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Spatial Variability of Soil Macronutrients and Chemical Properties in Ujjain Tehsil of Ujjain District of Madhya Pradesh, India

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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

Understanding the characteristics of soil and how it may be utilised sustainably makes soil property mapping a crucial process. To improve crop yield and preserve healthy soil, it is essential to understand the heterogeneity of the soil in each location in order to establish site-specific nutrient management strategies for that area. The current research was carried out in the Ujjain tehsil (Ujjain) district of Madhya Pradesh state, India, with the aim of measuring the spatial variability of several soil macronutrients and soil chemical characteristics. Throughout the research region, 150 geo-coded surface soil samples with a depth of 0 to 15 cm were collected. The soil characteristics, namely pH, electrical conductivity (EC), soil organic carbon (SOC), available nitrogen (Av-N), available phosphorous (Av-P), available potassium (Av-K), and available sulphur (Av-S), were assessed in these samples using standard methods. The research region's ranges for soil pH, EC, SOC, Av-N, Av-P, and Av-K were 7.01 to 8.15, 0.10 to 0.79 dSm-1, 0.30-0.60%, 139.00 – 235.00 kg ha^{-1}, 8.00 – 25.60 kg ha^{-1}, and 301.00 – 463.00 kg ha^{-1}, in that order. The data were analysed using classic statistics and geo--statistics by constructing semi-variograms and mapping by ordinary kriging techniques. Semi-variograms were calculated for soil characteristics and their spatial distributions were mapped. Best-fit models for measured soil properties were Exponential, Circular, Gaussian and Hole effect with Nugget/Sill (C_o/C_o+C) ratio for modelled variables indicated strong and moderate spatial dependences. The distribution maps of soil attributes could be utilized as a guide for site-specific crop management in similar soils. Further, this study demonstrates the usefulness of GIS- application in soil variability studies.

Keywords: Soil properties; soil variability; geo coded; geo-statistics; spatial dependence; semi-variogram; ordinary kriging.

1. INTRODUCTION

"Soil is a vital and finite natural resource for agriculture" [1,2]. "In this regard soil fertility plays a key role in increasing crop production. It comprises not only in supply of nutrients but also their efficient management. The fertility status of soil indicates their nutrient supplying capability" [2]. "The evaluation of soil fertility is perhaps the most basic decision-making tool in order to impose appropriate nutrient management strategies" [3]. "There are various techniques for soil fertility evaluation, among them soil testing is the most widely used in the world" [4]. "Soil testing assess the current fertility status and provides information regarding nutrient availability in soils which forms the basis for the fertilizer recommendations for maximizing crop yields and to maintain the adequate fertility in soils for longer period" [5].

"Spatial variability of soil properties has been effectively assessed across a variety of geographical and ecological settings by geostatistical methods in improvement of soil health, site specific management of plant nutrients, soil erosion and soil water stability impact of different land uses on soil variability" [6]. "Geo-statistics technique as confidence able, strongest and widest method for interpolation and has acknowledged that in geo-statistics is considered spatially variance, location and distribution of samples" [2].

"Information of spatial variability and distribution of soil properties is critical for farmers attempting to increase efficiency of fertilizers and crop productivity" [7]. "Geostatistical is a powerful tool are useful to estimate spatial variability of soil properties and soil nutrients at field, catchment as well as regional scales. Apart from farmer induced soil property variability it is also known that soil variability may result from edaphic factors such as the parent material (soil forming rock types) and position of soil on the catena, among others" [2,8].

"Many studies use geo-statistics for determination of spatial variability and map creation of soil characteristics spatially" [1, 9, 10, 11]. "Knowledge of soil variability is necessary for applied management as well as for model development" [12, 5]. Therefore, the present study has been planned to quantify the spatial variability of soils in Ujjain tehsil of Madhya Pradesh.

2. MATERIALS AND METHODS

2.1 Site Details

The Ujjain tehsil is towards north of Ghatiya, which is surrounded by Indore in south, Dewas, in east and Badnagar on the western side. This tehsil comes under the Ujjain district of Madhya Pradesh state. Ujjain is situated on the bank of Kshipra river and is located in between 23°10′ 45.4800″N latitude and 75°47′ 5.6832″ E longitude. Ujjain tehsil is situated at an altitude of 494 meters above the mean sea level. The entire geographical area of Ujjain tehsil is 60987.4 ha. Ujjain tehsil comes under the north western zone of Madhya Pradesh. The region. generally, experiences hot, sub-tropical climate, having average rainfall of 914.5 mm, with erratic pattern of distribution, mostly concentrated in the month of June to September, the hottest and coolest months are May and December, respectively. Ujjain district has moderate climate with average Maximum temperature 40.73°C. The average minimum temperature during winter season is 8.23°C.

