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GIS Interpolation and Mapping of Soil Physicochemical Properties in Deep Medium Black Soils of Established Citrus Orchards

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Soil properties are an important factor for orchard establishment, precise nutrient management and sustainable production of fruit crops. Therefore, it is important to assess the spatial distribution of fundamental soil properties in well-established orchards. Hence an attempt has been made to assess the extent of soil properties and its spatial distribution in citrus orchards in medium black soils of Madhya Pradesh. The present study was conducted for the assessment of the spatial

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distribution of physicochemical properties viz. pH, electrical conductivity (EC) and soil organic carbon (SOC) of citrus orchards in medium-deep black soils of India. Results revealed that soil pH ranged from 6.83-8.84 (mean 7.80), soil EC varied from 0.07-0.34dS m-1 (mean 0.18 dS m-1) and soil organic carbon ranged from 0.13-0.89% (mean 0.47%) in 0-20 cm of surface soil layer. Geostatistical analysis showed that the slope of the prediction function of best-fit model (exponential) for soil pH, EC and SOC was 0.31, 0.22 and 0.77, respectively. The corresponding values of root mean square error (RMSE) were 0.35, 0.03, and 0.14. Interpolation of soil properties indicated that 89.2 % area had soil pH between 7.20 to 8.00, 83.4 % area had soil EC between 0.10 to 0.20 dS m-1, while>90 % area had SOC content ranged from 0.25 to 0.75%. Geo-statistical analysis revealed that spatial dependency was moderate for pH and strong spatial dependency was estimated for EC and SOC content. Based on RMSE and slope of prediction function, an exponential model was best-fit model in ordinary kriging for interpolation of measured soil properties.

Keywords: Geo-statistics; Madhya Pradesh region; soil pH; soil EC; soil organic carbon; Spatial dependency.

1. INTRODUCTION

Mandarins (*Citrus reticulata* Blanco) contributes to the second largest production that is 26 percent after sweet oranges contributing 56 percent to global citrus basket [1]. In India, mandarins constitute about 5.27 million metric tonnes from land area of 0.42 million ha and ranks first among the citrus fruits grown here in the country. The average productivity of mandarins in India is 12.54 tonnes ha^{-1}, which is equitably low as compared to several advanced mandarin growing nations. Its cultivation is getting popularity specially in state of Madhya Pradesh due to high production and superior quality which is in much demand moreover citrus growers are preferring its cultivation due to its easy adaptability to diverse agro-climatic conditions and its persistent demand in the domestic market. Citrus is high nutrient demanding crop but faces improper nutrient supply to fruit trees either due to fertilizers insufficiency or imbalanced fertilization, which directly or indirectly affects sustainable production in orchards of region. Nutrient availability to fruit trees is affected by physicochemical properties of soil like pH, EC, SOC, cation-exchange capacity, soil texture, water-holding capacity, and drainage conditions [2]. In site-specific management and high-intensity soil surveys, soil pH reflects soil acidity or alkalinity, EC is used to partition units of management, differentiate soil type, predict soil fertility and crop yields [3]. Soil organic carbon (SOC) is the most important component in maintaining soil quality because of its role in improving physical, chemical and biological properties [2]. SOC is a key component of soil organic matter. Soil organic matter enhances nutrient availability to the crop plants by releasing organic substances which can chelate with micronutrients and thereby improving their availability [4]. Spatial variability of soil organic carbon (SOC) is an important indicator of soil quality, as well as carbon pools in the terrestrial ecosystem and it is important in ecological modeling, environmental prediction, precision agriculture, and natural resources management Zhang et al. [5], Liu et al. [6]. Scientific management of SOC and nutrients are important for sustainable production of agricultural system. So, there is a need of adequate information about the spatiotemporal behavior of SOC over a region (Bhunia et al., 2016). Soil organic carbon is the basis of sustainability in orchards as it improves soil health and increase yield. SOC helps in maintaining soil fertility improves soil aeration, water retention capacity, drainage, and enhances microbial growth, thus providing a better soil condition for tree growth and affecting overall sustainability of production system. Soil properties varied within and between the orchard [7]. The variability of soil properties has a profound, but often unrecognized, effect on the economic and environmental aspects of agricultural production it also has implications for farm workability, nutrient management and sustainability Kværnø et al. [8] and Patzold et al. [9]. Therefore, achieving sustainable fruit production is possible with a better understanding of basic soil properties and their site -specific management. Information concerning spatial variability and distribution of soil properties is critical for farmers attempting to increase the efficiency of fertilizers and farm productivity Mabit et al. [10], Tesfahunegn et al. [11].

