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Spatial distribution of soil physical properties of alluvial soils: a geostatistical approach

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ABSTRACT

Knowledge of spatial variation of soil is important in site-specific farming and environmental modeling. Soil particles size and water distribution are most important soil physical properties that governing nearly all of the other attributes of soils. The objectives of this study were to determine the degree of spatial variability of sand, silt and clay contents, and water content at field capacity (FC), permanent wilting point (PWP), and available water content (AWC) of alluvial floodplain soils. Data were analyzed both statistically and geostatistically to describe the spatial distribution of soil physical properties. Soil physical properties showed large variability with greatest variation was observed in sand content (68%). Exponential and spherical models were fit well for the soil physical properties. The nugget/sill ratio indicates except clay all other soil physical properties were moderate spatially dependent (37–70%). Cross-validation of the kriged map shows that prediction of the soil physical properties using semivariogram parameters is better than assuming mean of observed value for any unsampled location. The spatial distribution of water retention properties closely followed the distribution pattern of sand and clay contents. These maps will help to planner to develop the variable rate of irrigation (VRI) for the study area.

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Soil physical properties; spatial variability; geostatistics; semivariogram; accuracy assessment

Introduction

Soil water and soil texture, the relative percentage of sand, silt, and clay, are the most important soil physical properties that governing nearly all of the other attributes of soils (Adhikari et al. 2009). These two soil physical properties control plant growth and influence a variety of soil processes including, leaching and erosion potential (Adhikari et al. 2009), plant nutrient storage (Kettler et al. 2001), organic-matter dynamics (Kong et al. 2009), chemical exchange and microbial activity, and energy balance of the soil-plant system and pedogenesis (Western et al. 2003).

Spatial variability of soil physical properties within or among agricultural fields is inherent in nature due to geologic and pedologic soil forming factors, but some of the variability may be induced by tillage and other management practices. As other environmental variables, soil water and soil texture changes in space and time. This temporal and spatial variability of soil texture and soil water may lead to structural differences in soil quality (Kettler et al. 2001) and hydrologic cycle (Western et al. 2003) in an ecosystem. Studies (Iqbal et al. 2005; Santra et al. 2008; many others) showed that soil water content exhibited organized features under majority of the conditions. However, degree of the organization varies based on the soil and climatic conditions.

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Among the various soil physical properties, saturated hydraulic properties and related measures are reported to have the highest statistical variability (Biggar & Nielsen 1976). Vieira et al. (1981) used variogram, kriging, and co-kriging techniques to determine the magnitude of spatial variation. Vauclin et al. (1983) used classical and geostatistical techniques to study spatial viability of sand, silt and clay contents, and available water content (AWC).

Spatial variability in soil water properties have been studied widely since 1975. Most of these studies focused on nature of spatial variability and its relation to soil properties (Cassel & Bauer 1975) and others on terrain properties (Western et al. 2003), on soil management (van Vesenbeeck & Kachanoski 1988), and on spatial interpolation of soil water content (Yates & Warrick 1987). However, spatial variability in soil water potential [water content at field capacity (FC) (−33 kPa) and permanent wilting point (PWP) (−1500 kPa)] are two most hydraulic parameters which indicate plant-available soil water regime and help in scheduling irrigation to crops.

Geostatistics provides the means to characterize and quantify spatial variability, use this information for rational interpolation, and estimate the variance of the interpolated values. Variance estimation provides valuable information on the sampling density and configuration necessary to estimate a property to a specified precision. Geostatistics is a technology for estimating the soil property values in nonsampled areas or areas with sparse samplings (Yao et al. 2004). These nonsampled areas can vary in space (in one, two, or three dimensions) from the sampled data (Zhu et al. 2005). Geostatistical techniques incorporating spatial information into predictions can improve estimation and enhance map quality (Mueller & Pierce 2003). Among different methods of spatial interpolation of soil properties, ordinary kriging is most common (Franzen & Peck 1993). Kriging is a useful tool to predict and interpolate data between measured locations (Nourzadeh et al. 2012; Reza et al. 2012, 2013, 2015; Emadi et al. 2015).

