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Research Article

Spatial Variability of Soil Physico-Chemical Properties under Silvicultural Sytem in Alkaline Soil

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ABSTRACT

Spatial variability of soil physico-chemical properties in an agro-forestry system involving woody trees under sodic soil condition of northern India was assessed through geostatistical approaches. Soil samples from three layers (0-20 cm, 20-60 cm and 60-110 cm) were collected from multiple locations withn the orchard and soil physico-chemical properties e.g. organic carbon (OC) content, Ca content, electrical conductivity (EC) and phosphorus content. Descriptive analysis revealed that Ca content and EC of sub-surface layer was higher than surface layer indicating presence of calcium concretion in deeper soil layers. OC content was higher in surface layer compared to other layers. Phosphorus content was highest at root zone and minimum at surface layer. Semi-variogram analysis revealed spatial continuity of Ca content in deep soil layer. Spatial variation of EC within the study area was found highly random especially for surface and subsurface layer. Spatial correlation of OC content was found random in surface layer whereas in deeper soil layer little correlation was observed. Higher degree of spatial continuity in P content was observed in deeper layers. Predicted map of Ca content revealed the presence of calcite concretions at deeper soil layers at north-east corner of the study area. Soil EC showed patchy spatial pattern for surface and shallow depth OC content of surface soil layer was found almost homogeneous throughout the study area. Spatial pattern of P content at surface layer showed patchiness. Uncertainty of predicted soil properties were also assessed from standard deviation of prediction and was found generally higher in surface than subsurface layers. Thus soil physico-chemical properties of soil within the orchard were found highly variable and the soil maps generated through kriging can be used for best management of resources in the orchard.

Key words: Soil physico-chemical properties, Orchard management, Geostatistics, Kriging, Semivariogram

Introduction

Never before in the history of soil science has the knowledge of spatial variability been so pertinent. Agronomic research for limited resource farmers all too often comes face to face with micro-variability of soil that overshadows our usual method of analysis. Thus, there is a need to quantify the soil variability and determine the scale of its occurrence to optimize resource allocation. Variability in soil properties is a critical element across wide areas of research including the improvement of agricultural practices, environmental protection in agricultural areas (Robert *et al*., 1996), environmental protection at potential waste discharge sites, land–

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atmosphere interactions, and global climate change (Green *et al*., 2007).

Knowledge of soil spatial variability also contributes significantly towards precision agriculture with maximizing profit. This must be provided by on-site, intensive sampling that quantifies soil properties in the transition from one mapping unit to another, accounts for variability within mapping units, or otherwise generates data that is unavailable elsewhere. Spatial distribution of soil properties is extremely helpful in designing site-specific management strategies for practising precision farming, or applying simulation modelling. Soil variability is usually associated with spatial, temporal, or management-related factors and each of these sources canpartially or fully contribute to the variability of a soil propertyunder investigation (van Es *et al*., 1999). However, effective site-specific management requires soil data at a finer scale, which are obtained mostly by on-site detailed sampling across the mapping units and land use or management practices (Gaston et al., 2001). Geostatistics is a useful tool for analyzing spatial variability, interpolating between point observations, and ascertaining the interpolated values with a specified error using a minimum number of observations (Burrough, 1991).

Several attempts have been made to characterize the variability of soil properties, and spatial dependence is reported for scales ranging from a few meters (Gajem *et al*., 1981;Trangmar *et al*., 1987) to several meters (Trangmar *et al*., 1987; Cambardella *et al*., 1994; Sun *et al*., 2003; Shukla *et al*., 2004) to several kilometers (Ovalles and Collins, 1988; Lin *et al*., 2005). The short-range spatial variability of soil OC extends to several meters (Trangmar *et al*., 1987); however, long-range spatial dependence of OC seems doubtful (Ovalles and Collins, 1988).

Trangmar *et al*. (1987) found short-range, whereas Yost *et al*. (1982) and Trangmar *et al*. (1986) observed long-range, spatial dependence of soil pH. However, Campbell (1978) found that the pH of samples separated by only 10m were spatially independent.

However, most of these studies were restricted to field crops in agricultural land. Spatial variability of soil chemical properties in a jujube slope of China revealed that soil chemical properties are defined by spherical or exponential models. Nugget-to-sil ratio was found to be useful indicator of dependency of all chemical properties. Spatial prediction maps developed using ordinary krigging methods were reliable enough and could provide useful information for the development and application of precision agriculture on the Loess Plateau (Yiru and Youke, 2011). Scanning of available literature revealed that scanty information is available for spatial variability of sodic soil used for agroforestry. Studies on the effect of land use alteration on the spatial variability of soil properties are limited. The present study, therefore deals with the spatial variability of soil properties under agroforestry system in a sodic soil using geo-statistical methods. Woody trees are capable to produce biomass in highly sodic soil and contribute significantly towards balancing ecology in such soil. It was, therefore, considered worthwhile to study the spatial variability of soil physico-chemical properties in agro-forestry system under sodic soil condition.

Materials and Methods

Study area and soil sampling

Soils were sampled from 40 months-old agro-forestry planted on alkali wasteland by auger hole technique with *Acacia nilotica*, *Casurina equisetifolia*, *Dalbergia sisoo* and *Prosopis juliflora* at Saraswati range, Kurukshtra. Each augar hole pit measuring 20 to 25 cm diameter and 120 to 150 cm deep was filled with a mixture containing gypsum (3 kg), FYM (8 kg) and original soil. Samples were drawn from 0-20, 20-60 and 60-110 cm depth of soil along transects in E-W and N-S directions and were analyzed for pH (soil : water, 1:2), EC (soil : water, 1:2), organic carbon, $CaCO_3$ and available P. Organic carbon was estimated by Walkley and Black method and $CaCO_3$ by Collin's Calcimeter method. Available P was extracted by 0.5 M $NaHCO_3$ (Olsen *et al*., 1954) and its content in the extract was determined colorimetrically using vanadomolybdophosphoric yellow color method (Jackson, 1973). Other soil properties were estimated using standard analytical procedure.

