Spatial variability insoil's macronutrients and chemical propertiesof Ujjain Tehsil of Ujjain District of Madhya Pradesh

Abstract

Mapping of soil properties is an important operation as it plays an important role in the knowledge about soil properties and how it can be used sustainably. Knowledge of soil variability of any region is crucial for development of site-specific management practices for that region as this will enhance the crop productivity and maintain the good soil health. With this background, present study was conducted to quantify the spatial variability of different soil physico-chemical properties in Ujjain tehsil (Ujjain) district of Madhya Pradesh state, India. A total one hundred fifty geo-coded surface (0-15 cm depth) soil samples, were collected across the study area. These samples were analyzed using standard method for different soil properties *viz.*, pH, electrical conductivity (EC), Soil organic carbon (SOC), available Nitrogen (Av-N) available phosphorous (Av-P) and available potassium (Av-K). The range of soil pH, EC, SOC, Av-N, Av-P, Av-K sand, silt, clay, Zn, Cu, Fe and Mn in the study region were varied from 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}, 301.00 – 463.00 kg ha^{-1}, respectively. 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.

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.

Material 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.

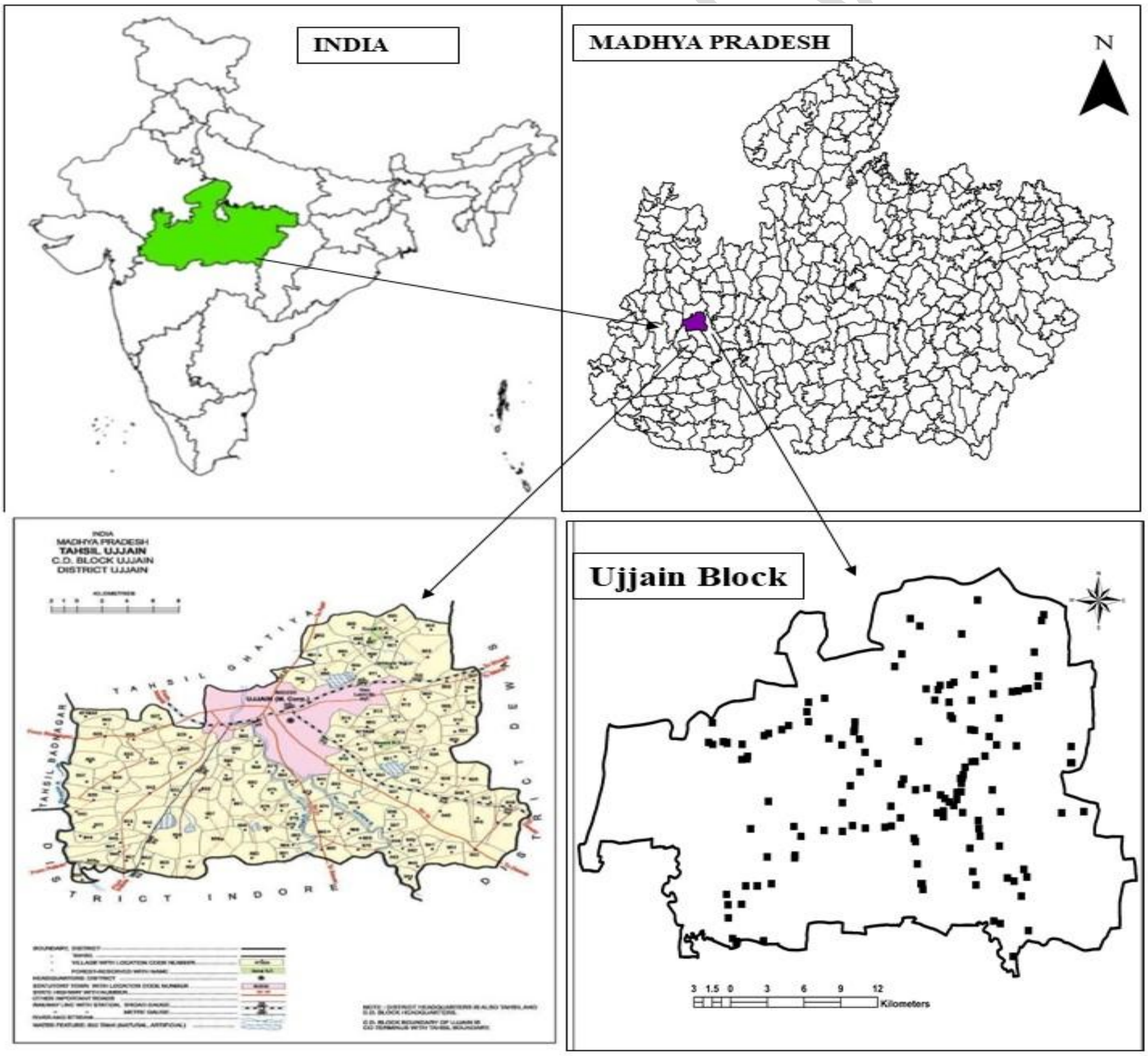


Fig.1 Location of study area

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.