Most of the studies showed the spatial variation of soil physical properties in plot, field, or farm scale (Iqbal et al. 2005; Santra et al. 2008), but such information on watershed or an administrative boundary level with sparsely distributed irregular samples is meager. Thus, the objective of this study was to determine the spatial variability of soil particles, such as sand, silt and clay contents, and water content at −33 kPa and −1500 kPa, and AWC with the classical statistics and geostatistical analysis for Kadwa block of Katihar district, Bihar, India.

Material and methods

Study area

The area under investigation belongs to the Kadwa block of Katihar district (25°30′–25°47′ N, 87° 35′–87°55′ E) covering an area 340.47 km^2 (Figure 1) in northeastern Bihar, India. The climate is moderate during the winter and hot in summer. The maximum temperature is 43ºC during July and August; a minimum temperature falls up to 8ºC in the month of January. Annual rainfall is 2100–2500 mm and about 85% of rainfall is from South-West monsoon. Geomorphologically, the study area represents a flat topography (1–2% slope) with regional slope toward south and divided into four major physiographic units viz. old alluvial plain, recent alluvial plain, meander plain, and flood plain. The elevation varied from 11 to 53 m above the mean sea level. The soils under investigation have been generally formed on unconsolidated sediments of Quaternary period. There are six broad soil subgroups in the study area according to Soil Taxonomy (USDA) namely – Typic Ustifluvents, Aquic Haplustepts, Fluventic Haplustepts, Typic Haplustepts, Typic Endoaquepts, and Ustipsamments.

Soil sampling and analysis

A total of 85 sampling sites were randomly selected throughout the study area, which included 10 old alluvial plain sites, 27 recent alluvial plain sites, 43 meander plain sites, and 5 flood plain sites

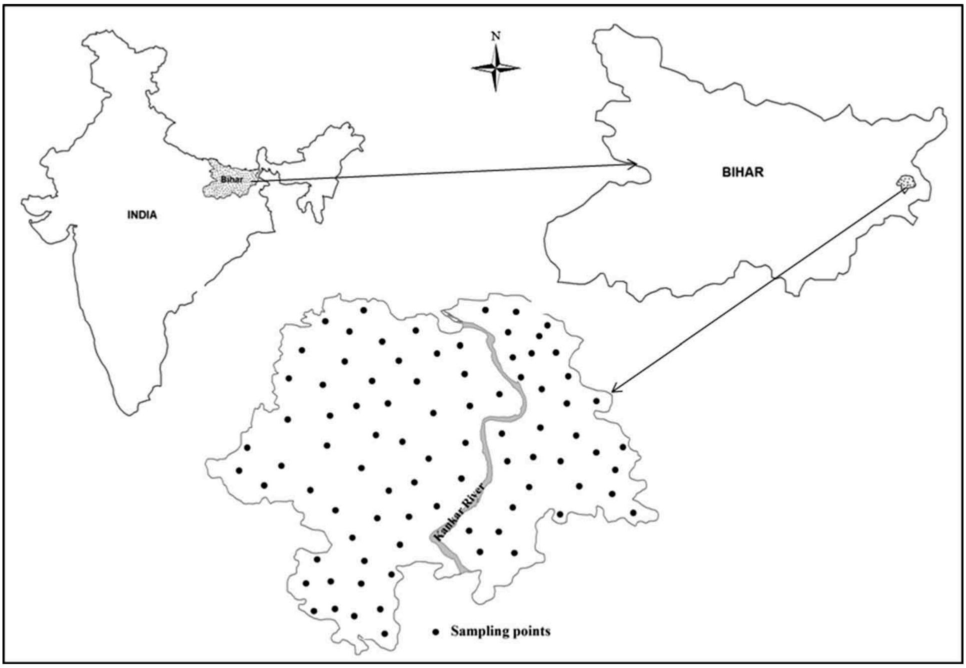

Figure 1. Location and sampling points map of the study area.

depending upon the area from the plough layer (0–25 cm depth) (Figure 1) with the help of hand-held global positioning system (GPS). Soil samples were air-dried and ground to pass through a 2-mm sieve and used to determine soil texture by hydrometer method. Organic carbon was determined by the Walkley and Black (1934) method. The pressure plate apparatus (Klute 1986) was used to determine the water content at FC (–33 kPa) and PWP (–1500 kPa). The AWC was calculated as the difference between water content at PWP – FC (Jury et al. 1991.)