Spatial variability of soil properties

Data on soil properties were checked and logarithmic transformation was carried out, if required, to fit in normal distribution. Spatial variation of soil properties e.g. pH, EC, OC concentration, $CaCO_3$ content and P content in surface as well as subsurface soil layers were determined to prepare the maps. Semi-variogram $\hat{\gamma}(h)$ representing the average dissimilarity between data separated by a lag distance of *h* was computed as half the average squared difference between the components of data pairs to characterize the spatial variation structure of soil carbon concentration (Goovaerts, 1998; Warrick *et al*., 1986):

$$\hat{\gamma}(h) = \frac{1}{2N(h)}\sum_{i=1}^{h}\left[Z(x_i) - Z(x_i + h)\right]^2 \qquad \ldots(1)$$

where $N(h)$ is the number of data pairs within a given class of distance and direction, $Z(x_i)$ is the value of the variable at the location x_i and $Z(x_i + h)$ is the value of the variable at a lag of h from the location x_i.

The semivariogram values were computed using 'gstat' package of R software (Pebesma and Benedikt, 2016). The directional trend of SOC content within the farm was found negligible and hence omni-directional semivariogram was computed. The computed semivariogram values $\hat{\gamma}(h)$ for corresponding lag (h) were fitted in four standard theoretical semivariogram models; spherical, exponential, Gaussian and linear model.

Spherical model

$$\gamma(h) = C_0 + C\left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right] \quad \text{if } 0 \leq h \leq a$$

$$\text{otherwise } C_0 + C \qquad \ldots(2)$$

Exponential model

$$\gamma(h) = C_0 + C_1\left[1 - \exp\left\{-\frac{h}{a}\right\}\right] \quad \text{for } h \geq 0 \qquad \ldots(3)$$

Gaussian model

$$\gamma(h) = C_0 + C\left[1 - \exp\left\{\frac{-h^2}{a^2}\right\}\right] \quad \text{for } h \geq 0 \qquad \ldots(4)$$

Linear model

$$\gamma(h) = C_0 + C_1\left[\frac{h}{a}\right] \quad \text{if } h < a \text{ otherwise} = C_0 + C_1 \qquad \ldots(5)$$

In all these semivariogram models, nugget, sill and range were expressed by C_0, (C+C_0) and *a,* respectively. Nugget (C_0) defines the micro-scale variability measurement error for the respective soil property, whereas partial sill (C) indicates the amount of variation which can be defined by spatial correlation structure. Fittings were carried out using weighted least square technique and weights were given as proportional to the number of sampling pairs and inversely proportional to the lag distance. Best-fit model with lowest sum of square error (SSE) was selected for further use in kriging:

$$SSE = \sum_{i=1}^{n}\frac{N_i(h)}{h^2}\left[\gamma_i(h) - \hat{\gamma}_i(h)\right]^2 \qquad \ldots(6)$$

where n is the number of lag classes, $N_i(h)$ is the number of sample pairs at the lag h, $\gamma_i(h)$ is the measured value of experimental semivariogram at the lag h, $\hat{\gamma}_i(h)$ is the estimated semivariogram value at the lag h. Fitted semivariogram parameters e.g. nugget (C_0), partial sill (C) and range (a) were used in ordinary kriging approach to generate surface maps.

Cross validation

Ordinary kriging approach was evaluated through a k-fold cross-validation approach and k = 10 was used in this study. The performance of each spatial interpolation method was evaluated using root-mean-squared error (RMSE) and root mean squared standardized error (RMSSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[Z(x_i) - \hat{Z}(x_i)\right]^2} \qquad \ldots(7)$$

$$\text{RMSSE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left[Z(x_i) - \hat{Z}(x_i)\right]^2}{\hat{\sigma}^2(x_i)} \qquad \ldots(8)$$

where $Z(x_i)$ is the observed values of the variable at the location x_i, $\hat{Z}(x_i)$ is the predicted values with variance σ^2 atthe location x_i, and n is the number of sampling location. The RMSE estimates the accuracy of prediction (e.g., larger RMSE values indicate less accuracy of prediction). The RMSSE measures the goodness of fit of the theoretical estimateof error (Bishop and Lark 2008). If the correct semi-variogram model is used, the RMSSE values should be close to 1.

Result and Discussion

Descriptive statistics

Descriptive statistics of soil properties are presented in Table 1. Calcium content of subsurface layer was found higher than surface layer. Mean Ca content at 0-20 cm was found 1.83 meq 100^{-1} g whereas at 60-110 cm soil layer, it was found 2.65 meq 100^{-1} g. it indicates the presence of calcium concretion at deeper soil layers. Similarly, electrical conductivity (EC) was found higher at subsurface layer (2.89 dS m^{-1} at 60-110 cm) than surface layer (1.22 dS m^{-1}). In contrast to these, OC content was found higher at surface soil layer (0.25%) than subsurface layers (0.20% and 0.16%, respectively at 20-60 cm and 60-110 cm soil layer). Phosphorus content at 20-60 cm soil layer was found slightly higher (12.80 kg/ha) than others while it is lowest at 0-20 cm soil layer (11.32 kg ha^{-1}). From the quantile distribution of data, it has been observed that soil properties mostly follow lognormal distribution, which was further checked by histogram plots. Therefore, necessary log-transformation has been done wherever it was required and the histogram plot of soil properties are presented in Fig. 1. It may be noted from histogram plot that except EC for 0-20 cm and 60-110 cm soil layer, rest soil properties were log-transformed for further data analysis.

Tree plantations in the study area

Tree girth and height at each sampling location are presented in Fig. 2. Tree girth was found to vary from 4 to 64 cm, whereas tree height varied from 30 to 450 cm.