Geographic information system (GIS) helps to integrate many types of spatial information like agro-climatic zone, land use, soil management etc; to derive useful information [12]. In past decades, geo-statistics has been used extensively to characterize the spatial variability of soil attributes due to its ability of quantifying and reducing sampling uncertainties and minimizing investigation costs (Cambule et al. [13] Mani et al. [14], Mishra et al. [15]). Soil fertility maps generated by GIS generated may serve as a decision support tool for nutrient management [16]; Habibie et al. [17]. Geospatial technique serve as a tool to address the growth limiting factors of citrus orchards that includes biotic, abiotic, edaphic stress efficiently, this technology is being largely used for mapping and area estimation of citrus orchards using object-based classification and approaches related with machine-learning [14]. The utilization of GIS technology offers users a comprehensive array of tools and methodologies for managing geospatial information. This technology assists users to gather, store, merge, interrogate, present, and examine geospatial data through different levels of detail by Avanidou et al. [48]; Raihan &Tuspekova, [19]. Few of the research work done in orchards on quantification of the soil properties using spatial interpolation from an apple orchard in the Kulgam district of the Valley of Kashmir [20], mango orchards of eastern plateau region of India [21], oil palm plantations in the southern plateau of India by Behera et al., [22] in fruit Growing Area in Kluang, Malaysia [23]. Very few mapping studies of soil characteristics were also done in the past using nondestructive methods like electromagnetic induction (EMI) method in wild blueberry (Vaccinium angustifolium Ait) in central Nova Scotia Khan et al. [24]. However, seldom studies report from Rajgarh district of Madhya Pradesh which is one of the major contributors to mandarin production of the state and being assigned for “Orange” under “*One District One Product”* scheme of government of India. Therefore, the present study was undertaken (a) to assess the status of soil pH, EC, and OC, in citrus orchards of Rajgarh district of Madhya Pradesh and to study spatial distribution of soil properties (soil pH, EC, and OC) in citrus orchards of study area. This study helps orchard growers and planners to take location, -specific soil management for achieving sustainable orchard production.

2. MATERIALS AND METHODS

2.1 Site Description and Sample Collection

For this study, soil samples were taken in the established orchard system in the Rajgarh area of Madhya Pradesh. It is situated in the western region of Madhya Pradesh. The district has a total land area of 6,154 square kilometers. The climate of the study area may be primarily categorized into three distinct seasons. The winter season spans from mid-October until late February. The summer season spans from March to May, while the monsoon season begins in the second week of June and lasts until the end of September. The average annual precipitation is 985.8 millimeters. The district experiences the highest amount of precipitation during the southwest monsoon season, which spans from June to November. The monsoon season accounts for around 92% of the total annual rainfall. In the winter season, December experiences the lowest temperatures, ranging from a minimum of 4.80°C to a maximum of 29.5°C. In June, the maximum temperature reaches 45. 60°C.The predominant intercropping system was soybean-wheat.

GPS-based 104 soil samples (0-20 cm) were collected in the orchard of the 8-10-year-old establishment (Fig. 1). In the selected orchard, citrus (*Citrus reticulata Blanco* var. Nagpur Mandarin) plants were grown for more than 8 years. Collected soil samples were processed and analyzed for different soil properties.

2.2 Analysis of Soil Properties

pH of soil samples was determined in a 1:2 soil and water ratio as outlined by Jackson [25]. Supernatants from the same samples used for the determination of soil pH, were used for the determination of soil electrical conductivity using a conductivity meter [25]. Organic carbon content in soil was determined using the chromic acid wet oxidation method as outlined by Walkely and Black [26].

2.3 Geo-Statistical Analysis and Mapping of Soil Properties

The semi-variograms and soil pH, EC, and OC spatial structure were analyzed using ArcMap 10.7. The semi-variogram analyses were conducted prior to the implementation of ordinary kriging interpolation, as the semi-variogram model plays a crucial role in determining the interpolation function Goovaerts, [27], as depicted below.

2.4 Spherical Model

$$Y(h) = C_0 + C\left[3/2\frac{h}{A_0} - 1/2\left(\frac{h}{A_0}\right)^3\right] \quad \text{for } 0 < h < a = C_0 + C \quad \text{for } h \geq a \; Y(h) = 0$$

Circular model:

$$Y(h) = C_0 + C\left[1 - \frac{2}{\pi}cos^{-1}\left(\frac{h}{A_0}\right) + \sqrt{1 - \frac{h^2}{A_0^2}}\right]$$

Gaussian model:

$$Y(h) = C_0 + C\left[1 - \exp\left(\frac{-h^2}{A_0^2}\right)\right]$$

Exponential model:

$$Y(h) = C_0 + C\left[1 - \exp\left(\frac{-h}{A_0}\right)\right]$$

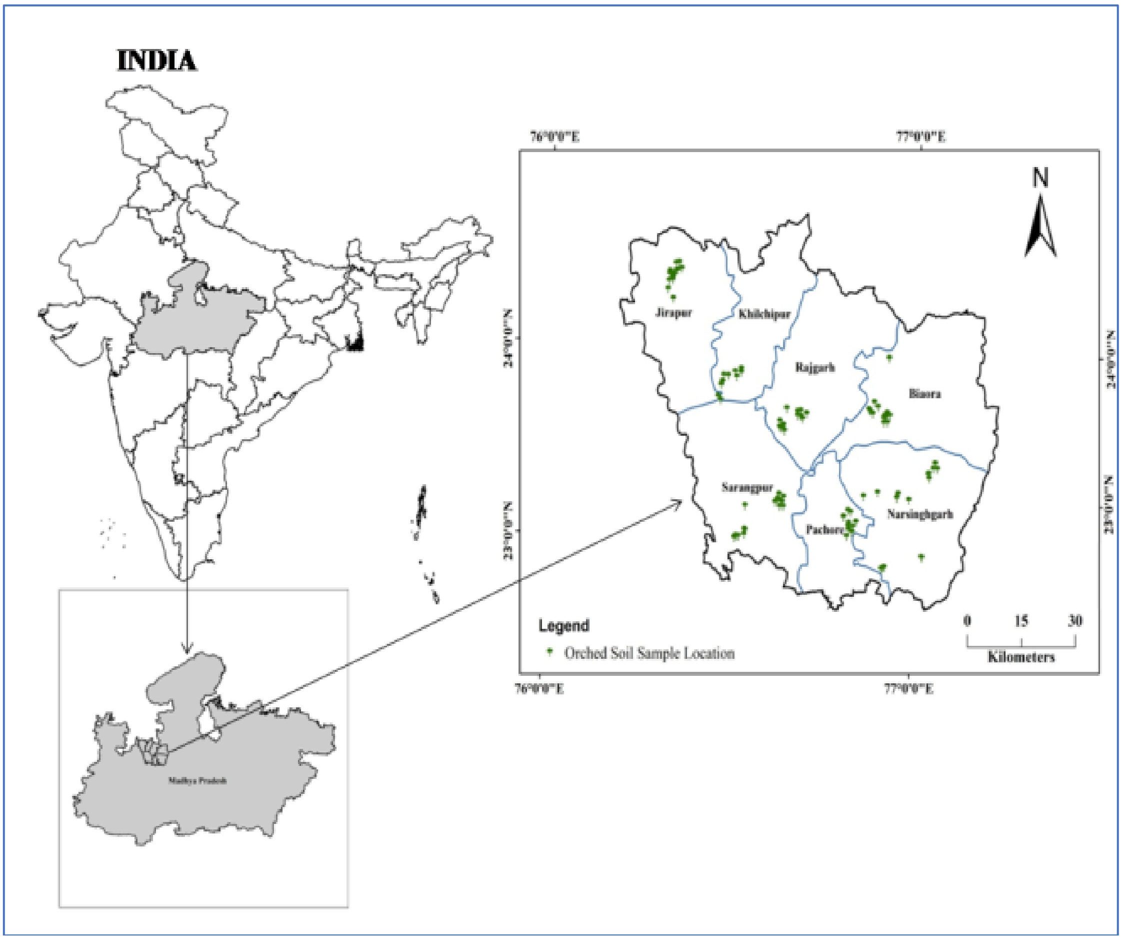

Fig. 1. Location of study area

The selection of semi-variogram models was performed through the utilization of the cross-validation technique. This involved comparing the observed values with the values estimated through kriging, employing the semi-variogram model. The evaluation of the predictive performance of semi-variogram models was conducted using the root mean square error (RMSE).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left\{z(x_i) - \hat{z}(x_i)\right\}^2}$$

C_0 is a nugget variance or the estimate ofthe residual or spatially uncorrelated noise (when Y(h)),C is partial sill, C_0+C equals the sill, the horizontal part when the curve levels off at a large value of distance h,A is a range of spatial dependence, the distance h to reach the sill,h is a lag or distance ,$z(x_i)$,$\hat{z}(x_i)$are observed value ,predicted value and N denotes number of observation .

2.5 Statistical Analysis

The SAS program (9.2) was used to calculate the minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV), skewness, and kurtosis values for each studied soil property (SAS, 2011).

3. RESULTS AND DISCUSSION

3.1 Soil Properties

Descriptive statistics of soil properties revealed that pH varied from 6.83 to 8.84 with a mean value of 7.80 (Table 1). The soil EC ranged from 0.07 to 0.34 dS $m^{-1}$with an average value of 0.18 dS m^{-1}. Soil organic carbon (SOC) content in soil varied from 0.13-0.89 % with an average value of 0.47% (Table 1). Data revealed that low variability was observed in soil pH (CV % = 4.92) while moderate variability was observed in soil EC (CV % = 26.6) and SOC (CV % = 46.1). These findings were in proximity of Dahule [27] that the safe limit for citrus ranged from pH 7.6 to 8.5 for citrus soil EC below 0.5 dSm^{-1} as safe limit for citrus orchards. Surwase [29] also reported soil pH range from 6.5 to 8.6 in citrus orchards of Katol and Kalmeshwar tehsil of Nagpur district for Nagpur mandarin orchards.

Low, moderate, and high variability are denoted by CV values <10.0, 10-100, and >100%, respectively (Nielsen and Bouma, [30]. Bogunovic et al. [31] reported low, medium, and high variability for pH, organic matter and E respectively in soils of Rasa River valley of Croatia. Behera and Shukla [32]. reported low (for pH and EC) to moderate (for SOC content) variability in Indian acid soils.