Geostatistical analysis based on GIS

Spatial interpolation and GIS mapping techniques were employed to produce spatial distribution ant maps for the investigated basic soil properties, and the software used for this purpose was ArcGIS v.10.1 (ESRI Co, Redlands, USA). In ArcGIS, kriging can express the spatial variation and allow a variety of map outputs, and at the same time minimize the errors of predicted values (González et al. 2014). Moreover, it is very flexible and allows users to investigate graphs of spatial auto-correlation. Kriging, as applied within moving data neighborhoods, is a nonstationary algorithm which corresponds to a nonstationary random function model with varying mean but stationary covariance (Deutsch & Journal 1992). In kriging, a semivariogram model was used to define the weights of the function (Webster & Oliver 2001), and the semivariance is an autocorrelation statistic defined as follows (Mabit & Bernard 2007):

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

where $z(x_i)$ is the value of the variable z at location of x_i, h the lag, and $N(h)$ the number of pairs of sample points separated by h.

During pair calculation for computing the semivariogram, maximum lag distance was taken as half of the minimum extent of sampling area. Anisotropic semivariograms did not show any differences in spatial dependence based on direction, for which reason isotropic semivariograms were chosen. Circular, spherical, exponential, and Gaussian models were fitted to the empirical semivariograms. Best-fit model with minimum root mean square error (RMSE) were selected for each soil property:

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

The spherical and exponential models were best fitted to all the soil physical properties. Expression for different semivariogram models used in this study is given below:

Exponential model:

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

Spherical model:

$$\gamma(h) = C_0 + C_1\left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right], \quad 0 \leq h \leq a = C_0 + C_1, \quad \text{Otherwise,} \tag{4}$$

Using the semivariogram model, basic spatial parameters such as nugget (C_0), sill$(C + C_0)$, and range (A) was calculated which provide information about the structure as well as the input parameters for the kriging interpolation. Nugget represents variation caused by stochastic factors, such as error in measurement, sill is the lag distance between measurements at which one value for a variable does not influence neighboring values, and range is the distance at which values of one variable become spatially independent of another (Lopez-Granados et al. 2002).

Accuracy assessment

Accuracy of the maps was evaluated through cross-validation approach (Davis 1987). Among the three evaluation indices used in this study, mean absolute error (MAE) and mean-squared error (MSE) measure the accuracy of prediction, whereas goodness of prediction (G) measures the effectiveness of prediction. MAE is a measure of the sum of the residuals (Voltz & Webster 1990).

$$MAE = \frac{1}{N}\sum_{i=1}^{N} z(x_i) - \hat{z}(x_i) \tag{5}$$

Where $\hat{z}(x_i)$ is the predicted value at location *i*. Small MAE values indicate less error. The MAE measure, however, does not reveal the magnitude of error that might occur at any point and hence MSE will be calculated.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2 \tag{6}$$

Squaring the difference at any point gives an indication of the magnitude, for example, small MSE values indicate more accurate estimation, point-by-point. The G measure gives an indication of how effective a prediction might be relative to that which could have been derived from using the sample mean alone (Schloeder et al. 2001).

$$G = \left[1 - \frac{\sum_{i=1}^{N} [z(x_i) - \hat{z}(x_i)]^2}{\sum_{i=1}^{N} [z(x_i) - \bar{z}]^2}\right] \times 100 \quad (7)$$

Where z is the sample mean. If G = 100, it indicates perfect prediction, while negative values indicate that the predictions are less reliable than using sample mean as the predictors. The comparison of performance between interpolations was achieved by using MAE.