2.2 Agricultural Scenario

During rainy season (kharif) major crop of the Ujjain tehsil is soybean and grown in 70% area of the Ujjain tehsil. other kharif crops are red gram, maize and fodder like, sorghum. The rabi season crops are wheat, chickpea, potato, onion and garlic. In summer season, field crops like blackgram and greengram are also grown and vegetables crops like coriander, chilli and brinjal are taken. Ground and surface water are used for irrigation purpose. Major area of the region is rainfed and partially irrigated.

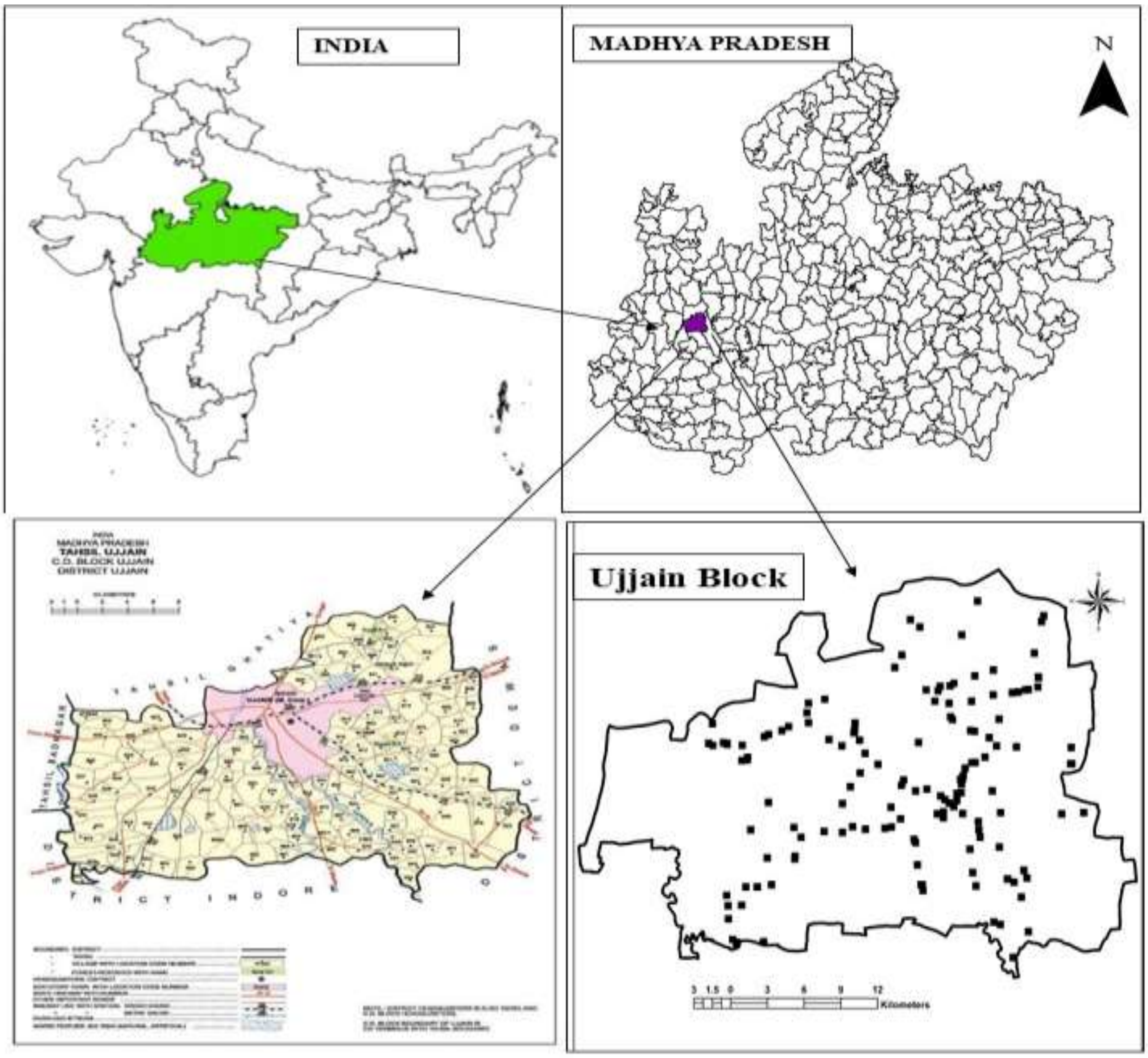


Fig. 1. Location of study area

2.3 Soil Survey and Sampling Techniques

The sampling sites decided randomly distributed over agricultural land of the study area by considering of land use and soil association maps, topography and heterogeneity of the soil type. Field data collection and soil sampling were carried out by using GPS by navigating those points. One hundred fifty surface soil samples (0-15 cm) were collected from farmer's field during the off season from the agricultural land to avoid the effect of fertilization during crop cultivation. For each main sampling point, 1.0 kg of representative composite soil sample was collected and logged into properly labeled sample bag. Soil samples were not taken from unusual areas like animal dung accumulation places, poorly drained and any other places that cannot give representative soil samples. During soil sampling, spatial information (latitude and longitude), topography, slope, elevation, land use type, crop type, local soil name, sampling depth, soil color, crop residue management, rate of last year fertilizer application and type were collected from each site.

2.4 Analysis of Soil Chemical Properties

A pH metre with a soil/water ratio of 1:2.5 was used to test the pH of the soil [13]. Using the conductivity-bridge, the electrical conductivity (EC) of the soil–water supernatant solution (1:2.5) was ascertained [13]. The procedure outlined by Walkley and Black [14] was used to calculate the quantity of soil organic carbon (SOC) present in the soil. The alkaline permanganate technique was used to assess the available nitrogen in the soil samples [15]. Olsen et al. [16] presented the 0.5 M sodium bicarbonate technique for estimating available phosphorus, whereas Jackson [13] detailed the extraction of available potassium using neutral 1 N ammonium acetate, which was then measured using a flame photometer. Using a 0.15% $CaCl_2$ solution, the available sulphur (S) was extracted, and a spectrophotometer was used to quantify the sulphur content using the turbidimetric technique [17].

