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Prediction and spatial distribution mapping of soil electrical conductivity using geo-statistical method for Mirzapur district, Uttar Pradesh

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Abstract
Soil electrical conductivity is more like soil pH; a limiting factor in crop growth and production as well as it corresponds to the soil conditions that is excess of salt in the soil or not hence define suitability of soil for crops. The present research was undertaken in Mirzapur district of Uttar Pradesh to assess the spatial variation in electrical conductivity (EC), its prediction and mapping. A sum of 48 representative soil samples were yielded from twelve geo-referenced soil profiles excavated in the study area. Following physic-chemical analysis of soil samples from various depth (i.e. 0-15, 15-30, 30-45 and 45-60 cm) of 12 profiles, more specifically determination of electrical conductivity (dS/m). Further, classical and geo-statistical methods have been employed to characterize soil parameter i.e. EC (dS/m) and its spatial distribution. Ordinary kriging interpolation was used to create spatial variability map and semivariogram model was applied for quantification of electrical conductivity.

Keywords: Spatial, mapping, geo-statistics, semivariogram, kriging, soil properties, electrical conductivity

1. Introduction

Soil productivity attributed to various characteristics of the soil which contributes to soil fertility like soil pH, electrical conductivity, organic carbon content, micronutrient (Fe, Cu, Zn, and Mn) and major nutrient (N, P, and K) concentration in soil. Soil electrical conductivity is the major of soil salinity or saltiness/ accumulation of salt in the soil and determinant of different soil properties. Soil EC can be use both as direct and indirect indicator of soil physical, chemical and biological properties. Buildup of salt in soil may hamper the agriculture crop production that will be of great concern for farmers, government and agricultural scientists [1]. For this purpose mapping and accurate assessment of soil- EC which in turn correspond to soil salinization are must needed for soil management thus crop production [2]. Soil-EC governs by many environmental such as climate, rainfall, temperature and edaphic factors such as soil moisture content (porosity and water filled pore space), texture, soil type, geology as well as influenced by human activities; irrigation practices, land use, ground water table and drainage [3, 4, 5].

Increasing interest in precision agriculture in recent years has led to a need for soil maps that are more detailed and accurate than those traditionally produced. Site specific management proved to be potential strategy for managing soil inherent variability hence optimize production and economic return while conserving resources (soil and water) and improve soil quality [6]. To avoid the intensive soil sampling as it is laborious and costlier way implementation of selective soil sampling based on soil characteristics such as soil colour, texture, depth, slope and erosion to examine spatial variation at field scale [7]. Further laboratory analysis of electrical conductivity provide highly correlated measures in terms of crop production at surface soil up to a depth of 90 cm [3]. Mirzapur have many constraints in relation to agricultural crop production as it comes under rainfed region and nutrient deficient zone determined by various soil physic-chemical properties that limits productivity.

Different approaches have been developed to map and delineate the spatial variation and distribution pattern of soil characteristics. Soil electrical conductivity can be mapped using: geostatistical methods, such as ordinary kriging (OK) [8]; regression kriging (RK) [9]; classical statistics, such as multiple linear regressions (MLR) [10], artificial neural networks [11] and random forest [12]. Ordinary kriging an interpolation method has been widely used as it is very simple, precise and basic geo-statistical model does not account environmental variable which in addition at different local position has variable influence on different soil properties [13].

The objective of the study is to evaluate the mapping accuracy of the ordinary kriging in mapping spatial distribution of soil electrical conductivity and estimate efficiency in prediction mapping via cross validation with semivariogram parameters such as mean error (ME), root mean square error (RMSE), average standard error (ASE), and root mean square standard error (RMSSE) to examine the suitability of methods employed [7]. With this objective present research was undertaken to perform prediction mapping of soil electrical conductivity for rainfed agricultural land of Mirzapur district, U.P.

2. Materials and Methods

2.1 Study area

Our study area is Mirzapur district located in state of Uttar Pradesh, India. It occupy an area 4522 Km^2 and situated at latitude 24.41’30” to 24.47’N and at longitude of 82.21’45” to 82.30’E (Fig. 1). It has a sub-humid climate; with the mean annual rainfall is 1085 mm and temperature ranges from minimum 14.18 °C in January to 39.80 °C maximum temperature during June with 85% relative humidity. Area is dominated by alluvial soil in endo-Gangatic belt belongs to Sandy to Clay loam classes and red soil (Alfisols) in vindhyan region where rain-fed agriculture is plasticized.