Results and discussion

Descriptive statistics of soil physical properties

Measured variables in the data set were analyzed using SPSS 17.0 software to obtain the minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV), skewness, and kurtosis. The statistical characteristics of sand, silt, clay, organic carbon (OC), volumetric water content (θ_v) at FC, PWP, and AWC are listed in Table 1. There was a difference in the CV of the soil physical properties. According to Wilding (1985), the silt content of soil had low variability (CV of 17%), sand and clay contents which made high variability (CV of 68% and 39%, respectively). Other researchers also documented a higher variation of sand and clay contents for alluvial soils compared to silt content in surface soil (Iqbal et al. 2005). All the soil hydraulic properties like FC, PWP and AWC, and OC exhibited medium variability (CV of 15–35%). A similar result was reported by Mulla and McBratney (2001).

Although these statistical studies provide useful information about the soil physical properties distribution, they do not describe the spatial continuity of the data, that is, the relationship between the value for a property in one location and the values for the same property at other location through the landscape. Hence, geostatistical techniques were applied to better understand of spatial distribution pattern of the studied variables. Besides, normality may not be strictly required in geostatistical analyses but normal distribution may lead to more reliable results (Webster & Oliver 2001). Therefore, the data distribution was tested for normality using the Kolmogorov–Smirnov test. The AWC which was not normally distributed (Table 1), was subjected to a natural log transformation.

Semivariogram analysis of soil physical properties

Semivariogram parameters (nugget, sill, and range) for each soil physical properties with best-fitted modal were identified based on minimum RMSE. Analysis of the isotropic variogram indicated that the sand, silt, and clay contents semivariograms were well-described by exponential model, with the distance of spatial dependence being 2437, 2012, and 2342 m, respectively, while the FC, PWP, and AWC semivariograms were well-described by spherical model, with the distance of spatial dependence being 1989, 1787, and 1654 m, respectively

Table 1. Summary statistics for selected soil physical properties.

Soil property	Mean	Minimum	Maximum	SD	CV (%)	Skewness	Kurtosis	Distribution pattern
Sand (%)	14.4	1.1	37.9	9.8	68	0.53	−0.65	Normal
Silt (%)	65.7	45.6	84.5	11.1	17	−0.02	−1.30	Normal
Clay (%)	19.9	6.8	46.8	7.9	39	0.95	1.57	Normal
OC (%)	0.67	0.22	1.18	0.19	28	0.40	0.67	Normal
FC (%, v/v)	42.2	19.0	75.0	10.6	25	0.18	0.84	Normal
PWP (%, v/v)	16.5	8.0	35.0	5.6	34	0.97	1.16	Normal
AWC (%, v/v)	25.7	11.0	63.0	8.9	35	1.20	4.52	Log

Notes: SD: standard deviation; CV: coefficient of variation; OC = organic carbon; FC: field capacity, volumetric water content (v/v) at −33 kPa; PWP: permanent wilting point, volumetric water content at −1500 kPa; AWC: available water content, calculated as the difference between −33 and −1500 kPa.

Table 2. Geostatistical parameters of the fitted semivariogram models for soil physical properties.

Soil properties	Fitted model	Nugget	Sill	Range*	Nugget/Sill (%)	RMSE**
Sand	Exponential	70	100	2438	0.70	9.40
Silt	Exponential	68	114	2012	0.60	14.46
Clay	Exponential	2	65	2342	0.03	7.63
FC	Spherical	62	132	1989	0.47	11.46
PWP	Spherical	16	34	1787	0.47	5.99
AWC	Spherical	35	94	1654	0.37	8.52

Notes: *range in m; **root mean square error.

(Table 2). Within the study area, the soil particles displayed slight difference in the distance of spatial dependence. Such differences in the distance of spatial dependence for soil particles were reported in other studies (Cambardella et al. 1994; Safari et al. 2013). The ratios of nugget and sill between 0.25 and 0.75 represented moderate spatial dependence; those below 0.25 represented strong spatial dependence (Cambardella et al. 1994). The resulting semivariograms indicated that except clay all other soil physical properties were moderate spatially dependent (37–70%), imprinted by intrinsic factor (soil forming process), and extrinsic factors (tillage operation and cultivation practices) (Cambardella et al. 1994). Some other researchers had also found the moderate spatial dependence of soil physical properties (Iqbal et al. 2005; Safari et al. 2013).

