and southwest corner of the study site. Spatial distribution of topsoil of P did not vary extremely with land use properties; however, well reflected changes were observed in the spatial distribution for OC and soil pH. The OK interpolation technique predicted significant decreases of OC in the central part where land use was dominated by fallow land (Fig. 5e). The value of OC increased in the western part which extends to the higher altitudes with agricultural plantation. Alteration of forest and grassland ecosystem into wasteland and fallow land had resulted a significant turn down of OC at topsoil at depth of 0–20 cm. Plowing forest soils is expectant fast mineralization of the OC that was accumulated earlier at the topsoil and transported through the overland flow in lower part (western part) of the study area. This result suggests certain management practices, e.g., minimum tillage, cover crops, and crop rotations, should be followed to recover OC of the topsoil. The greater amount of soil OC perhaps is due to the maximum concentration of root mass, waste material and secretes root increases growing physical steadiness and microbial activity [35,36]. In this analysis, it is found that storage of OC in soil is mainly influenced by the land use characteristics. Earlier reports also suggested that the amount and quality of litter input, the litter decomposition rate and processes control the organic matter stabilizes the soils [37,38].

The spatial distribution of the soil pH was shown in Fig. 5f. The soil pH was represented as acidic and varied between 4.63 and 5.51. Soil pH values of the entire study area varied between 4.80 and 5.20 whereas soil pH of 4.8–5.5 was recorded in the northern and southern part of the farm area and low value is recorded in the eastern part. This may be due to the fallow land and the undulating topography in the eastern part of the area. A map of soil EC (Fig. 5d) showed that areas of higher soil salinity area was more towards the southern part (low altitude) and most of the central part of the study area, whereas minimum salinity of soil was documented at high altitude of relief. This maximum changeability over short distances could be accredited to variations in the instability, surface drainage and micro-topography [12]. The spatial relation of soil properties evidenced the different amounts of heterogeneity of field management factors such as landscape pattern, pollination, irrigation, or intrinsic factors such as relief, drainage, erosion, and soil texture [39]. Therefore, results of this study are corroborated with the previous studies [40–42].

Validation

Internal (cross-validation) and external validation were used to confirm the results. The cross-validation technique generated for testing the semivariogram model validates the OK method at each sample