Similarly, variability was low for pH and medium for EC and organic matter in soils of Alequeva reservoir of Portugal [33]. In the present study, low value of CV (4.92) was observed for soil pH, which according to Nielsen and Bouma, [30] comes under low variability .Similar findings were reported by Behera et al [32] that soil acidity showed a low variability in four soil series namely Hariharapur, Debatoli, Rajpora and Neeleswaram situated in Orissa, Jharkhand, Himachal Pradesh and Kerala states of India, respectively .This low variability value obtained was due to transformed measurement of hydrogen ion concentration. Houlong et al. [34] observed lowest CV in case of soil pH as compared to other soil properties recorded in tobacco plantations of southern china. Mulla & McBratney [35] also reported low variability of soil pH and moderate to high variability for organic matter content, our findings for SOC are in line with this as our results reflected moderate variability for EC and SOC. Tesfahunegn et al. [11] also reported CV values of 8·6 to 73·4% for a several soil properties in Ethiopia.

This variability might be due to interaction of factors like geological, pedological, microclimatic and land use factors that includes soil management practices, fertilization and crop rotation on spatial and temporal scales (Cambardella & Karlen, [36] Mallarino et al. [37]. Skewness is a measure of the asymmetry of a distribution If skewness value lies above +1 or below -1, data is highly skewed. If it lies between +0.5 to -0.5, it is moderately skewed. If the value is 0, then the data is symmetric. Generally higher values of skewness (greater than 1), are required to be transformed to follow normal distribution. All the measured values of soil properties were positively skewed (Table 1). For parameters under study, observed kurtosis values were 0.22, 1.90 and -1.30 for pH, EC, and SOC respectively. Kurtosis is an essential statistical concept that measures the degree of peakedness and tail-heaviness of a probability distribution and it can be used to identify outliers in a dataset where Outliers are the observations that are different significantly from rest of the data and can heavily influence the statistical analysis. A high kurtosis indicates the presence of outliers on both ends of the distribution. The skewness and kurtosis coefficients are zero for a normally distributed random variable. If the data distributions are largely deviated from a normal distribution, to lessen the influence of extreme values on spatial analysis it is often suggested to perform data transformations [38]. The expected value of kurtosis is 3, it is observed in a symmetric distribution. A kurtosis greater than three will indicate Positive Kurtosis. In this case, the value of kurtosis will range from 1 to infinity. Further, a kurtosis less than three indicated a negative kurtosis. The range of values for a negative kurtosis is from -2 to infinity. The greater the value of kurtosis, the higher the peak.

3.2 Geostatistical Analysis

Ordinary kriging was used for mapping and semi-variogram for soil pH, EC, and SOC were calculated. The predicted minimum soil pH was 7.21, 7.21, 7.12 and 7.23 for circular, spherical, exponential, and Gaussian, model the corresponding value for the predicted maximum was 8.21, 8.10, 8.15 and 8.06. Map prepared using circular, spherical, exponential, and gaussian showed that <0.20% area falls under ≤ 7.20 soil pH while around 70% of the area falls under soil pH range of 7.50 to 8.0 (Table 2). In the pH range of 8.00 to 8.20, around 8-10% area was occupied on a map while negligible samples had pH >8.20 (Table 2). Predicted minimum and maximum values were in close agreement with measured values through an exponential model in OK. Soil electrical conductivity (EC) of the orchard were mapped using various models revealed that none of the areas had EC value <0.10 dS m^{-1} by any model (circular, spherical, exponential, and gaussian) while each model predicted around 75 % area in the range of 0.15 to 0.20 dS m^{-1} (Table 3). The EC value of >0.20 dS m^{-1} occupied around 16.2% area in the map (Table 3). Predicted minimum soil EC was 0.11, 0.11, 0.10, and 0.13dS m^{-1} in circular, spherical, exponential, and Gaussian model while corresponding predicted maximum values were 0.29, 0.28, 0.30, and 0.26 dS m^{-1}. The predicted minimum and maximum EC were close to the measured EC values (0.07 and 0.34 dS m^{-1}) through the exponential model. Mapping of SOC content in soil indicated that around 2.20% of area had SOC content <0.25% and 0.30% area had >0.75% while around 97.5.0% area had SOC content between 0.25 to 0.75 % (Table 4). Predicted minimum and maximum values were in close agreement with measured SOC content (0.13% and 0.89%) in the exponential model (Table 4). These evaluations can be used for optimum fertilization recommendations because suitable use of nutrients can contribute to enhanced crop productivity and quality as well as environmental sustainability [39]. Geostatistical analysis is superior over Classical statistics as it could not identify the spatial variability of soil properties at the un-sampled sites. Geostatistical analysis, permits examination and understanding of spatial dependency of a soil property [40]. It is revealed from present study that the value of the nugget sill ratio was 0.59, 0.06 and 0.10 for pH, EC and SOC, respectively. Nugget to sill ratio indicates spatial dependency of soil properties. Ratio with value less than or equal to 0.25 were considered to have strong spatial dependence, whereas values between 0.25 and 0.75 indicate moderate spatial dependence and those greater than 0.75 show weak spatial dependence [41]. The semi-variogram of best fitted model was presented in Fig. 2. Bhunia et al. [42] found that in semi-variograms analysis SOC was best fitted to exponential model with nugget, sill, and nugget/sill equal to 0.15, 1.10, and 0.14, respectively for 0 – 20 cm depth whereas Behera [43] reported strong spatial class for soil pH and moderate class for SOC and EC.