Semivariogram of soil properties

Ca content

Semivariogram parameters of soil properties at three soil layers (0-20 cm, 20-60 cm and 60-110 cm) are presented in Table 2 to 5. Sum of square of errors for fitting the experimental semivariogram to theoretical models are presented in each table. It has been observed from table 2 that linear model is best fitted model for Ca content at 0-20 cm and 20-60 cm soil layer whereas spherical model is the best for 60-110 cm soil layer. Semivariogram structures of Ca content are also presented in Fig. 3. The range

Table 1. Descriptive statistics of soil properties

Soil property	Soil layer	Min	1st Quantile	Median	Mean	3rd Quantile	Max
Ca (meq 100^{-1} g soil)	0-20 cm	0.20	0.80	1.60	1.83	2.30	6.60
	20-60 cm	0.20	1.10	2.00	2.08	2.70	8.50
	60-110 cm	0.40	1.10	1.40	2.65	2.90	13.5
EC (dS m^{-1})	0-20 cm	0.20	0.71	1.14	1.22	1.70	2.72
	20-60 cm	0.20	0.89	2.18	2.23	3.40	5.11
	60-110 cm	0.39	1.30	2.81	2.89	4.49	6.40
OC (%)	0-20 cm	0.01	0.14	0.20	0.25	0.30	0.77
	20-60 cm	0.01	0.12	0.15	0.20	0.23	0.66
	60-110 cm	0.02	0.06	0.12	0.16	0.17	0.62
P (kg ha^{-1})	0-20 cm	0.84	5.40	9.46	11.32	15.95	34.75
	20-60 cm	0.47	5.25	12.05	12.80	19.06	37.00
	60-110 cm	0.21	4.49	11.41	12.19	18.93	37.71

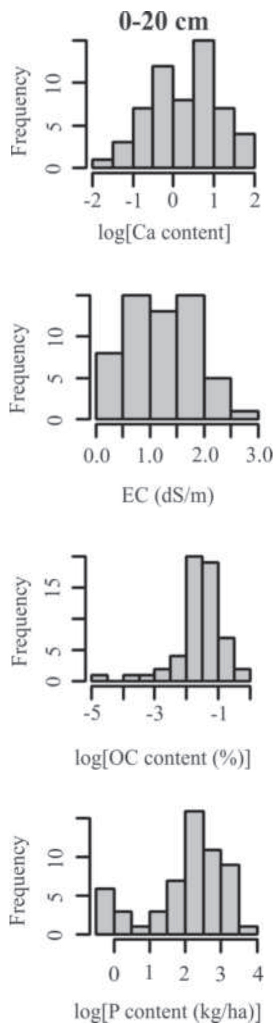

Fig. 1. Histogram of soil properties

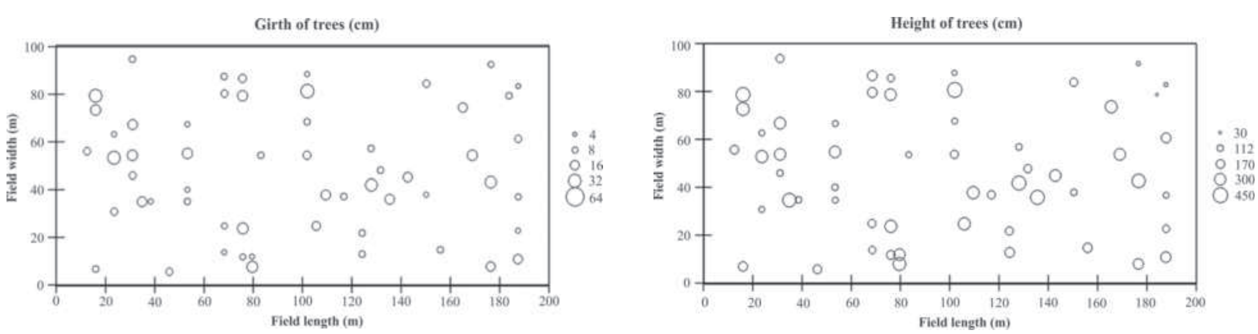

Fig. 2. Soil sampling locations along with girth and height of trees in the orchard

parameters were found very low at surface layer (8.20 m), which indicates the existence of spatial correlation of Ca content between two points very short distance apart. However, the range parameter was found higher for deeper soil, e.g., at 60-110 cm soil layer it was 59.74 m. it indicates spatial continuity of Ca content at deeper soils whereas at surface soil it is distributed randomly in patches. Nugget component was found 30% of total sill (nugget + sill) at 20-60 cm and 60-110

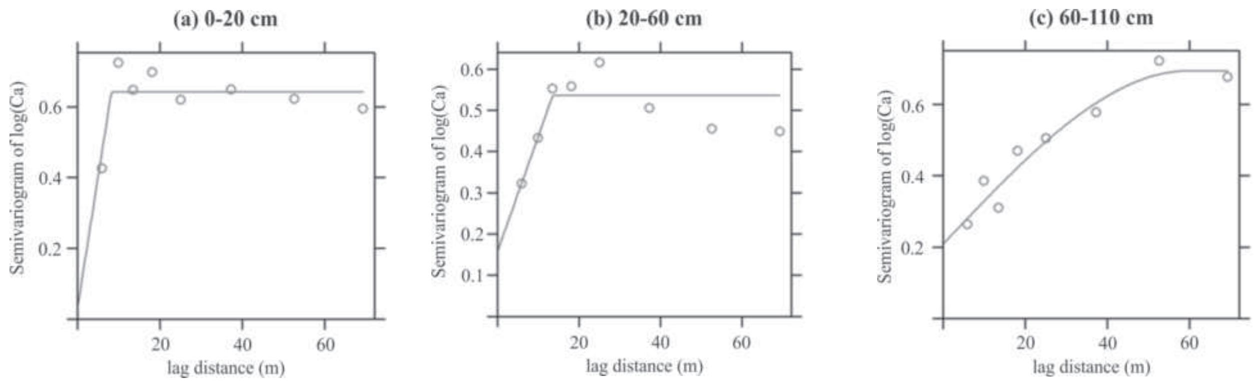

Fig. 3. Semivariogram properties of Ca content (meq/100 gm)