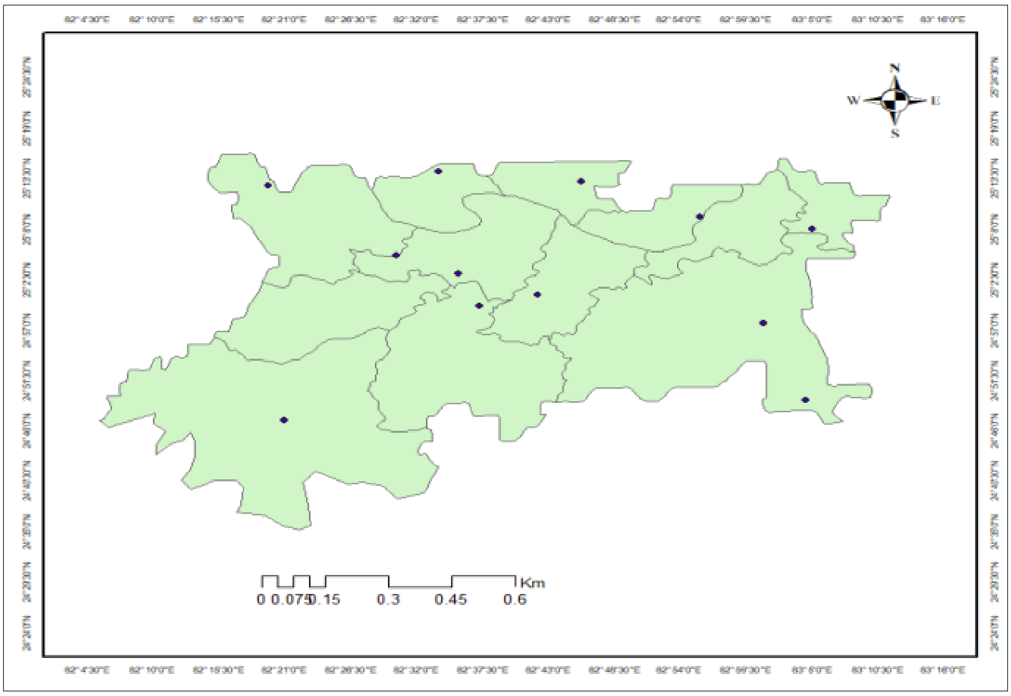

Fig 1: Sampling site and location map of study area

2.2 Soil sampling

Ground truthing was conducted in study area to execute the present research objectives. A sum of 48 representative soil samples were recovered from 12 geo-referenced profile dig in the study area using auger sampling method from various horizon with equal interval class (i.e. 0-15, 15-30, 30-45 and 45-60 cm) up to 60 cm based on morphological variation in the area. Profile locations were note down in the field using Garmin GPS. Collected samples thus processed using standard protocol; drying, grinding, sieving through 2 mm and stored in polythene bags for characterization. Then after these processed soil samples were subjected to physic-chemical analysis via standard analytical procedure. Electrical conductivity of samples was determined using a dilution ratio of 1: 2 (soil: water). According to Jackson 10 gm soil added with 20 mL of distilled water and stirred well, allow to settle for 30 minutes and the reading was taken using EC meter. Before to take reading instrument was calliberated using 0.01N KCl accounts for EC of 1.41 dSm^{-1}.

2.3 Statistical analysis

Statistical analysis was performed using IBM SPSS (version 20) software and descriptive statistics viz; skewness, kurtosis, range, standard deviation, mean, max^m and min^m etc. were also applied to EC datasets. Moreover, present variation in the datasets classified based on coefficient of variation ranging from <15%, 15-35% and >35% denotes low, medium and high variation respectively.

2.4 Geo-statistical analysis

Geo-statistics were employed to determine the pattern in spatial variation of soil electrical conductivity (EC) in the area of interest. For mapping the spatial variability ArcGIS version 10.8 Software was used in which geo-referenced sampling location was linked to soil attribute to create maps.

The geo-statistics analyses were implemented in ArcGIS 10.8. The ordinary kriging method of interpolation was performed to estimate the EC of unsampled area because of its simplicity and accuracy rather to use other methods of interpolation or kriging. For roughly normal distribution these methods of kriging have high efficiency. Eq. (1) used to calculate kriging.

$$Z^*(x_0) = \sum_{i=1}^{N} \lambda_i Z^*(x_i) \qquad (1)$$

Where $Z^*(x_0)$ is the estimated value for unsampled sitex_0; x_i is sample points in a selected nearness; Z (x_i) is the observed value for the given attribute atx_i; λ_i is weight of the determined value at locationx_i, and N is the number of locations in the nearness searched for the interpolation.

Semivariogram were created to determine the pattern in spatial distribution of soil attributes. Semivariogram parameters i.e. Nugget, sill and range were computed using following eq. (2) [14].

