Spatial variability in soil micronutrients and soil separates of 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 physical properties and soil available micronutrients 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 some soil properties viz: soil texture (sand, silt and clay) and soil available micronutrients, viz. extractable zinc (Zn), copper (Cu), manganese (Mn) and iron (Fe) in laboratory. The range of sand, silt, clay, Zn, Cu, Fe and Mn in the study region were varied from 9.15 to 24.06 %, 24.00 to 41.55 %, 40.20 to 58.60 %, 0.12 to 1.66 mg kg^{-1}, 2.06 to 6.22 mg kg^{-1}, 3.70 to 10.40 mg kg^{-1}, and 2.41 to 14.64 mg kg^{-1}, respectively. The data were analyzed using standard statistical methods and geostatistics, which included creating semi-variograms and mapping by standard kriging procedures. Semi-variograms were produced for soil properties and their regional distributions were plotted. The observed soil parameters were best represented by four models: Exponential, Circular, Gaussian, and Hole effect. The modelled variables showed strong and moderate spatial dependencies, as demonstrated by the Nugget/Sill (Co/Co+C) ratio. The distribution maps of soil features may serve as a reference for implementing site-specific crop management in soils with comparable characteristics. Further, this research indicates the relevance of GIS- application in soil variability investigations.

Keywords: Soil separates, Soil variability, Geo coded, Geo-statistics, Spatial dependence,Semi-variogram, Ordinary kriging.

Introduction:

Soil is an essential and limited natural resource for agriculture [1, 2]. Soil fertility is crucial for enhancing agricultural yield. It encompasses not only the provision of nutrients but also their effective management. The soil's fertility condition denotes its capacity to deliver nutrients [2]. Assessing soil fertility is a fundamental tool for making informed decisions about implementing effective nutrient management techniques [3]. Soil fertility assessment encompasses many methodologies, with soil testing being the predominant method used worldwide [4]. Soil testing evaluates the present fertility level and gives data on nutrient accessibility in soils, which serves as the foundation for fertilizer recommendations to optimize crop yields and sustain soil fertility over an extended time [5].

Geostatistical methods have successfully evaluated the spatial variability of soil properties in different geographical and ecological contexts. This assessment has contributed to improving soil health, managing plant nutrients in a site-specific manner, understanding soil erosion, and determining the impact of different land uses on soil variability [6]. The approach of geo-statistics is widely recognized as the most reliable and comprehensive method for interpolation. It takes into account the geographical variance, position, and distribution of samples [2].

Accurate knowledge of the geographical variability and distribution of soil qualities is crucial for farmers aiming to enhance the effectiveness of fertilizers and improve crop output [7]. Geostatistics is a potent method that is valuable for estimating the spatial variability of soil characteristics and soil nutrients at many scales, including field, catchment, and regional levels. In addition to the variety in soil properties caused by farmers, it is also recognized that soil variability may arise from edaphic variables, including the parent material (rock types that produce the soil) and the location of the soil on the catena, among other causes [2, 8].

Several research use geo-statistics to ascertain spatial variability and create maps of soil attributes in a spatial context [1, 9, 10, 11]. Understanding the variability of soil is essential for both practical management and the creation of models [12, 5].

Hence, this research aims to measure the spatial variability of soils in Ujjain tehsil of Madhya Pradesh.

Material and Methods

2.1 Site details

The Ujjain tehsil is located to the north of Ghatiya, with Indore to the south, Dewas to the east, and Badnagar to the west. This tehsil is located inside the Ujjain district of the state of Madhya Pradesh. Ujjain is positioned on the bank of the Kshipra river and is situated at the coordinates of 23°10'45.4800"N latitude and 75°47'5.6832"E longitude. Ujjain tehsil is located at a height of 494 meters above the mean sea level. The total land area of Ujjain tehsil is 60987.4 hectares. Ujjain tehsil is located in the northwestern region of Madhya Pradesh. The area typically has a hot, sub-tropical climate with an average rainfall of 914.5 mm. The rainfall is unevenly distributed, with the majority occurring between June and September. The warmest month is May, while December is the coldest. The Ujjain district has a temperate environment, with an average maximum temperature of 40.73°C. The mean lowest temperature throughout the winter season is 8.23°C.