Table 1. Descriptive statistics of soil physicochemical properties of established orchard

Parameters	pH	EC (dSm^{-1})	SOC (%)
Mean	7.80	0.18	0.47
Minimum	6.83	0.07	0.13
Maximum	8.84	0.34	0.89
Median	7.82	0.17	0.43
Mode	7.88	0.12	0.73
Standard Deviation	0.38	0.05	0.22
Variance	0.15	0.00	0.05
CV (%)	4.92	26.6	46.1
Kurtosis	0.22	1.90	-1.30
Skewness	0.10	1.05	0.21
Standard Error	0.04	0.01	0.02

Table 2. Semi-variogram functions of ordinary kriging in different models for soil pH

Parameter	pH			
	Circular	**Spherical**	**Exponential**	**Gaussian**
Mean	0.001	0.001	0.001	-0.001
RMSE	0.35	0.35	0.35	0.36
Prediction Function	0.29* x + 5.49	0.30 * x + 5.47	0.31* x + 5.34	0.26* x+ 5.76
Error function	-0.70 *x +5.49	-0.69 * x + 5.47	-0.68 *x +5.34	-0.73* x + 5.76
Predicted minimum	7.21	7.21	7.12	7.23
Predicted maximum	8.10	8.10	8.20	8.06
Range	**Area (%)**			
≤ 7.2	0.90	0.80	0.20	0.30
>7.2 to ≤7.5	19.7	19.7	22.4	21.9
>7.5 to ≤7.8	38.8	38.6	37.3	38.8
>7.8 to ≤8.0	32.0	32.0	29.5	31.2
>8.0 to ≤8.2	8.70	8.90	10.6	7.90
>8.2	0.00	0.00	0.00	0.00

Table 3. Semi-variogram functions of ordinary kriging in different models for soil electrical conductivity (EC)

Parameter	Electrical conductivity (dS m^{-1})			
	Circular	**Spherical**	**Exponential**	**Gaussian**
Mean	0.00	0.00	0.00	0.00
RMSE	0.04	0.04	0.03	0.05
Prediction Function	0.23 * x + 0.12	0. 21* x+ 0.13	0.22 * x + 0.14	0.09 * x + 0.15
Error function	-0.76* x + 0.12	-0.78 *x +0.13	-0.78* x + 0.14	-0.90 * x + 0.15
Predicted minimum	0.11	0.11	0.10	0.13
Predicted maximum	0.29	0.28	0.30	0.26
Range (dSm^{-1})	**Area (%)**			
≤ 0.10	0.00	0.00	0.00	0.00
>0.10 to ≤0.15	7.50	7.70	8.20	9.20
>0.15 to ≤0.18	38.0	37.8	37.5	37.6
>0.18 to ≤0.20	37.8	37.8	38.0	36.6
>0.20	16.7	16.7	16.2	16.6

Table 4. Semi-variogram functions of ordinary kriging in different models for soil organic carbon (SOC)

Parameter	Soil organic carbon			
	Circular	**Spherical**	**Exponential**	**Gaussian**
Mean	0.01	0.01	0.01	0.01
RMSE	0.14	0.14	0.14	0.14
Prediction Function	0.74* x + 0.12	0.76* x + 0.11	0.77 * x + 0.13	0.76 * x + 0.12
Error function	-0.25 * x + 0.12	-0.23 * x + 0.11	-0.22 * x + 0.13	-0.23 * x + 0.12
Predicted minimum	0.17	0.18	0.18	0.19
Predicted maximum	0.82	0.82	0.86	0.85
Range (%)	**Area (%)**			
≤0.25	1.70	1.80	2.20	1.60
>0.25 to ≤0.50	45.0	43.2	57.0	44.8
>0.50 to ≤0.75	51.0	52.7	40.5	51.1
>0.75 to ≤1.0	2.30	2.20	0.30	2.40
>1.0	0.00	0.00	0.00	0.00