Spatial distribution map and cross-validation

The parameters of the exponential and spherical models were used for kriging to produce the spatial distribution maps of soil physical properties of the study area. Spatial maps of sand, silt, and clay (Figure 2a–c) showed that high sand content was found in NW quadrant, high silt content in NE quadrant, and high clay content in the center of the study area. Spatial maps of θ_v at FC, PWP, and AWC (Figure 3a–c) indicated that soils in the NW part of the study area have low water retention at FC and PWP, as well as lower AWC. As expected, a significant ($P < 0.01$, two-tailed) negative relationships were obtained of sand content with FC (−0.57), PWP (−0.41), and AWC (−0.43), positive relationship of clay with FC (0.32, $P < 0.05$, two-tailed) and PWP (0.75), and highly significant positive relationship of OC with FC (0.42) and PWP (0.73) (Table 3).

In summary, the distribution maps of various soil physical properties across the study area have implications for variable rate application of fertilizer, water, seed rate, and so forth. For instance, the spatial distribution of water retention properties closely followed the distribution of pattern of sand and clay contents. These maps will help to planner to develop the variable rate of irrigation (VRI) for the study area. The VRI plan for the study area would not only optimize yield of crops by avoiding crop water stress in highly prone areas, but would also reduce groundwater and surface water nitrogen pollution due to over irrigation resulting in runoff and percolation.

Table 4 showed the evaluation indices resulting from cross-validation of spatial maps of soil physical properties. It was observed that, sand content, FC, and AWC had low MAE however, clay content and PWP had relatively low MSE than other soil physical properties. For all the soil physical properties, the G value was greater than 0, which indicates that spatial prediction using semivariogram parameters is better than assuming mean of observed value as the property value for any unsampled location. This also shows that semivariogram parameters obtained from fitting of experimental semivariogram values were reasonable to describe the spatial variation of all the studied soil physical properties.