2.5 Descriptive Statistics

The soil characteristics were shown using descriptive statistics derived from the soil data. With the use of SPSS 21.0 software, each soil parameter's minimum, maximum, mean, standard deviation, coefficient of variation, and skewness values were ascertained. Positive or negative skewness is the greatest significant deviation from normalcy that Webster [18] found in soil data. As a result, it is also acknowledged that the skewness-described forms of parameter distributions indicate normalcy. In the case of non-normally distributed variables, a square root transformation was applied to those with skewness values larger than 0·5, while a log transformation was used to those with values more than 1·0. Before doing a geostatistical analysis, data with non-normal distributions were transformed into log normal distributions using Kolmogorov-Smirnov (K-S) and skewness tests. the Goovaerts et al. [19] computation of the specific soil variable's semi-variance. To look at the relationship between the variables and Microsoft Excel, a Pearson correlation matrix including every soil variable was also created.

2.6 Geostatistical Analysis

Geostatistical analyst of ArcGIS 10.5 was used for modeling semivariogram and fitting the best semivariogram model. Before fitting the semivariogram models, skewed soil properties were transformed to a nearly normal distribution using natural logarithm. The data was back transformed using back transformation.

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

Where: N (h) is the number of pairs of points distant from each other by h. "Several semivariogram models were evaluated to best fit with the experimental data in the ArcGIS v 10.3. 1 The circular, spherical, tetra spherical, exponential, Gaussian, K-Bessel, J-Bessel, and stable model were evaluated for different soil parameters. A semivariogram model with the lowest value of nugget/sill ratio was selected as the best fit model for the given soil properties" [20]. The exponential, Gaussian, spherical, and circular models were best fitted for the studied soil properties.