Table 2. Semivariogram parameters of Ca content (meq 100^{-1} g) in the orchard

Semivariogram models and parameters	0-20 cm	20-60 cm	60-110 cm
Sum of square of errors			
Linear	0.0025	0.0020	0.0018
Gaussian	0.0040	0.0030	0.0021
Exponential	0.0057	0.0031	0.0018
Spherical	0.0026	0.0022	0.0017
Semivariogram parameters of best fitted model			
Nugget	0.03	0.16	0.21
Sill	0.60	0.38	0.47
Range (m)	8.20	13.54	59.74

Table 3. Semivariogram parameters of electrical conductivity (dS m^{-1}) in the orchard

Semivariogram models and parameters	0-20 cm	20-60 cm	60-110 cm
Sum of square of errors			
Linear	0.0073	0.0480	0.3303
Gaussian	0.0050	**0.0302**	**0.3290**
Exponential	0.0069	0.0380	0.3330
Spherical	**0.0051**	0.0304	0.3304
Semivariogram parameters of best fitted model			
Nugget	0	0	2.74
Sill	0.34	0.77	0.27
Range (m)	3.93	3.78	32.65

cm soil layer whereas at surface layer nugget contributes only 5% of total sill.

Electrical conductivity

For electrical conductivity (EC), Gaussian model was found best for 20-60 cm soil layers, whereas spherical model is the best for 0-20 cm soil layer (Table 3). Semivariogram structures also showed very short range variation (~4 m) for 0-20 cm and 20-60 cm soil layers whereas at 60-110 cm layer, it is slightly higher (Fig. 4 and Table 3). It indicates that spatial variation of EC within the study area is highly random especially for surface and subsurface layer. At deeper layer (60-110 cm), slight spatial correlation was observed as showed by a range value of about 32.65 m, however the nugget component is very high (>90%).

Organic carbon content

Fitting results of semi-variogram for OC content are presented in Table 4. Spherical model has been found best for all soil layers. For surface layer, spatial correlation has been found as almost random whereas for deeper layers (20-60 cm and 60-110 cm) little spatial correlation was observed (Fig. 5). Range parameters of OC variation at 20-60 cm soil layer was found quite high (2300 m) whereas at 60-110 cm layer, it was 72 m. Nugget component of variation at 20-60 cm and 60-110 cm has been found <30% of total sill.

Phosphorus content

While fitting the spatial variation of phosphorus content, different models fits well at different depths. Gaussian, linear and spherical model was found best for 0-20 cm, 20-60 cm and

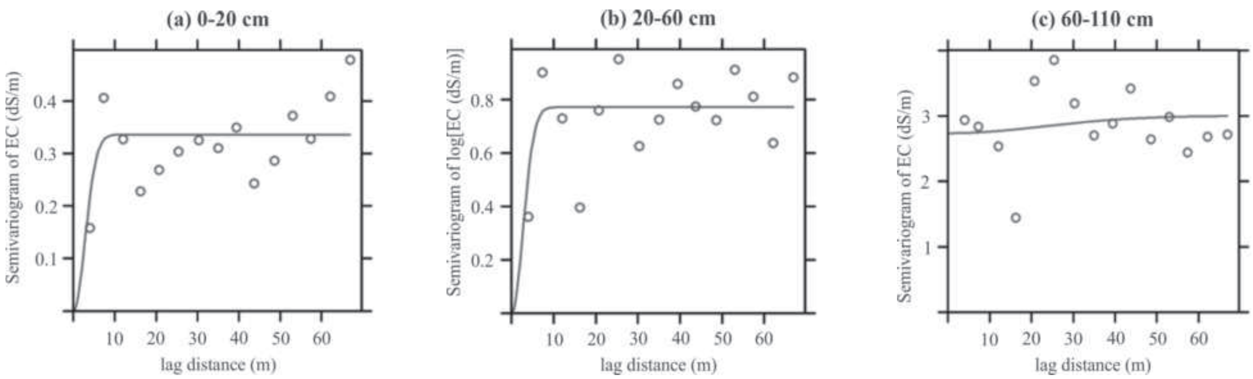

Fig. 4. Semivariogram properties of EC (dSm^{-1})

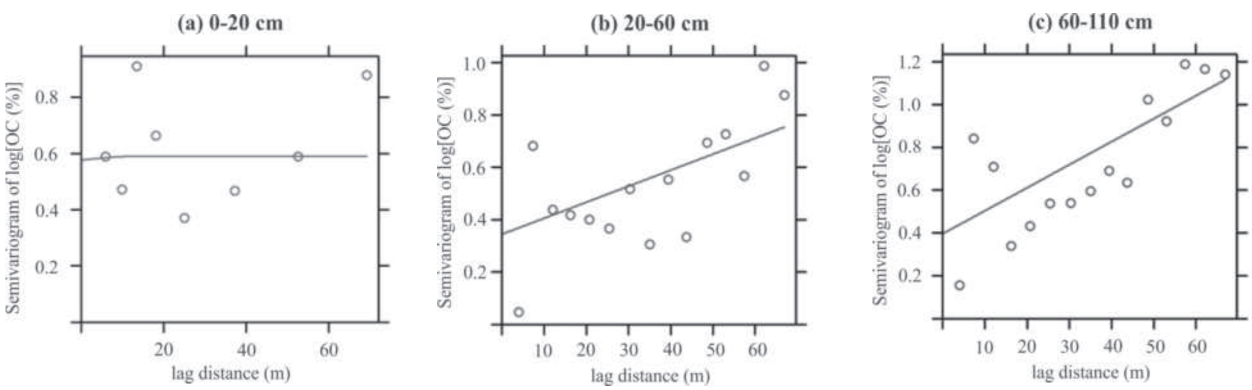

Fig. 5. Semivariogram properties of soil organic carbon content (%)

Table 4. Semivariogram parameters of soil organic carbon content (%) in the orchard