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

Where γ(h) is the empirical semi-variogram value at the lag interval distance h; N(h) is the number of sample pairs within the lag interval distance h; Z(xi) and Z(xi + h) are sample values at the two spatial locations xi and xi + h, respectively.
In the present investigation semivariogram model was evaluated for electrical conductivity of surface soil as well as soil underneath. Model fitness and prediction accuracy was determined through cross validation technique via cross-comparison with possible committed error values. The prediction errors included (1) ME (mean error) describe the bias level in estimate, (2) RMSE (root-mean-square error) quantifies accuracy of model to predict observed value, (3) RMSSE (root-mean-square standardized error), and (4) ASE (average standard error) were computed using eq. (3 to 6), respectively. The less significant the error degree is, the further accurate the findings will be [15].

$$\mathrm{ME}=\frac{1}{N}\sum_{i=1}^{N}(Z^* x_i - Zx_i) \quad (3)$$

$$\mathrm{RMSE}=\left[\sum_{i=1}^{N}(Z^* x_i - Zx_i)^2/N\right]^{1/2} \quad (4)$$

$$\mathrm{RMSSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{[(Z^* x_i - Zx_i)]^2}{\delta^2(x_i)}} \quad (5)$$

$$\mathrm{ASE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\delta^2(x_i)} \quad (6)$$

Where N is the number of validation point; Zx_i and $Z^* x_i$ is the measured and predicted value.

For say, ME should be near to zero, RMSE and ASE must be small and have value close to each other and RMSSE approximately one for a model to fit for mapping spatial variability of soil attributes and to make considerable prediction [16].

3. Results and Discussion

Statistical description of the electrical conductivity of the soil from different layers of studied profiles presented in Table 1. Our finding shows that EC ranged from 0.02 dS m^{-1} to 0.206 dS m^{-1} and mean EC of 0.084±0.24 dSm^{-1} and 53.8 % coefficient of variation indicates that EC showed a moderate variation in the region [17]. Profile study at particular depth revealed that at 0-15 cm depth EC varies from 0.024 to 0.206 dS m^{-1} with mean EC of 0.094 dS m^{-1} and down the profile it varies from 0.031 to 0.186 dS m^{-1}, 0.020 to 0.123 dS m^{-1} and 0.043 to 0.170 dS m^{-1} with average EC of 0.079, 0.074 and 0.087 dS m^{-1} at 15-30 cm, 30-45 cm and 45-60 cm profile depth respectively. It could be depicted from the observed values that EC of deepest horizon is higher than other top layer but comparable to that of surface layer. Initially it decreased from surface 0-15 cm to 45 cm and then increases and becomes highest in the last layer i.e. 45-60 cm. this might be due to dynamic nature of top soil salts may get accumulated to surface layer due higher rate of evaporation in the area [18] though intensive leaching processes tend it to deposited in deeper layer [19]. Overall, the maximum EC in various depth of profile observed in Ori, Badauhi, Jalalpur Mafi and Karanpura at 0-15, 15-30, 30-45 and 45-60 cm respectively while at Belahi lowest EC was recorded throughout the profile. Further skewness and kurtosis (Table 2) revealed that data sets was moderate to highly skewed with skewness varied from 0.79 to 1.19 for all layers except electrical conductivity of 3rd depth (30-45 cm) had approximately symmetric distribution with skewness of -0.03. Further the distribution of EC had platykurtic to leptokurtic curve with kurtosis ranged from 2.30 to 3.15.

Table 1: Descriptive Statistical parameters for Soil electrical conductivity

Depth (cm)	Geostatistical parameters					
	Average	Maximum	Minimum	SD	Skewness	Kurtosis
0-15	0.09	0.206	0.024	0.06	0.93	2.40
15-30	0.07	0.186	0.031	0.04	1.19	3.15
30-45	0.07	0.123	0.020	0.02	-0.03	2.30
45-60	0.08	0.170	0.040	0.04	0.79	2.51

Ordinary kriging an interpolation technique has been applied in mapping spatial variability in soil electrical conductivity (Fig. 2). There were remarkable changes detected in the EC map through the whole depth of soil profiles in the study area. Entire area was found in the safe range of EC <0.34 dS m^{-1} indicates the non-salinity of soil. Throughout the depth of profile all the layer are non-saline that means no accumulation of salts in the profile. According to soil salinity classess; non-saline, slightly, moderate, severe and saline-sodic soil that corresponds to soil electrical conductivity of < 0.34, 0.34–0.98, 0.98–1.87, 1.87–2.96, > 2.96 dS/m respectively [20, 21].

However, higher soil-EC could be seen in south-western part while lower soil-EC in the central part of study area at all the layer of soil profiles excavated. Nugget/sill ratio indicate that in all three (0-15, 15-30 and 30-45 cm) depth electrical conductivity was found to have strong spatial dependence (i.e. nugget/sill < 0.25) while at deeper depth (45-60 cm) moderate spatial dependence of soil-EC was observed i.e. nugget/sill between 0.25-0.75. Cambardella *et al.* (1994) classified the strong, moderate and weak spatial dependency based on the ratios of nugget/sill at < 25%, 25%–75% and > 75%, respectively [22].