Exponential model

$$\gamma(h) = C_0 + C\left[1 - \exp\left\{-\frac{h}{r}\right\}\right] \text{ for } h > 0$$

Gaussian Model

$$\gamma(h) = C_0 + C\left[1 - \exp\left\{-\frac{h^2}{r^2}\right\}\right] \text{ for } h > 0$$

Spherical Model

$$\gamma(h) = C_0 + C\left[\frac{3h}{2r} - \frac{1}{2}\left(\frac{h^3}{r^3}\right)\right] \text{ for } 0 < h \leq r \text{ and } C_0 + C \text{ for } h > r$$

Circular Model

$$\gamma(h) = C_0 + \left[\frac{2c}{\pi}\frac{h}{r}\sqrt{1-\left(\frac{h^2}{r^2}\right)} + \arcsin\left(\frac{h}{r}\right)\right] \text{ for } 0 < h \leq r \text{ and } C_0 + C \text{ for } h > r$$

Where

h = lag distance,
C_0 = nugget variance,
C = structural variance (partial sill) and
r = range

The parameters of the semivariogram i.e., nugget (C_0), partial sill (C), sill (C+ C0), and range (r) were calculated that provide information about the spatial structure of the given soil variables, also serve as input for the kriging interpolation.

The nugget/sill ratio, i.e. (C0) /(C+C0) and the range, are the parameters that characterize the spatial structure of a soil property. The range defines the distance over which the soil property values are correlated with each other. "A low value of (C_0) /(C+C_0) and a high range generally indicates that high precision of the property can be obtained by kriging" [21]. "The nugget/sill ratio was used as the criterion to classify the spatial dependence of variables. Ratio values lower than or equal to 0.25 were considered to have strong spatial dependence, whereas values between 0.25 and 0.75 indicate moderate dependence, and those greater than 0.75 show weak spatial dependence" [21].

The ordinary kriging (OK) method was performed to estimate different soil parameters at the un-sampled locations. As suggested by Schepers et al. [22], OK is the best unbiased predicting method for randomly distributed soil samples. OK also reduces the impact of outliers on prediction, which makes it most appropriate for estimation of soil properties for un-sampled locations [23]. Accuracy of the soil maps was evaluated through cross-validation approach [24].

2.7 Principal Component Analysis

"Principal component analysis (PCA) is a multivariate analysis technique for dimension reduction that uses correlated attributes, or variables, and identifies orthogonal linear recombination of the attributes that summarize the principal sources of variability in the data. A correlation matrix involving selected soil properties was used as input for analysis in lieu of a covariance matrix, resulting in normalized PCA. There are many principal component (PC) variables included in the analysis. It was assumed that principal components (PCs) receiving high Eigen values are the best to represent the field properties" [22]. In the present study, PCs with Eigen values of ≥1.0 were selected to develop the management zone classes.

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics of Selected Soil Properties

The descriptive statistics on selected soil properties (pH, EC, SOC, N, P, K and S) are presented in Table 1 that showed the pH, EC, SOC, varied from 7.01-8.15, 0.10-0.79 dSm^{-1}, 0.30 -0.60%, with mean value of 7.61, 0.28, 0.48, respectively. The available N, P, and K varied from 139.0 – 235.0 kg ha^{-1}, 8.00 – 25.60 kg ha^{-1}, 301.00 – 463.00 kg ha^{-1}, with mean value of 198.27,15.08, 358.38, respectively. The S varied from 8.06 to 24.36 mg kg^{-1}, with a mean value of 16.27 mg kg^{-1}.

The coefficient of variation, which is the ratio of the standard deviation to mean expressed, as a percentage is a useful measure of overall variability. Considering CV <10% as low, 10 to 100% as moderate, >100% as high variability. CV data presented in Table 1 revealed that the EC had the largest variation (CV = 51.92 percent) followed by P (CV = 26.25), S (CV = 22.92), K (CV = 10.07), N (CV = 9.83), and pH had least variability (CV = 2.99 percent). The range of CV for the area suggested different degrees of heterogeneity among the properties studied. The pH and N had low variability and all other soil properties showed moderate variability. The normality of data was tested by Kolmogorov-Smirnov (K-S) method (P-value > 0.05) and a result of soil parameters is presented in Table 1. "With due attention to the levels of skewness for these parameters were normal. The skewness and kurtosis coefficients are zero for a normally distributed random variable. If the data distributions are largely deviated from a normal distribution, data transformations are often performed in order to reduce the influence of extreme values on spatial analysis" [18]. However, it was observed from the Table 1 that the skewness coefficients of the data set ranged from -0.87 to 1.89 considering the observed skewness coefficient values data were not transformed. Among the soil fertility parameters, EC, available P and K were found not normally distributed due to higher value of skewness and kurtosis.