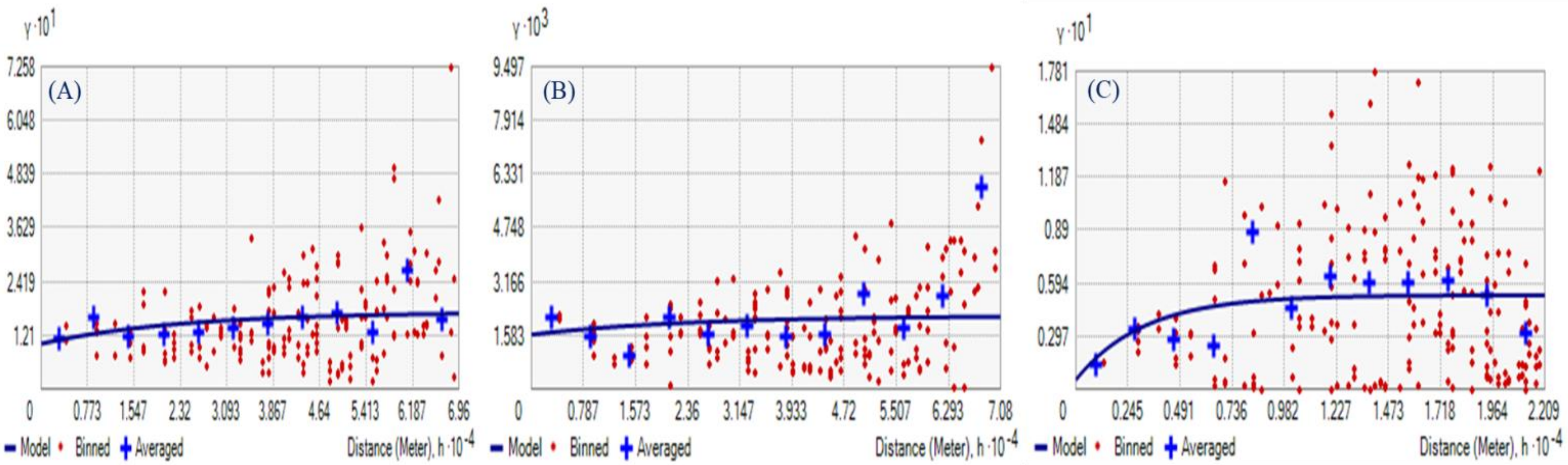

Fig. 2. Semi-variogram of Ordinary kriging best-fitted model (exponential) (A) pH (B) Soil EC (C) Soil organic carbon

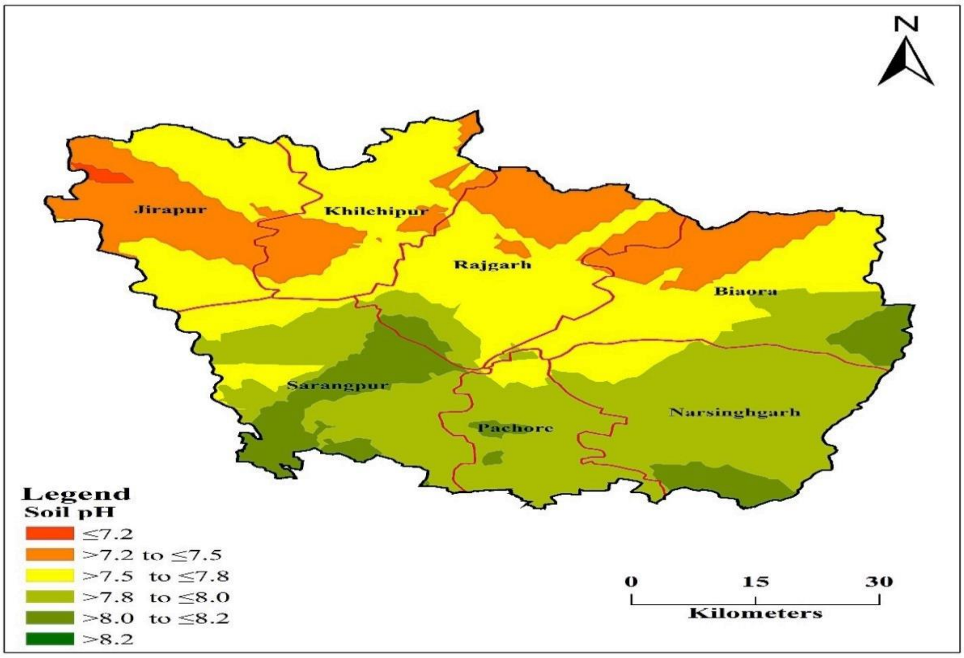

Fig. 3. Map of Soil pH (0-20 cm) with best fitted model (Ordinary kriging; exponential)