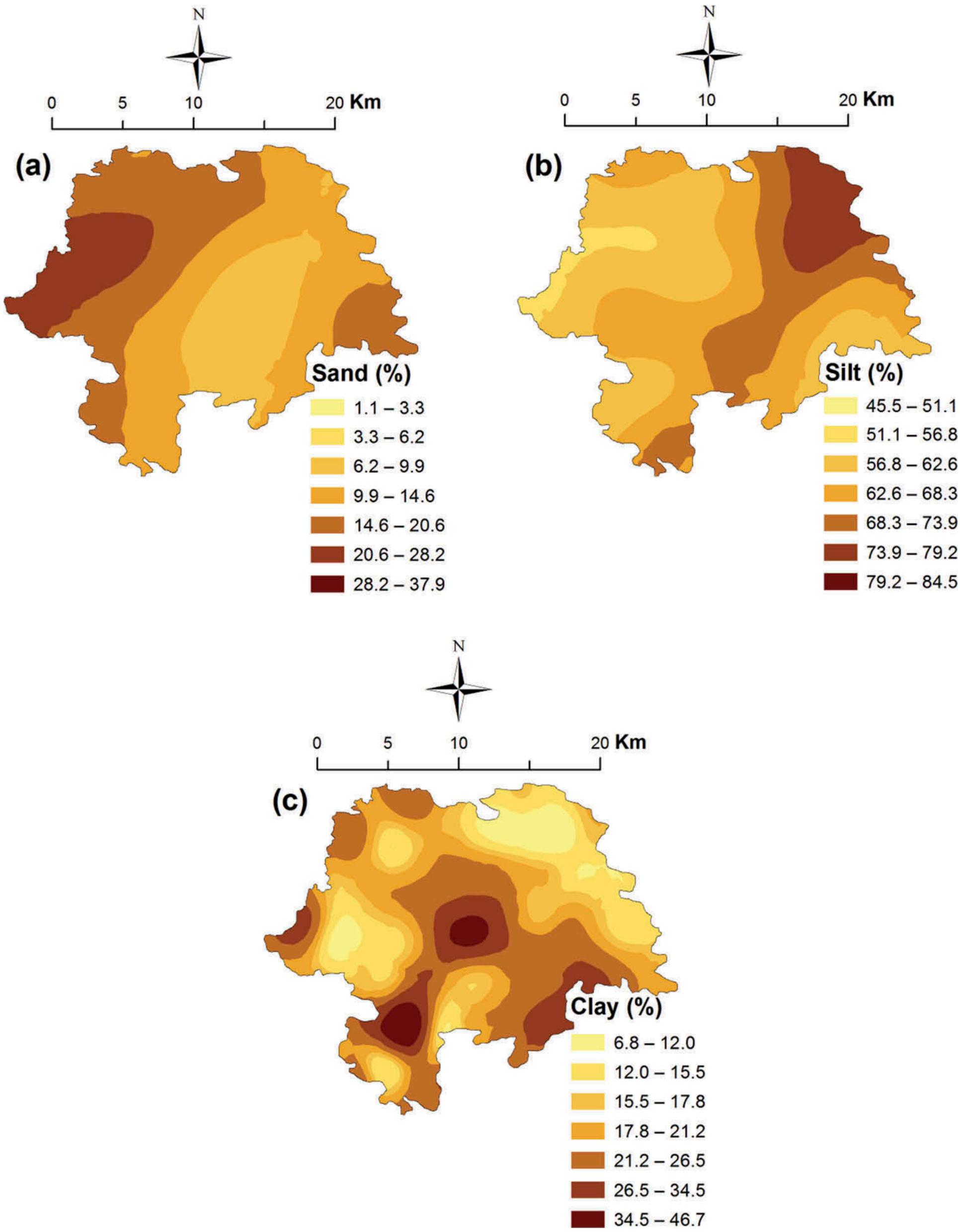

Figure 2. Spatial distribution maps of percentage: (a) sand content, (b) silt content, and (c) clay content.

Conclusions

The classical and geostatistical method on a large scale could be accurately used to evaluate spatial variability of soil physical properties. The raw data sets of AWC strongly positively skewed and the application of log transformation was effective in normalizing the data. Among the four models selected, the exponential model fits the experimental semivariogram for soil particles, while for soil hydraulic properties, the spherical model was found the best to fit the experimental semivariogram. Semivariograms for soil properties indicated that except clay content all other soil physical properties were moderate spatially dependent. Spatial maps of sand, silt, and clay contents showed