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 physico-chemical properties

Soil pH was measured using a pH metre with a soil/water ratio of 1:2.5 [13]. The electrical conductivity (EC) was determined from the soil–water supernatant solution (1:2.5) with the help of the conductivity-bridge [13]. The amount of soil organic carbon (SOC) in soil was determined using the method as described by Walkley and Black [14]. The available N of the soil samples was analysed by the alkaline permanganate method [15]. The available phosphorus was estimated by the 0.5 M sodium bicarbonate method as described by Olsen et al. [16] and available potassium was extracted with neutral 1 N ammonium acetate as described by

Jackson [13] and determined by flame photometer. The available sulphur (S) was extracted with a 0.15% CaCl2 solution and the concentration of sulphur was determined by the turbidimetric method using a Spectrophotometer [17].

2.5 Descriptive statistics

Descriptive statistics of the soil data were calculated to present the soil parameters. The minimum, maximum, mean, standard deviation, coefficient of variation, and skewness values of each soil parameters were determined using SPSS 21.0 software. Webster [18] indicated that the most serious departure from normality encountered with soil data is positive or negative skewness. Thus, the shapes of parameter distributions that are described by skewness are also accepted as an indication of normality. For variables without normal distributions, those with positive or negative skewness values of greater than 0·5 were subjected to square root transformation whereas those with values greater than 1·0 were subjected to log transformation. Data showed non-normal distribution were subjected to the log normal distribution before the geostatistical analysis, data of all the soil variables were tested for normality using Kolmogorov-Smirnov (K-S) and skewness. the calculation of semi-variance of the particular soil variable according to Goovaerts et al. [19]. A Pearson correlation matrix among all the soil variables was also generated to investigate the association between the variables and Microsoft Excel.

2.6 Geostatistical analysis

Geostatistical analyst of ArcGIS 10.5 was used for modelingsemivariogram 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:

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

Gaussian Model

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

Spherical Model

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

Circular Model

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

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.

Results and Discussions

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 of7.61, 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

Considering the soils having the nutrient index values <1.67 for low, 1.67 to 2.33 for medium and >2.33 for high fertility class [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.

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)

3.2 Pearson's' correlation

A positive significant correlation was found between pH, EC and N in soils of area. Further the correlation studies of OC with available N resulted significant positive correlation in all soils, whereas, pH with available P and K had positive non-significant correlation in all soils of Ujjain tehsil. However, OC showed non significantly positive correlation with K in Ujjain tehsil.

Correlation studies amongst available major nutrients revealed that only available N and K had positive non-significant correlation amongst them in soils of tehsil. Again, the available N had positively non-significant correlation with P in the study soils. All the remaining correlations have been found non-significant either positive or negative in all soil of Ujjain tehsil (Table 3). The results were in line with the earlier findings of [1, 2, 5].

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

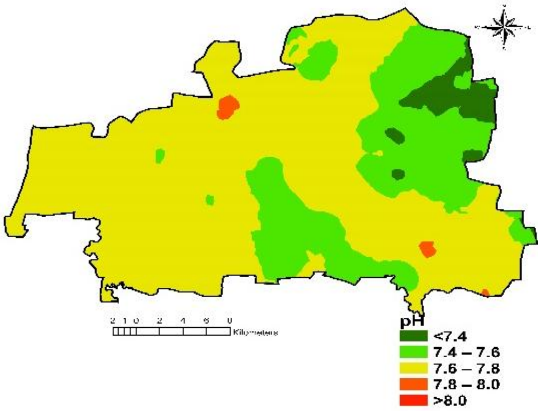
3.3 Spatial variability analysis

Semivariograms were calculated and the best models were identified which can describe the spatial structures of different soil properties. The results of semivariogram analysis are shown in Table 4 and Fig. 3. The best fit theoretical models for most of the soil properties were exponentialmodels except for AP, SOC and EC, for which Gaussian, circular and Hole Effect models were fitted respectively. Several authors reported similar results with most soil properties best fitted with spherical models [9, 26]. The results indicated that soil properties had spatial autocorrelation, and that structural factors, such as proximity to creeks or river, parent material, mangrove ecosystem properties, and water table depth, as well as human induced factors, such as soil crop management practices, fertilizer application, and farming systems prevalent in the study area, codetermined the spatial correlation of soil properties [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). Incorporation of leaf litter and enhanced biological activities increased the nutrient content in mangrove forests whereas application of very low or no inorganic fertilizer and heterogeneous management of cultivated rice fields resulted in low nutrients in these agricultural soils. The maps provided quantitative information about the nutrient content which could be used to implement recommendations for site-specific nutrient management and variable-rate fertilizer application technology for getting maximum output and rice yield and ultimately increasing the farmer's income by reducing the input cost coupled with best management practices.