Table 1. Statistical summary of selected soil properties

Soil properties	Unit	Minimum	Maximum	Mean	Std. Deviation	CV	Skewness	Kurtosis
pH		7.01	8.15	7.61	0.23	2.99	-0.87	0.27
EC	dSm^{-1}	0.10	0.79	0.28	0.15	51.92	**1.89**	**3.71**
SOC	%	0.30	0.60	0.48	0.07	14.00	-0.17	-0.25
N	kg ha^{-1}	139.00	235.00	198.27	19.49	9.83	-0.14	0.58
P		8.00	25.60	15.08	3.96	26.25	**0.19**	-0.30
K		301.00	463.00	358.85	36.14	10.07	**0.47**	-0.17
S	mg kg^{-1}	8.06	24.36	16.27	3.73	22.92	-0.37	-0.59

Note. EC = electrical conductivity; SOC = soil organic carbon; SD = standard deviation; CV = coefficient of variation

3.2 Soil Fertility Index and Soil Fertility Classes

Taking into account soils with nutrient index values of less than 1.67 for low fertility, 1.67 to 2.33 for medium fertility, and more than 2.33 for high fertility [2,5,25]. The nutrient index mean value of N, P, K, S were found 1.0, 1.96, 2.16, 2.10, respectively (Table 2) that showed N was in low fertility class, P, K and S were in medium fertility class. Gehlot et al. [1] reported similar result with respect.

3.3 Pearson's Correlation

In the area's soils, a substantial positive association was discovered between pH, EC, and N. Further correlation tests revealed that all soils in the Ujjain tehsil exhibited a positive, non-significant connection between pH and available P and K, whereas OC and available N showed a significant positive association in all soils. In Ujjain tehsil, however, OC had a non-significantly positive connection with K. Only accessible N and K displayed positive, non-significant correlations with one other among the key nutrients that were available, according to correlation tests conducted on tehsil soils. Once again, in the soils under investigation, the available N exhibited a positively non-significant connection with P. In all of Ujjain Tehsil's soil, the remaining correlations—whether positive or negative—have been determined to be non-significant (Table 3). The results agreed with the previous research findings of [1,2,5].

3.4 Spatial Variability Analysis

After calculating semivariograms, the best models for describing the spatial structures of various soil parameters were found. Table 4 and Fig. 3 show the semivariogram analysis findings. With the exception of AP, SOC, and EC, which were best suited by Gaussian, circular, and Hole Effect models, respectively, exponential models were the best fits theoretical models for the majority of the soil variables. Numerous writers presented comparable findings, concluding that spherical models best match the majority of soil attributes [9,26]. The findings showed that soil properties exhibited spatial autocorrelation. Additionally, the spatial correlation of soil properties was found to be influenced by both human-induced factors, such as farming systems that are common in the study area and fertiliser application practises, as well as structural factors, such as proximity to creeks or rivers, parent material, properties of the mangrove ecosystem, and water table depth [27]. Comparison of the nugget/sill ratio was checked for selected soil variables (Table 4). "The ratio of nugget to sill indicates the spatial dependency of soil properties" [21,28]. In this study, similar criteria to those reported by Cambardella et al. [21] were used. A low ratio (25%) means that a large part of variance is introduced spatially, implying a strong spatial dependence of the variable. The variable has a moderate dependence if the ratio is between 25 and 75%, otherwise the variable has a weak spatial dependence. Moderate spatial dependence was observed for other soil properties studied which might be due to differences in soil fertilization and cultivation practices, strong hydrological processes prevalent in this region due to presence of various rivers and creeks. Jiang et al. [9] and Ausari et al. [2] reported the similar results. Moreover, Av-N, Av-P and Av-K had a large nugget which may be attributed to ecological processes such as natural disturbances created in mangrove ecosystem, hydrological differences, nutrient cycling and biotic and abiotic interactions over a small scale which are quite obvious in the study area. Spatial distribution maps for all soil properties are shown in Fig. 2. Almost all soil nutrients showed high levels in the mangrove forest and its vicinity whereas low levels of soil nutrients and SOC were recorded in other parts of study area which are primarily rice cultivated fields (Fig. 2). While the use of very little or no artificial fertiliser and the uneven management of farmed rice fields led to poor nutrients in these agricultural soils, the incorporation of leaf litter and increased biological activities improved the nutrient content in mangrove forests. In order to achieve maximum output and rice yield, as well as to reduce input costs in conjunction with best management practises, farmers can use the quantitative information about nutrient content provided by the maps to implement recommendations for site-specific nutrient management and variable-rate fertiliser application technology. This will ultimately increase farmer income.