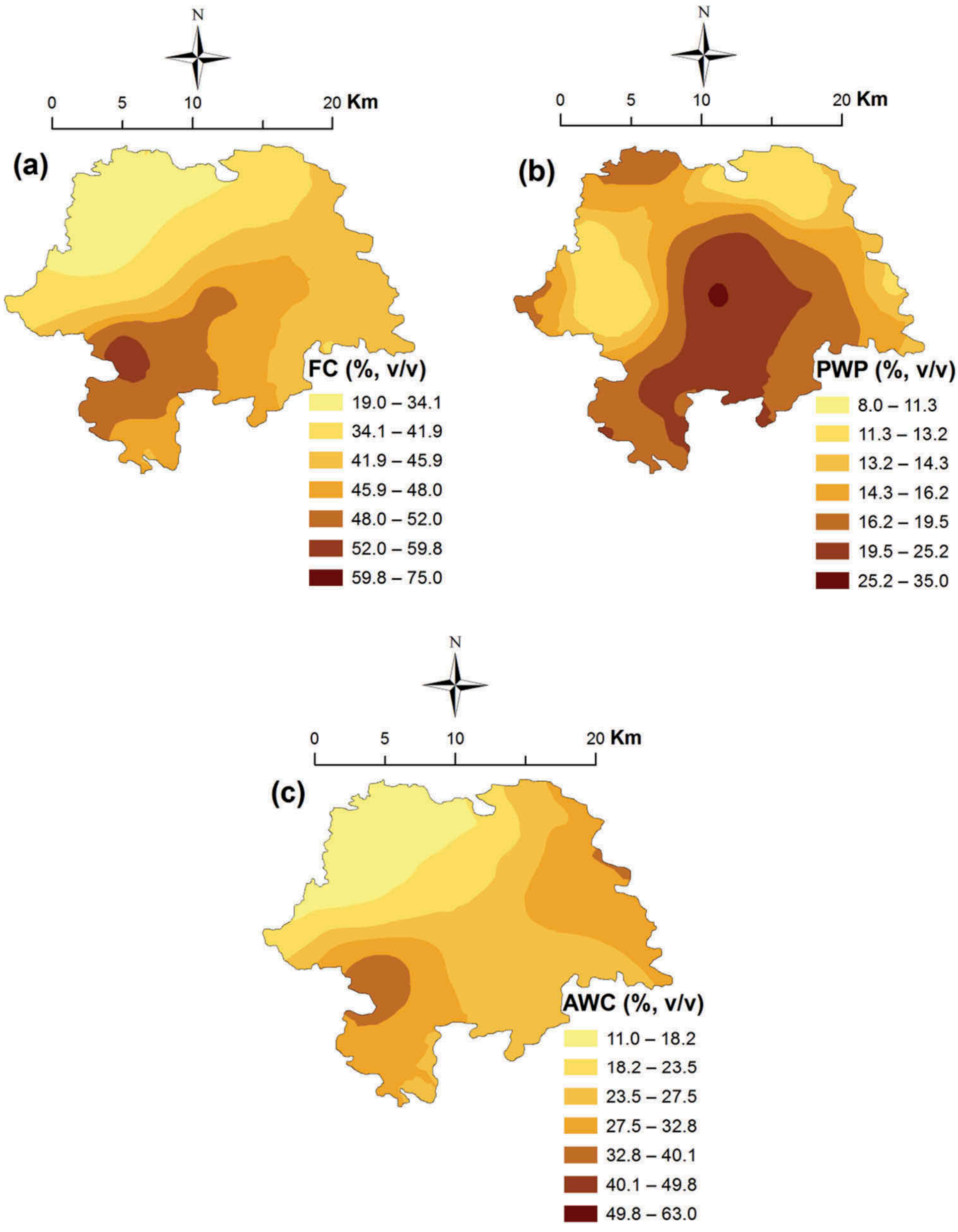

Figure 3. Spatial distribution maps of volumetric water content (v/v), expressed in percentage: (a) at field capacity (FC) (−33 kPa), (b) at permanent wilting point (PWP) (−1500 kPa), and (c) available water content (AWC) (calculated as the difference between −33 and −1500 kPa).

that high sand content was found in NW, high silt content in NE, and high clay content while, low water retention at FC and PWP, as well as lower AWC in the NW part of the study area. Cross-validation of kriged map shows that spatial prediction of soil physical properties using semivariogram parameters is better than mean of the observed value for any unsampled location. Spatial variability maps of various soil physical properties will help in site-specific farming, for example, variable rate irrigation in the study area.

Table 3. Correlation coefficients among soil properties and their level of significance.

	Sand	Silt	Clay	OC	FC	PWP	AWC
Sand	1.00						
Silt	−0.72**	1.00					
Clay	−0.23	−0.52**	1.00				
OC	−0.29*	−0.26	0.71**	1.00			
FC	−0.57**	0.23*	0.32*	0.42**	1.00		
PWP	−0.41**	−0.18	0.75**	0.73**	0.54**	1.00	
AWC	−0.43**	0.44**	−0.09	0.04	0.85**	0.02	1.00

Notes: *Correlation is significant at $P < 0.05$ level (two-tailed); **correlation is significant at $P < 0.01$ level (two-tailed).

Table 4. Evaluation performance of kriged map of soil physical properties through cross-validation.

Soil properties	Mean absolute error	Mean square error	Goodness of prediction
Sand (%)	0.64	88	14
Silt (%)	0.77	102	16
Clay (%)	0.36	53	14
FC (%, v/v)	0.62	84	24
PWP (%, v/v)	0.06	27	11
AWC (%, v/v)	0.12	58	26

Disclosure statement

No potential conflict of interest was reported by the authors.

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