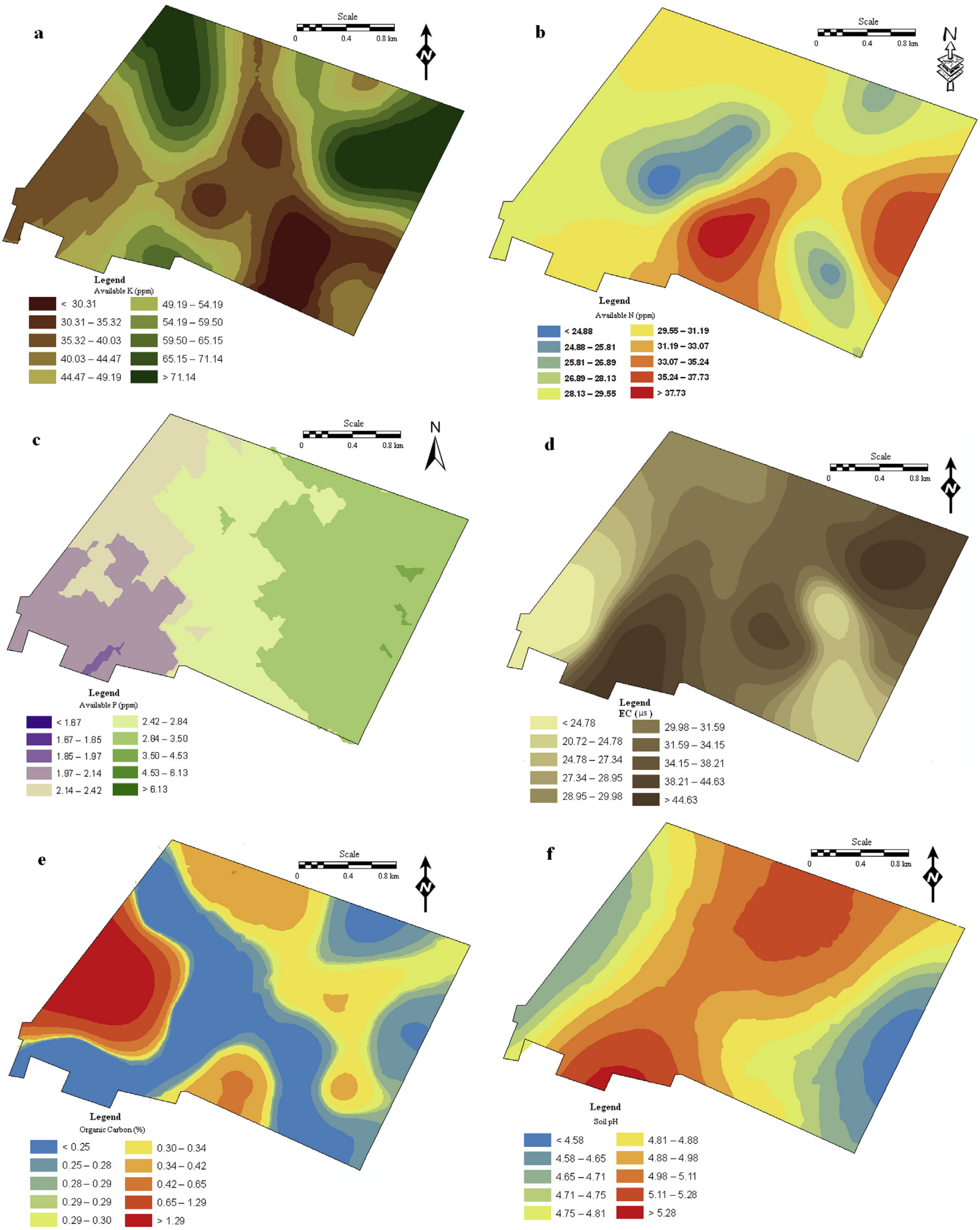

Fig. 5. Spatial Distribution of Soil Properties, (a) K (ppm), (b) N (ppm), (c) P (ppm), (d) EC, (e) Organic Carbon (%), (f) Soil pH.

location by neighbouring samples; after that evaluates approximates with actual values. Present analysis also reports that most of soil properties had low ME (Table 3), demonstrating a lack of logical bias for forecast spatial distribution using OK method and a good fit of the semivariogram to the data set. The RMSE was calculated form the validation dataset and values are near to zero (Table 3). The cross-validation analysis showed the smoothing effect of the spatial prediction. The calculated values of R^2 area approximate to 1 estimated through actual and predicted values. However, ME and RMSE are approximate to 0. Both indices express that the projected maps of soil properties form Ordinary Kriging and the results are consistent.

Conclusion

Understanding geographical distribution and precise mapping of soil properties at large scale are very important for soil conservation and environmental modeling. Geostatistical models were fitted for six soil properties, namely nitrogen (N), phosphorus (P), potassium (K), soil pH, electrical conductivity (EC), and soil organic carbon (OC). Semivariogram models for each soil property were identified using a cross validation approach. Cross-validation of semivariogram techniques derived through OK portrayed that spatial extrapolation of soil properties was more accurate than assuming the mean of the observed values at any unmeasured location. Finally, six prediction maps were developed using best fit semivariogram models with OK. The outcomes of the present work were valuables by depicting the effect of poor management practices on soil quality parameters. The preponderance of soil properties represented a moderate spatial dependency at short distances in the topsoil. However, the study has been limited by small soil samples and thereby a large number of samples is required for future research. Finally, the result derived in this study may help farmers and decision makers for improving the soil-water management plan.

Conflicts of interest

Conflict of interest on behalf of all authors states that there is no conflict of interest.

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