Semivariogram models and parameters	0-20 cm	20-60 cm	60-110 cm
Sum of square of errors			
Linear	0.03360	0.058	0.080
Gaussian	0.03329	0.058	0.096
Exponential	0.04730	0.060	0.092
Spherical	**0.03326**	**0.056**	**0.082**
Semivariogram parameters of best fitted model			
Nugget	0.58	0.34	0.40
Sill	0.01	9.39	0.78
Range (m)	12.98	2300	72.00

Table 5. Semivariogram parameters of soil phosphorus content (kg/ha) in the orchard

Semivariogram models and parameters	0-20 cm	20-60 cm	60-110 cm
Sum of square of errors			
Linear	0.442	**0.03949**	0.657
Gaussian	**0.308**	0.03966	3.366
Exponential	0.375	0.03971	0.886
Spherical	0.321	0.03962	**0.635**
Semivariogram parameters of best fitted model			
Nugget	0	1.30	1.36
Sill	1.46	0.05	3.16
Range (m)	3.91	28.30	1533

60-110 cm, respectively (Table 5). For surface layer, spatial variation of P content may be considered as highly random since the range parameter is only 3.91 m indicating the possible correlation of P content between two locations <4 m apart (Fig. 6). For 20-60 cm soil layer, variation of P content is largely contributed by random variation and a little is contributed by spatial component since nugget is >95% of total sill. At 60-110 cm layer, range has been found quite high (1533 m), which shows higher degree of spatial continuity in P content.

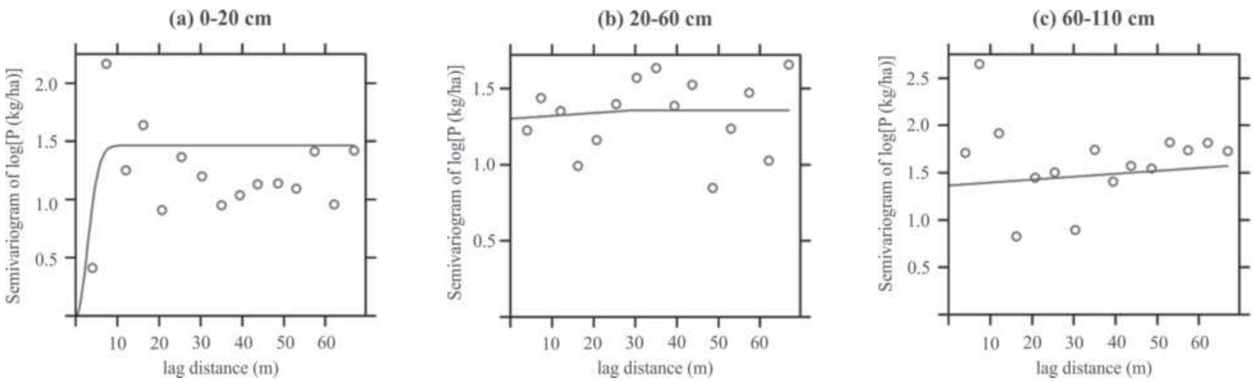

Fig. 6. Semivariogram properties of soil phosphorus content (kg ha^{-1})

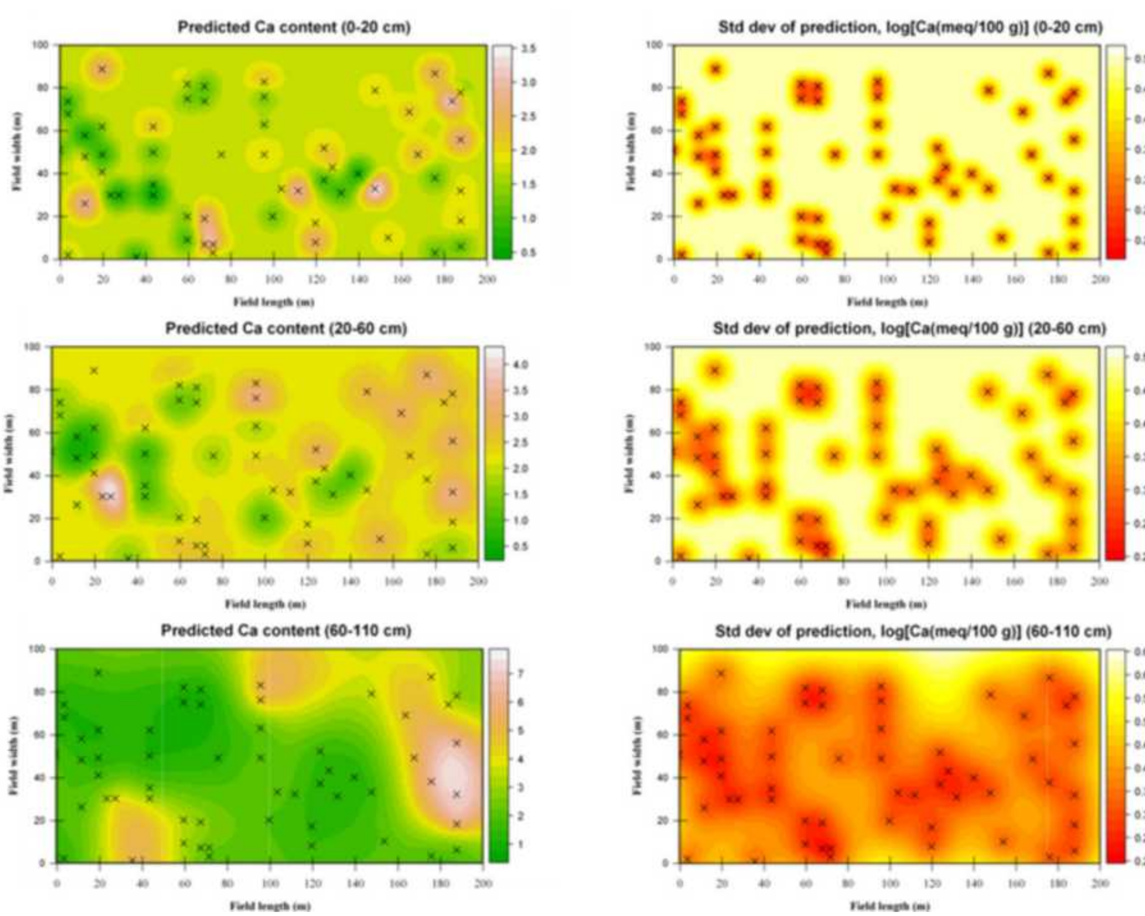

Fig. 7. Spatial maps of Ca content (meq/100 gm) along with standard deviation of prediction map