Table 2. Mean value of soil fertility index and percent distribution of soil fertility classes in soils of Ujjain tehsil

Available Nutrients	No. of samples	Mean value of soil index fertility	Percent distribution of soil fertility class		
			Low	Medium	High
N	150	1.0	100% (150)	0% (0)	0% (0)
P	150	1.96	14% (21)	76% (114)	10% (15)
K	150	2.16	0% (0)	83.4% (125)	16.6% (25)
S	150	2.10	7.3% (11)	75.4% (113)	17.3% (26)

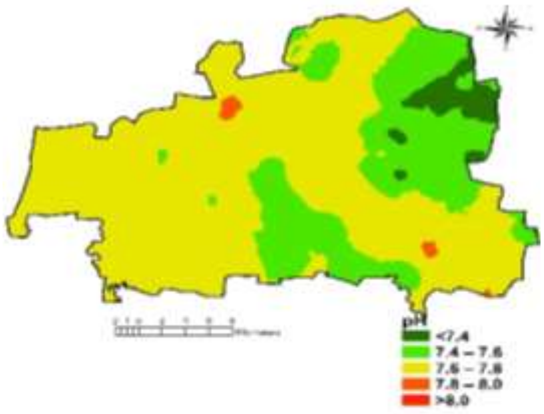
Table 3. Pearson's correlation coefficients for selected soil properties

Corr.	pH	EC	SOC	N	P	K	S
pH	1.00						
EC	0.14	1.00					
SOC	-0.15	**0.172***	1.00				
N	-0.16	**0.177***	**0.966****	1.00			
P	0.05	0.02	-0.08	-0.07	1.00		
K	0.03	0.13	0.08	0.06	**-0.248****	1.00	
S	0.08	0.07	0.00	-0.01	0.03	-0.229**	1.00

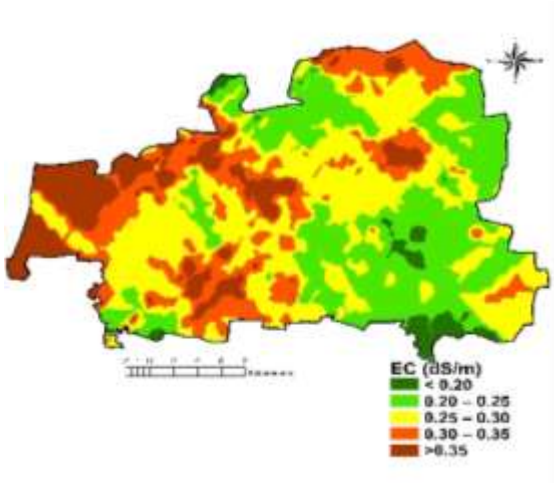
Table 4. Theoretical model parameters fitted to experimental semi-variograms for soil properties

Para-meters	Trans formation	Model	C_0	$C + C_0$	Range (km)	$C_0/C+C_0*100$	Spatial dependence
pH	None	Exponential	0.03	0.06	6465.59	0.52	Moderate
EC	Log	Circular	0.06	0.18	1077.05	0.34	Moderate
SOC	None	Gaussion	0.00	0.00	767.39	0.46	Moderate
N	None	Exponential	182.32	388.33	607.46	0.47	Moderate
P	None	Gaussion	13.82	15.85	2319.02	0.87	Weak
K	Log	Exponential	0.01	0.01	6235.61	0.63	Moderate
S	None	Exponential	3.92	15.01	3322.20	0.26	Moderate

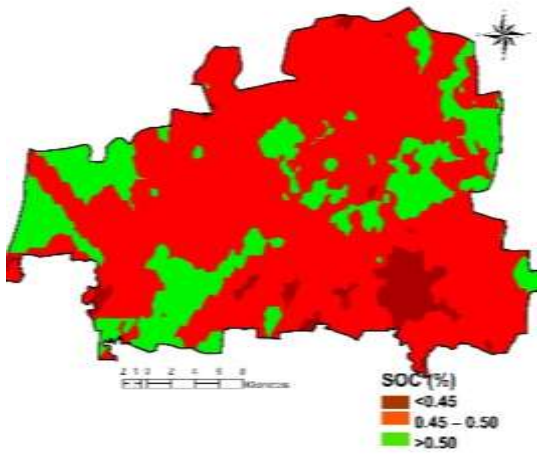
Abbreviations – C_0= Nugget, C= Partial sill, $C+C_0$, = Sill