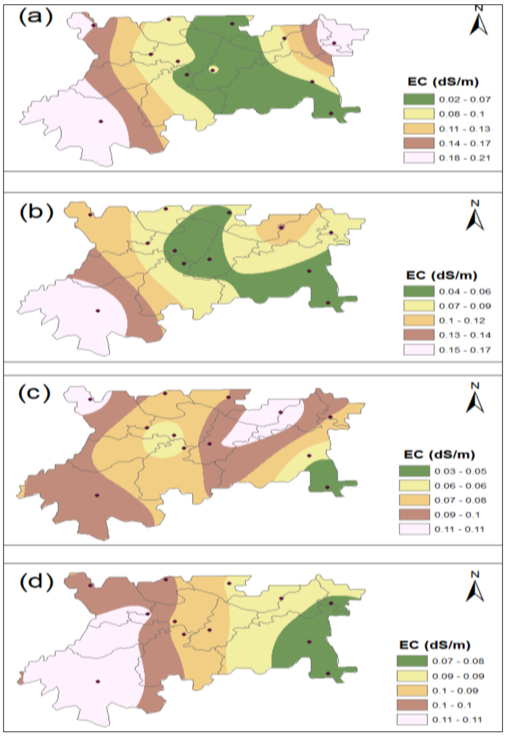

Fig 2: Spatial variability map of soil electrical conductivity from different depth of soil profile (a) 0-15 cm, (b) 15-30 cm (c) 30-45 cm and (d) 45-60 cm

Table 2: Output from semivariogram model of Ordinary kriging

Depth (cm)	Semivariogram parameters						
	Range	Nugget (°C)	Nugget/ Sill ratio	RMSE	RMSSE	ASE	Mean Error
0-15	0.520	0	0	0.070	2.07	0.03	-0.02
15-30	0.456	0	0	0.049	1.46	0.03	-0.001
30-45	0.525	0	0	0.028	0.96	0.03	-0.0004
45-60	1.320	0.001	0.58	0.041	0.98	0.04	0.0001

Semivariogram model parameters are presented in Table 2. These results are confirmed by cross validation using prediction error such as RMSE, RMSSE, ASE and ME from the semivariogram model of ordinary kriging. Prediction error shows that RMSE and ME were found close to zero varied from 0.028 to 0.070 and -0.02 to 10^{-4} confirm the usefulness of the technique for prediction and suggested that OK model was best fit to predict the distribution of EC in Mirzapur district with higher accuracy and yield better results (Fig. 3).

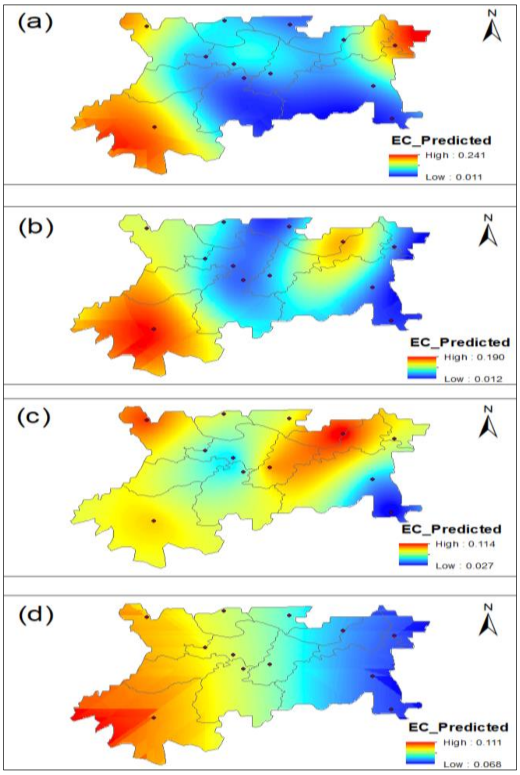

Fig 3: Prediction map of soil electrical conductivity as yielded from semivariogram model of Ordinary kriging

4. Conclusion

Geo-statistical method of ordinary kriging was found best fit to delineate soil electrical conductivity well estimates the electrical conductivity of soil from area that was not surveyed hence prove to be best method in prediction mapping for soil EC based on which the study area was overall non-saline having electrical conductivity of < 1 dS m^{-1} and profile study reveals that there was not significant changes occurred in EC of top and deeper layer while middle layer was found with somewhat lower EC than that of both above said layers. Spatial distribution map detailed the finding that EC in the study area has moderate to strong spatial dependency. Further need to strengthen our research system to cop up the upcoming challenges in crop production and resources management.

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