Surface map of soil properties

Spatial map of soil properties for three soil layers are presented in Fig. 7-10 along with standard deviation of prediction map indicating the uncertainty of prediction. It is to be noted here that the maps were back-transformed to original variables in case of kriging was performed on log-transformed variable using the following formula:

$$\hat{Z}_{OK} = \exp\left(\hat{Y}_{OK} + 0.5 \times \sigma^2_{OK}\right) \qquad \ldots(9)$$

where, $\hat{Z}_{OK}$ is the back-transformed original variable predicted through ordinary kriging, $\hat{Y}_{OK}$ is the predicted log-transformed variable, σ^2_{OK} is the variation of prediction of the log-transformed variable in ordinary kriging. However, back-transformation on standard deviation of prediction map was avoided because of its complexity and moreover, the presented map on standard deviation of prediction maps shows relative error at different locations within the study area.

Ca content of soil

Predicted map of Ca content for 0-20 cm and 20-60 cm soil layer showed patchiness and varied from 0.5 to 4.0 meq 100^{-1} g. North-east corner of the study area showed comparatively higher Ca content (3-4.0 meq 100^{-1} g) than rest. However at 60-110 cm soil layer, Ca content was observed quite high at north-east corner (5-7 meq 100^{-1} g) than rest portion. It indicates the presence of calcite concretions at deeper soil layers of north-east corner of the study area. Standard deviation of prediction maps for 0-20 cm and 20-60 cm specifically showed lower values only around sampling locations, which indicates that spatial variation of Ca content at these two depths are not strong enough.

Soil EC

EC content shows patchy spatial pattern for 0-20 cm and 20-60 cm soil layer whereas at 60-110 cm soil layers, zone of higher values was observed at central, bottom left cornerand right portion of the study area whereas middle left portion has low EC. Comparatively, soil EC was lower at surface layer (0.8-1.8 dS m^{-1}) than 20-60 cm soil layer (1.0-3.5 dS m^{-1}) and 60-110 cm soil layer (2.5-3.5 dS m^{-1}). Standard deviation of prediction maps showed smaller values very near to sampling points at 0-20 cm and 20-60 cm soil layers whereas at 60-110 cm soil layer, it is almost homogeneously distributed.

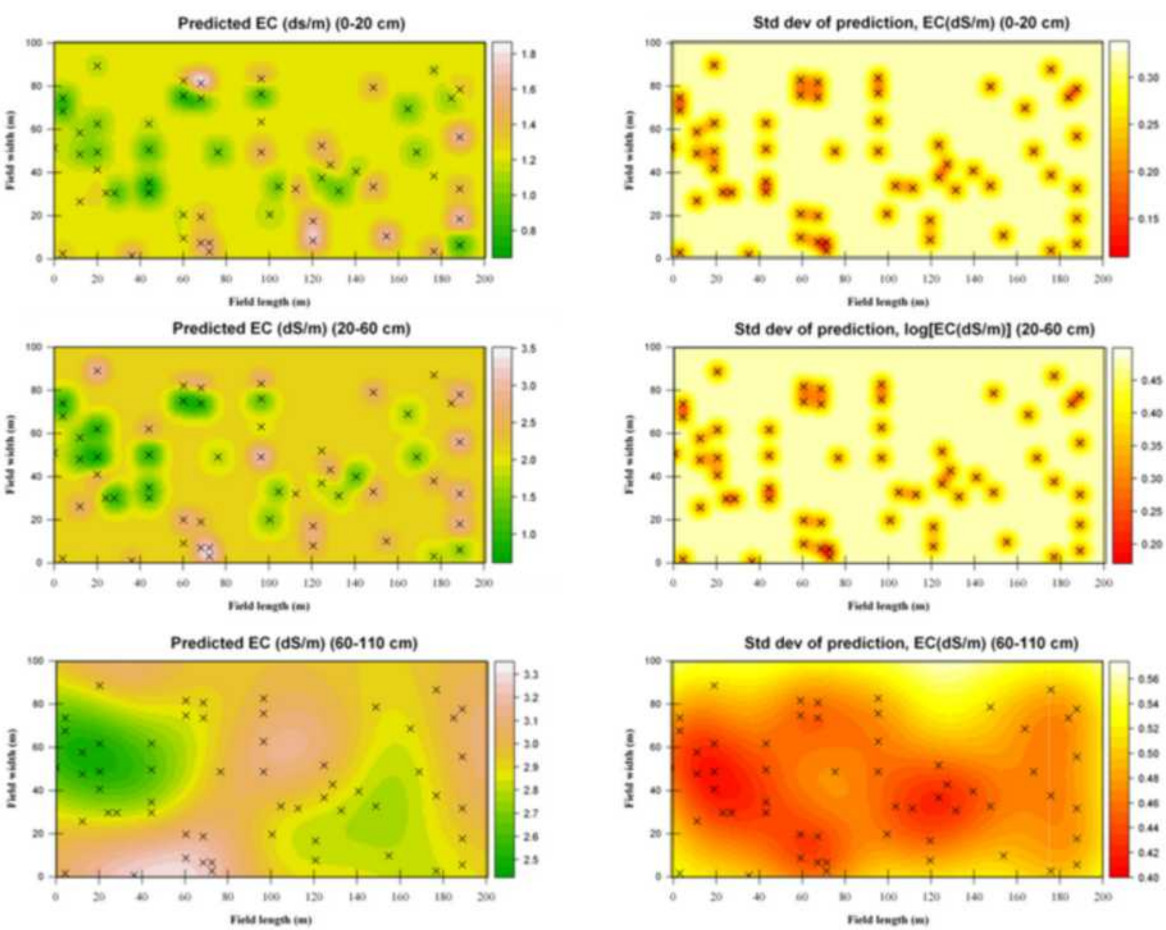

Fig. 8. Spatial maps of electrical conductivity (dSm^{-1}) along with standard deviation of prediction map