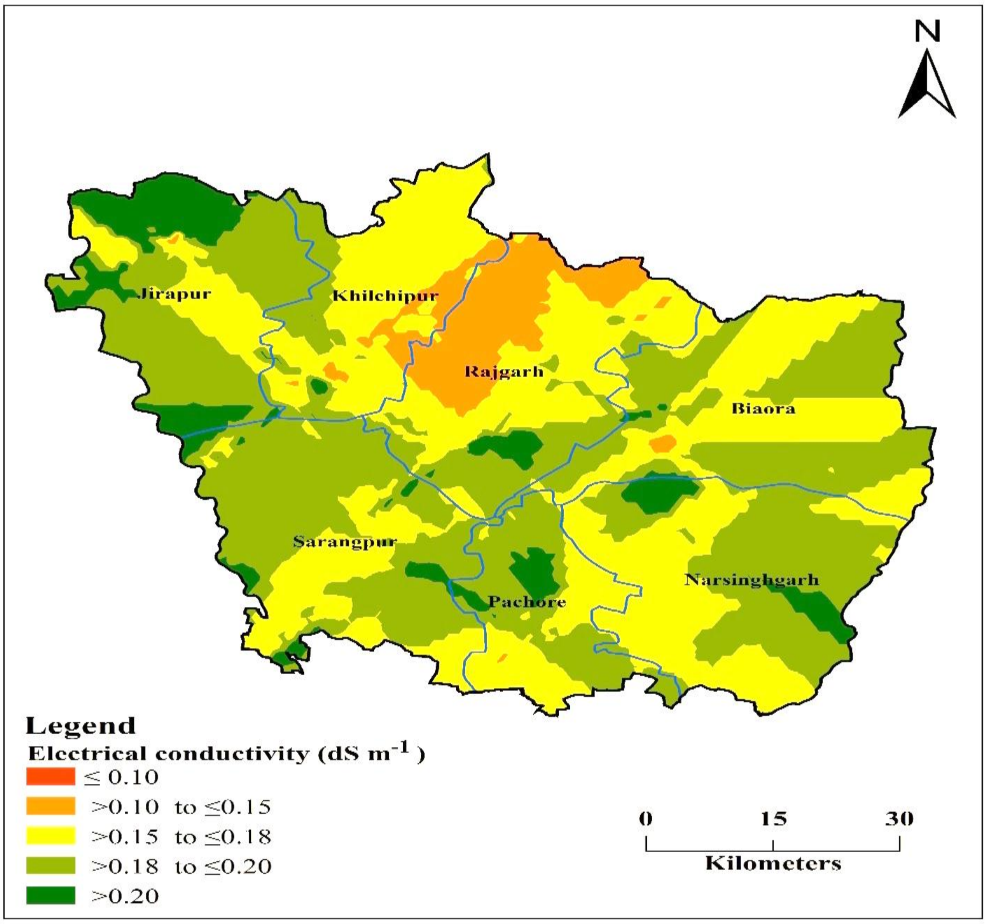

Fig. 4. Map of Soil EC (dS m^{-1}) (0-20 cm) with best-fitted model (Ordinary kriging; exponential)