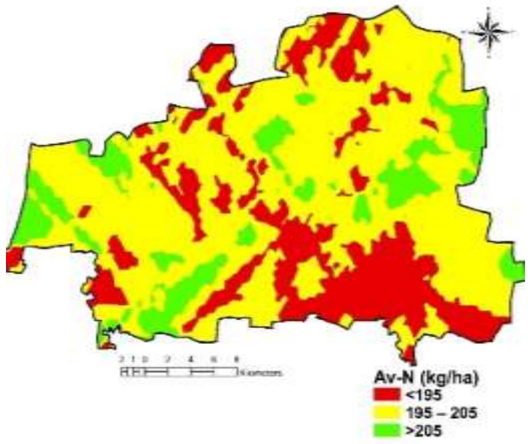
a) pH



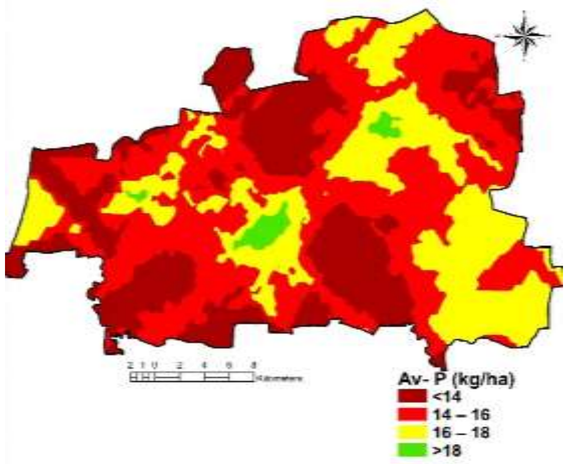
b) EC



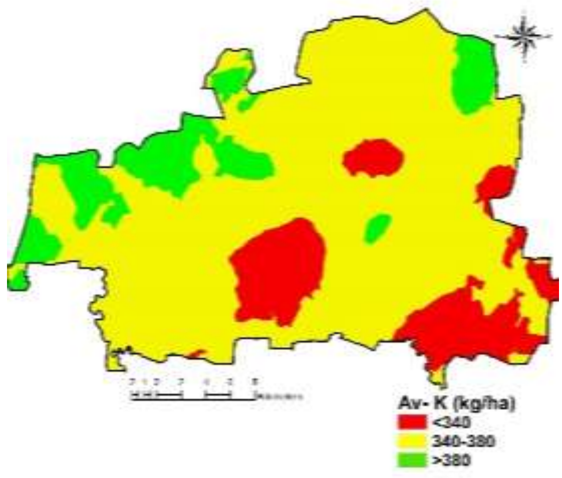
c) SOC



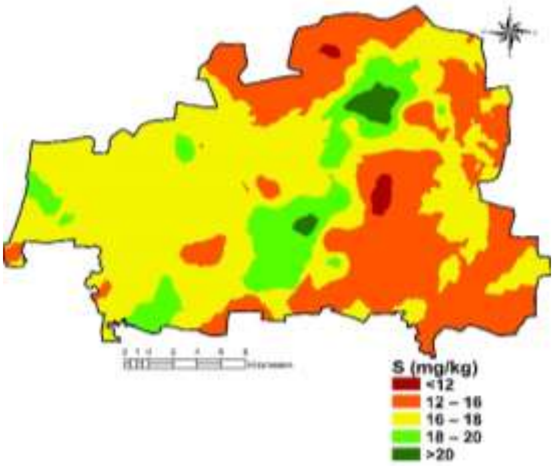
d) Av-N



e) Av-P

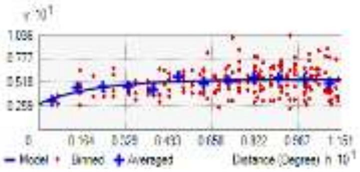


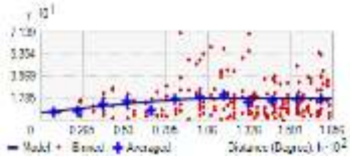
f) Av-K

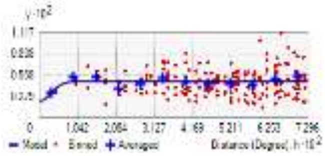


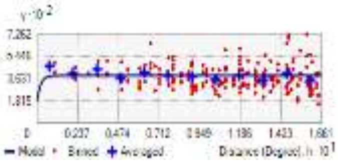
g) Av-S

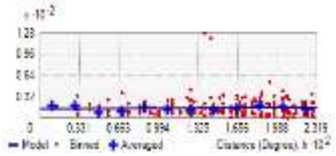
Fig. 2. Distribution maps soil chemical properties and available macronutrients in the soil generated by ordinary kriging

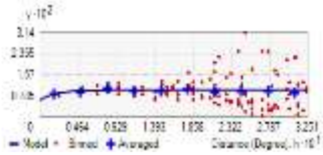

a) pH


b) EC


c) SOC


d) Avail. - N


e) Avail. - P


F) Avail. - K

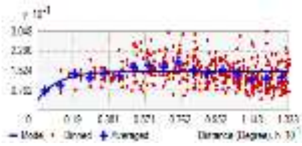

g) Avail. - S

Fig. 3. Experimental semi-variograms and their fitted models for a) pH, b) EC, c) SOC, d) Avail. – N, e) Avail. – P, f) Avail. – K and g) Avail. - S

3.5 Principal Component Analysis

The 07 soil variables considered for this study were highly correlated. Principal component analysis (PCA) was performed to aggregate and summarize the variability in the 07 variables, retaining principal components producing eigenvalues greater than 1 and accumulative contribution rate greater than 60%. Using this criterion, only first three principal components were considered for the final analysis, accounting for 60.27% of the total variability (Table 5). The eigenvalues for these three PCs were N1, which indicates that a PC explains more variance than an individual attribute [29]. Principal component 1 (PC 1) explained 34.61% of the total variance and was dominated by pH, EC, AK and AP (Table 5). Consequently, the kriged map of PC 1 was similar to the maps of EC, AK and AP. The second principal component (PC 2) explained an additional 13.33% of total variance and was dominated by SOC. Likewise, the kriged map of PC 2 was similar to the map of SOC. In summary, the principal component analysis aggregated the 07 variables into three principal components, accounting for a majority of the overall spatial variability in these attributes.