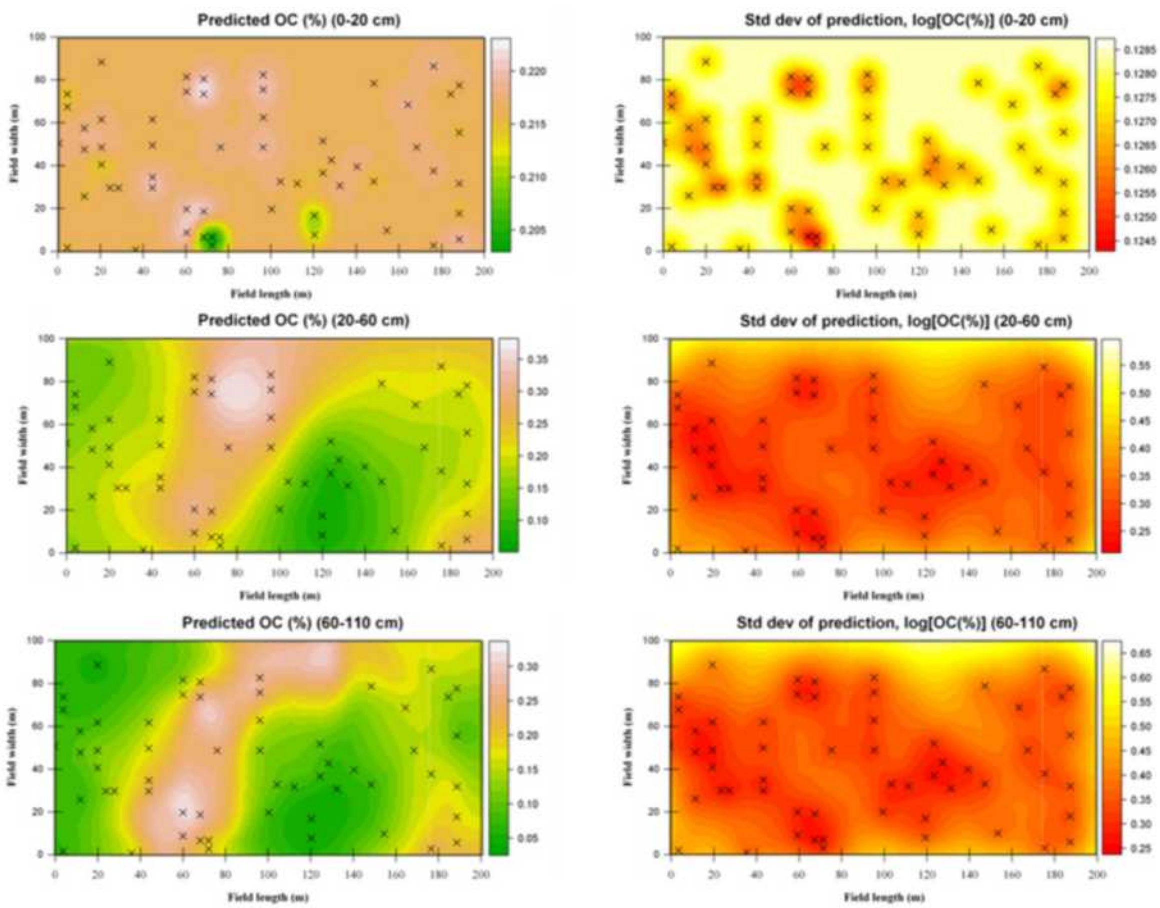

Fig. 9. Spatial maps of soil organic carbon content (%) along with standard deviation of prediction map

OC content

Thematic maps of OC content for 0-20 cm, 20-60 cm and 60-110 cm soil layer are presented in Fig. 9. OC content of surface soil layer is almost homogeneous with a content of 0.22% at most places. However, at 20-60 cm and 60-110 cm soil layers, a zone of higher OC content (~0.30%) was observed at the middle portion of the study area. OC content of these two subsurface layers varied from as low as 0.05% to as high as 0.35%. Uncertainty of prediction was observed low surrounding sampling locations at 0-20 cm soil layer, whereas for subsurface layers it is almost homogeneous throughout the study area. Relatively, uncertainty component is lower in surface layer than subsurface layers.

Phosphorus content

Spatial maps of P content are presented in Fig. 10. Spatial pattern of P content at surface layer shows patchiness with its value ranging from 4 to 18 kg ha^{-1}. For 20-60 cm soil layer, P content is almost similar throughout the study area (~10 kg ha^{-1}) except a pocketed area at left middle portion of the study area, where it is quite low (7.5-8.5 kg ha^{-1}). At 60-110 cm soil layer bottom right corner of the study area showed higher P content (14-16 kg ha^{-1}) whereas at rest portion it is low (6-10 kg ha^{-1}). Standard deviation of prediction showed higher values at unsampled locations for 0-20 cm soil layer, whereas at sub-surface layers, the uncertainty of prediction is almost same throughout the study area. Standard deviation of prediction was comparatively lower for 20-60 cm soil layer than layers above or below it.