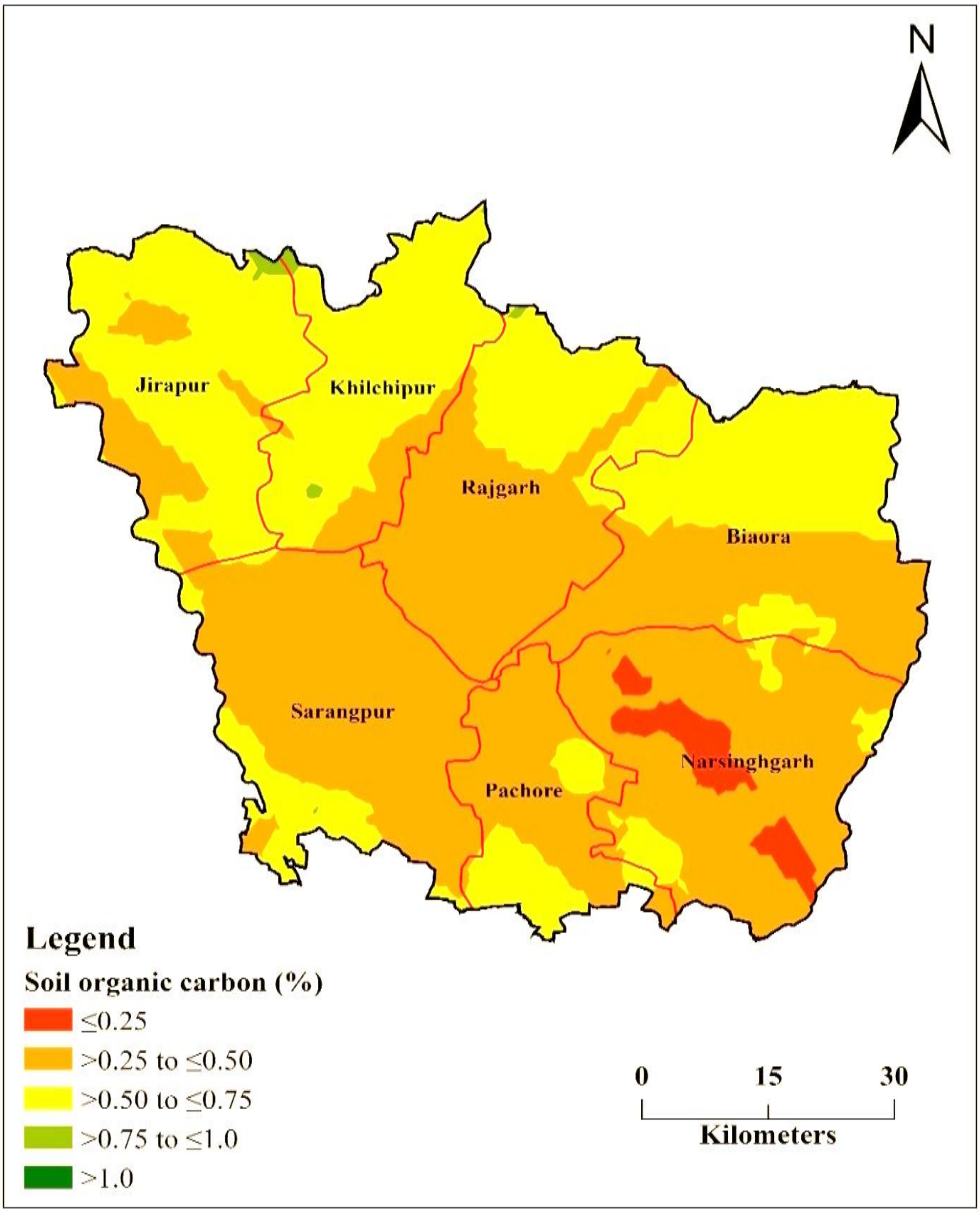

Fig. 5. Map of Soil organic carbon (0-20 cm) with best-fitted model (Ordinary kriging; exponential)

Our result supports moderate spatial dependency in case of soil pH. Strong spatial dependency for soil EC and SOC in orchard soils. Similar results were reported by Kumar et al. [44] in apple orchards of the Kinnaur region of Trans Himalayas for pH and SOC content. Strong spatial dependence of soil properties can be attributed to intrinsic factors such as soil properties and mineralogy, moderate spatial dependence is owing to both intrinsic and extrinsic factors [43].

3.3 Selection of Best-Fit Models

Most common measures for cross-validation and selection of best fit model are mean of cross validation (Mean CV), RMSE, slope of prediction, and error function (Mishra et al., [15] Fischer et al., [45]. Throughout the study area and measured soil properties, all the modes predicted soil properties with more or less equal accuracy, however, present study revealed that RMSE value for soil pH was ranged from 0.35 to 0.36 while slope of prediction function was highest in exponential model (Table 2). It indicated that exponential model was best for predicting spatial variability of soil pH therefore final map was prepared using exponential model (Fig. 3). Map of soil EC was prepared using exponential model (Fig. 4). The RMSE value in circular, spherical, exponential, and gaussian model for soil EC was 0.04, 0.04, 0.03 and 0.05, respectively (Table 3). The slope of prediction function was 0.23, 0.21, 0.22 and 0.09 for circular, spherical, exponential, and gaussian, respectively indicated that circular and exponential models were best fitted for prediction of soil EC, however, lowest RMSE was observed in exponential modes. High prediction accuracy was observed in SOC content in soil by all the applied models due to higher slope of prediction function (>0.75) (Table 4). Among the model utilized, highest slope of prediction function was observed in exponential model (0.77). The RMSE value (0.14) was similar in all the models used for predicting spatial distribution of SOC content in orchard soil at depth of 0-20 cm (Table 4). Based on based on slope of prediction function and RMSE value, exponential model was best for mapping of SOC content in soil. Thus, SOC map was prepared with exponential model (Fig. 5). The RMSE values of the interpolations served as a tool to assess the agreement between the projected and measured soil parameters. A value near to zero indicated a high level of accuracy in the predictions [45]. Positive or zero mean CV value was observed in interpolation of soil properties except in interpolation of soil pH with gaussian model where mean CV value was (-0.001). The mean CV values identified bias and smoothing effects in the interpolations; values greater than zero indicate that the soil properties (pH, EC, and SOC) were overestimated, while values less than zero indicate that the pH, EC, and SOC content were underestimated [46]. In addition to the RMSE and mean CV data, the interpolation procedure automatically generates prediction and error plots. The plots were used to verify the precision of the interpolation models. Slope of prediction function close to one indicted more precise prediction of values (Lange and Krause, [39]. In the present study it was found that exponential model was best fitted model for pH, EC and SOC.Studies reported that exponential model as best fitted model for soil pH (Behera et al. [43], soil EC (Kumar et al. [44], Bangroo et al. [47] and SOC (Bhunia et al.,2016; Kumar et al. [44] in orchard soils in different parts of India.

The kriged maps for different soil properties (soil pH, Soil EC and SOC) presented in Fig. 3 to 5 indicated the variability in distribution of soil properties, which might be helpful for planning suitable strategies for efficient management of orchards. According to our findings, the soils are variable and heterogeneous, hence use of blanket nutrient management practices cannot supply plants with their necessary nutrients. Therefore, site specific soil management will be useful.

4. CONCLUSION

This study concluded that descriptive statistics and Geostatistical analysis are important for understanding the spatial variability of soil properties for sustainable soil resource management under citrus orchards of deep medium black soil of Madhya Pradesh. The pH in the study area was near neutral to alkaline in nature with normal electrical conductivity. Organic carbon content in soil was low to high in nature. Geostatistical analysis revealed that pH had low spatial variability whereas EC and SOC had moderate variability. Best-fit model for interpolation was exponential for studied soil properties (pH, soil EC and SOC). The maps generated by geostatistical analysis will be helpful to understand the spatial distribution of respective soil properties and prove useful for site-specific soil nutrient management in mandarin orchards of the area [48,49,50].

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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