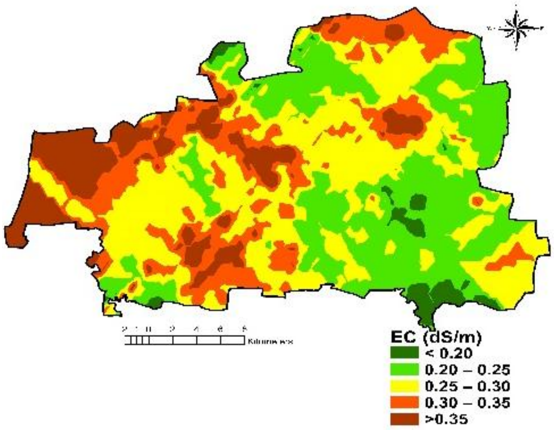
Table 4. Theoretical model parameters fitted to experimental semi-variograms for soil properties.

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

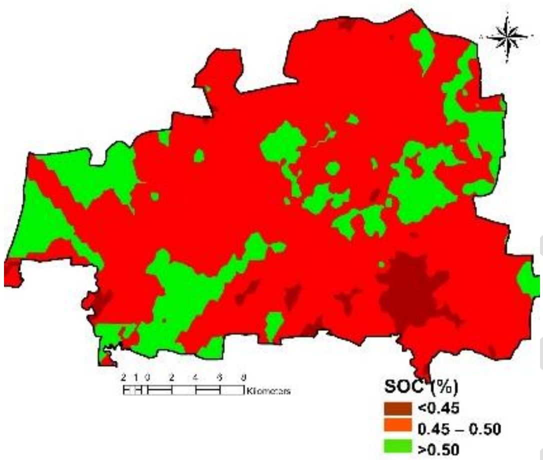
Abbreviations – C_0= Nugget, C= Partial sill, $C+C_0$, = Sill