Validation of krigged maps

Cross-validation results of krigged maps of soil properties are presented in Table 6 in terms

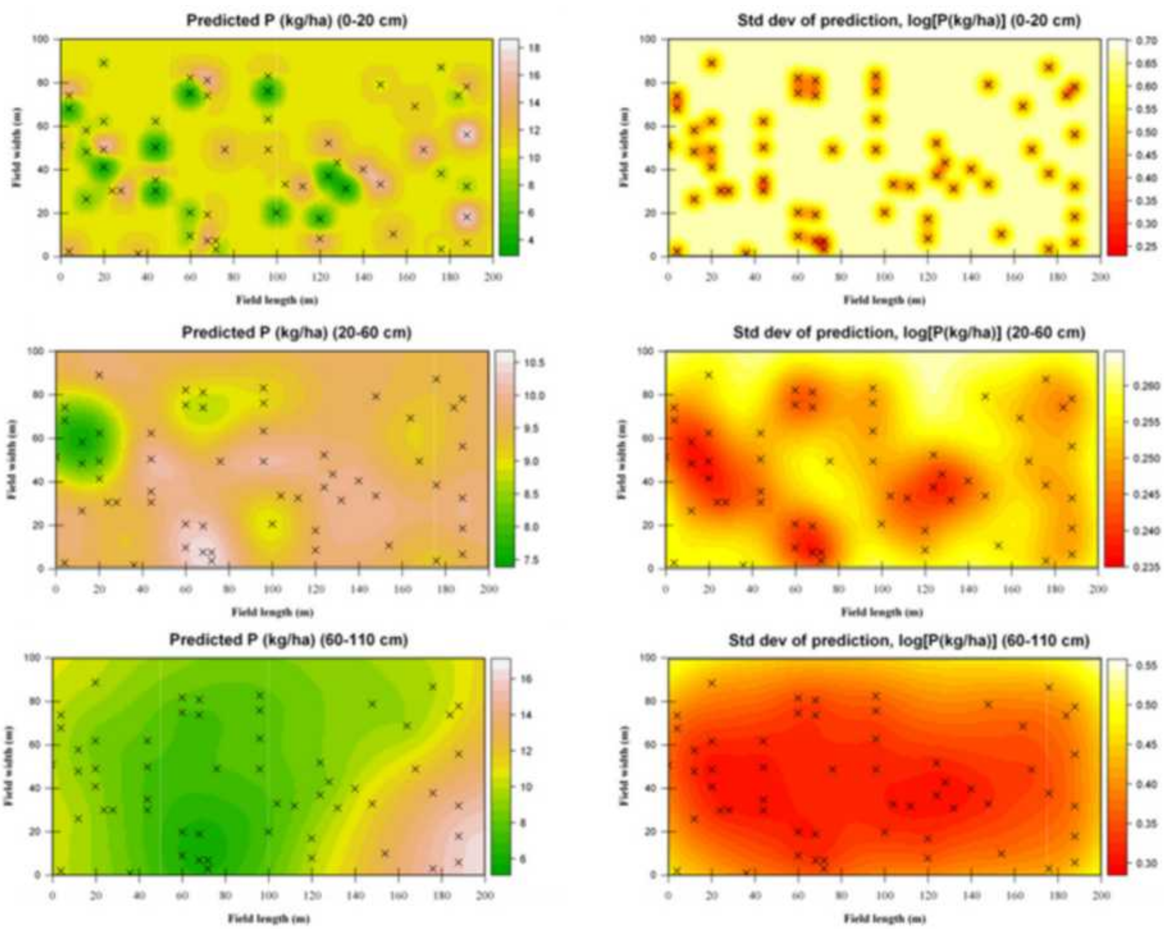

Fig. 10. Spatial maps of soil phosphorus content (kg ha^{-1}) along with standard deviation of prediction map

Table 6. Accuracy and uncertainty of the spatial maps of soil properties prepared through kriging approach

Soil property	Soil layer	Transformed data	RMSE	RMSSE
Ca (meq 100^{-1} g soil)	0-20 cm	log (Ca)	0.78	0.93
	20-60 cm	log (Ca)	0.65	0.81
	60-110 cm	log (Ca)	0.66	0.64
EC (dS m^{-1})	0-20 cm	EC	0.60	1.00
	20-60 cm	log(EC)	0.87	0.96
	60-110 cm	EC	1.66	1.00
OC (%)	0-20 cm	log(OC)	0.76	1.01
	20-60 cm	log (OC)	0.64	0.77
	60-110 cm	log(OC)	0.78	0.78
P (kg ha^{-1})	0-20 cm	log(P)	1.08	1.06
	20-60 cm	log(P)	1.14	0.99
	60-110 cm	log(P)	1.24	1.00

of RMSE and RMSSE. Error in prediction of Ca content was higher in surface layer than subsurface layers as shown by RMSE values although the RMSSE was more close to 1 in surface layer indicating good fit to theoretical semi-variogram model leading to low uncertainty. In case of EC, error of prediction was lower in surface layer than subsurface layer as indicated by lower RMSE value in surface soil than subsurface soils although the uncertainty as calculated by RMSSE was very close to 1 for all three soil layers. For log(OC) prediction, lowest RMSE was observed for 20-60 cm soil layer, whereas RMSSE was very close to 1 for 0-20 soil layer. For subsurface soil layers, RMSSE value of prediction was 0.77-0.78, indicating larger uncertainty of prediction. For phosphorus content, lowest RMSE values was observed for 0-20 cm soil layer whereas RMSSE was very close to 1 for all three soil layers indicating low uncertainty of prediction.

Conclusion

The study on spatial variability of soil properties under agro-forestry system in sodic soil using geo-statistical methods reveals that the semi-variogram parameters are very effective tools to estimate soil physico-chemical parameters. Biomass of woody trees in agro-forestry system of sodic soil of Haryana contributed significantly towards variation of soil physico-chemical properties. Different trends of the spatial variability of different soil physico-chemical parameters were observed across the soil profile as well as surface in the agro-forestry system under sodic soil condition. More detailed study is called for to establish the relationship between spatial variability of tree growth parameters and spatial variability of soil physico-chemical properties.

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