Table 5. Principal component analysis

Principal Components	PC-1	PC-2	PC-3	PC-4	PC-5	PC-6	PC-7
Total	2.295	1.667	1.576	1.420	1.229	1.141	1.112
% of Variance	16.392	11.909	11.257	10.143	8.776	8.147	7.941
Cumulative %	16.392	28.301	39.558	49.701	58.477	66.624	74.565
pH	-0.265	0.075	0.042	0.124	0.609	0.180	-0.414
EC	0.268	0.416	0.106	0.135	0.526	0.339	-0.018
SOC	0.875	0.055	0.395	0.054	-0.059	-0.070	-0.091
N	0.880	0.030	0.389	0.067	-0.073	-0.055	-0.078
P	-0.141	0.227	-0.092	0.613	-0.123	-0.095	0.121
K	0.212	-0.204	-0.057	-0.543	0.501	0.205	0.309
S	-0.058	-0.189	0.091	0.482	-0.156	0.528	-0.411

4. CONCLUSIONS

The detected soil chemical characteristics of the area varied greatly, according to the present research. It was uncovered that the soil reaction in the Ujjain block district of Madhya Pradesh was neutral to alkaline, the electrical conductivity was safe, and the organic carbon content ranged from low to medium. The study's findings indicated that the best-fitting models for the investigated soil characteristics were the exponential, spherical, gaussian, and circular models. The results of the correlation study showed a strong positive association between soil pH and EC and soil organic carbon. The soils of the Ujjain tehsil in the district Ujjain, Madhya Pradesh, are low in available N, medium in available P, medium to high in available K, and medium to high in available S, according to the study's overall findings. There was a substantial positive link found between the available nitrogen content and the organic carbon concentration, with the latter showing low to medium status. The maps of soil characteristics that are produced might serve as the main reference for sustainable soil management techniques, including recommending fertiliser based on micronutrients at a variable rate to maximise the region's output.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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