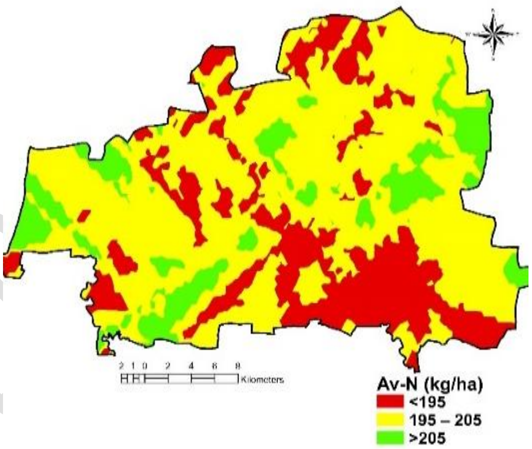
a) pH



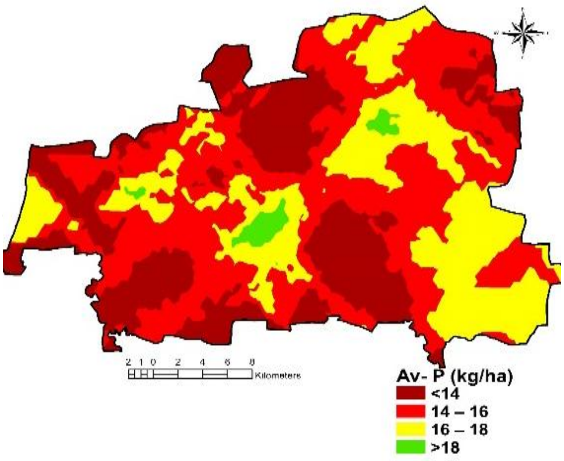
b) EC



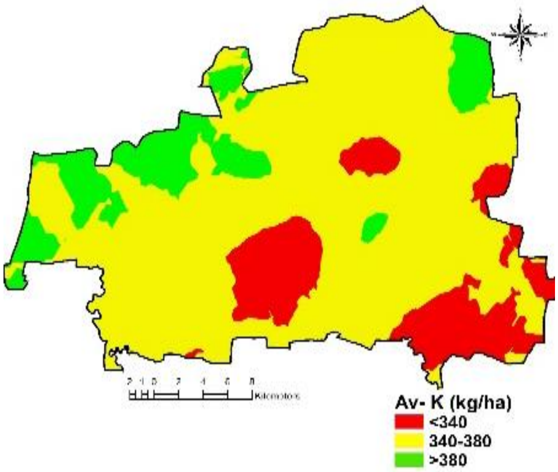
c) SOC



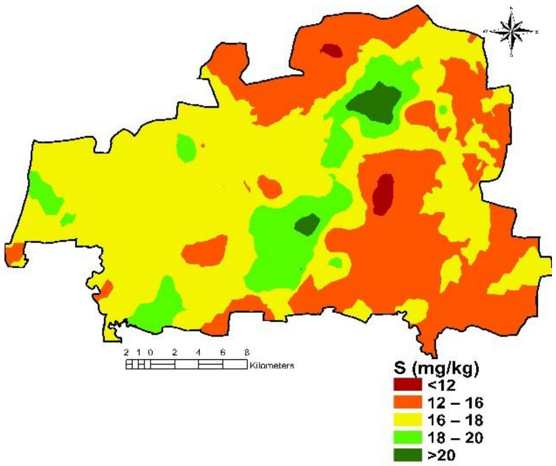
d) Av-N



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.

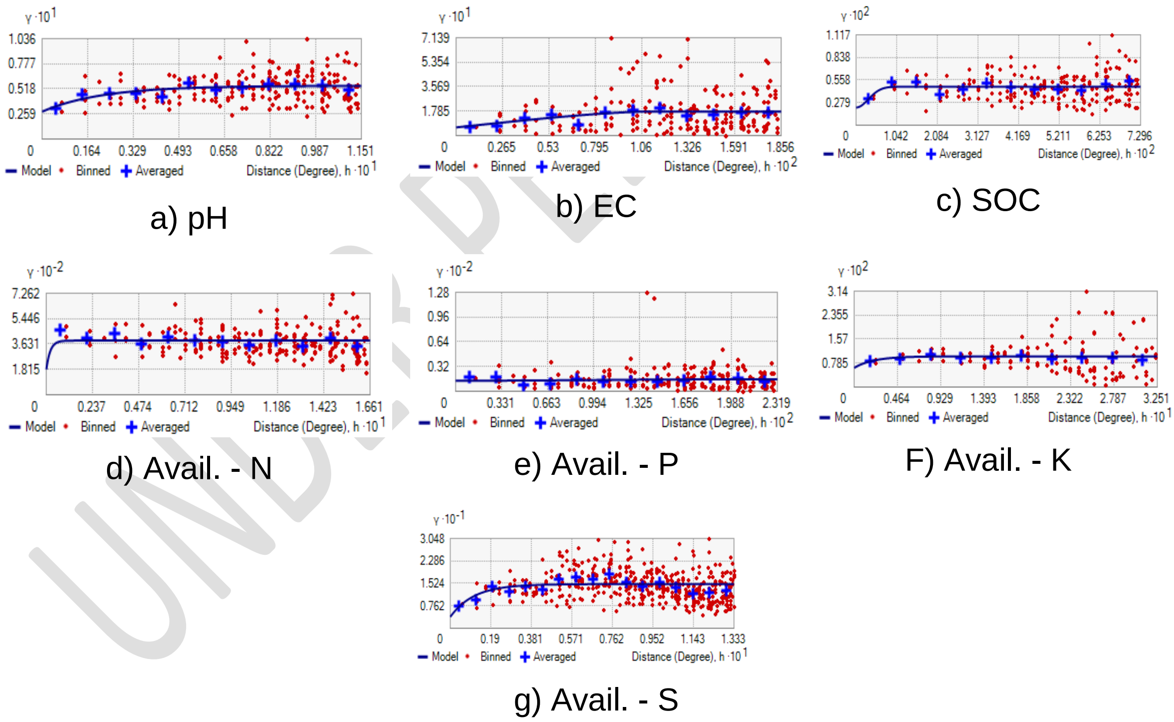


Fig. 3. Experimental semi-variograms and their fitted models for a) pH, b) EC, c) SOC, d) Avail. – N, e) Avail. – P, f) Avail. – K and g) Avail. - S

3.3. 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

Conclusions

The current study revealed a wide variation in measured soil chemical properties of the region. The soils of Ujjain block district Ujjain of Madhya Pradesh were found neutral to alkaline in soil reaction, safe in electrical conductivity, low to medium in organic carbon content. The result of this study suggested that the exponential, spherical, gaussian, circular models were the best fitted model for studied soil parameters. The correlation analysis revealed a significant positive correlation of soil pH with soil organic carbon and EC. By the overall study, it can be concluded from the above results that the soils of Ujjain tehsil of 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. The organic carbon content exhibited low to medium status and positive significant correlation was obtained between OC and available N. The maps generated of soil attributes could be utilized as a primary guide for sustainable soil management practices such as variable rate of micronutrient-based fertilizer recommendation for getting maximum productivity of the region.

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