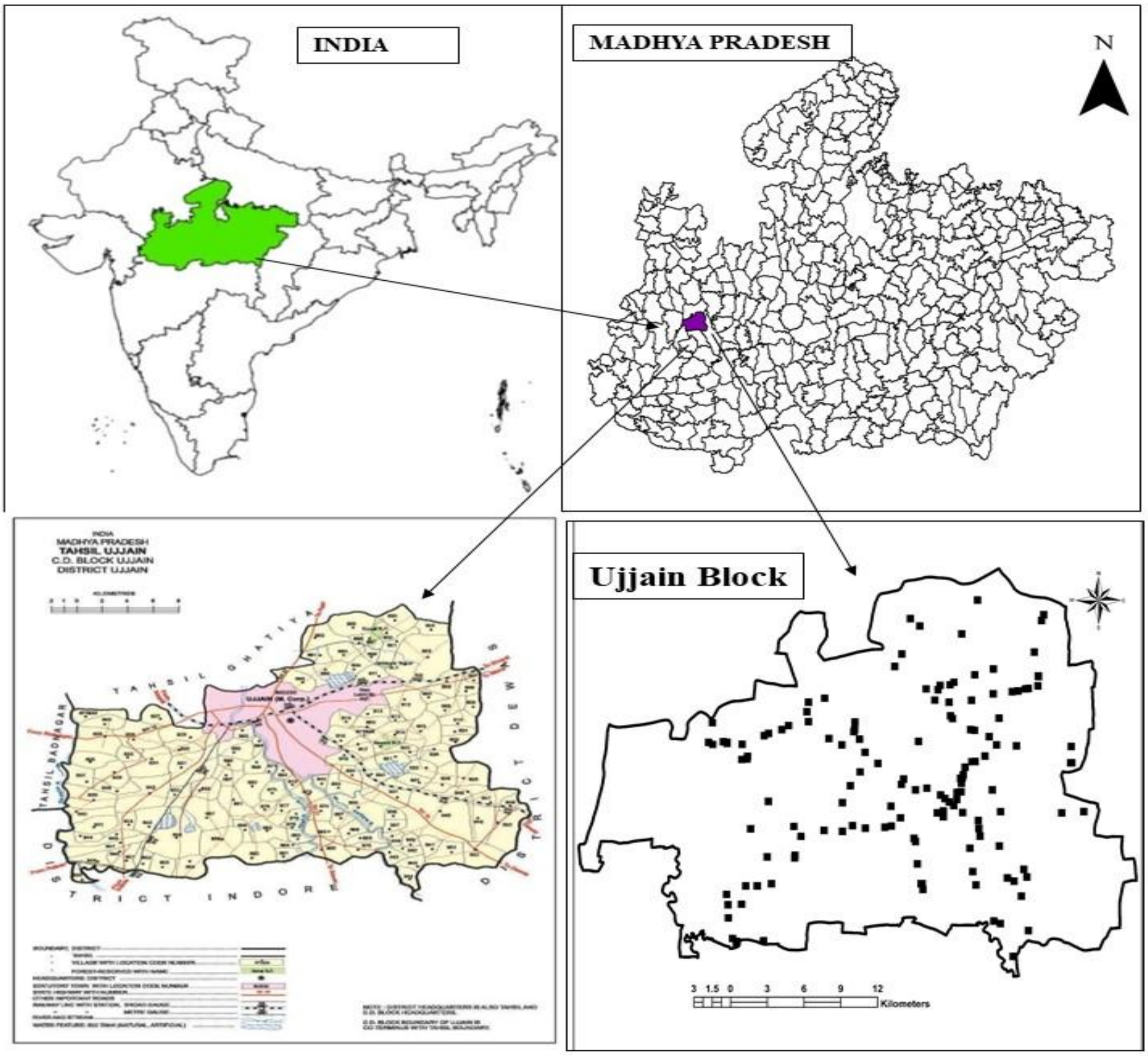


Fig.1 Location of study area

2.2 Agricultural Scenario

Soybean is the predominant crop cultivated in 70% of the Ujjain tehsil during the rainy season (kharif). Additional kharif crops include red gram, maize, and sorghum, which is used as feed. The crops cultivated during the rabi season include wheat, chickpea, potato, onion, and garlic. During the summer season, farmers cultivate field crops such as blackgram and greengram, as well as vegetable crops like coriander, chilli, and brinjal. Groundwater and surface water are used for irrigation. The predominant portion of the region consists of rainfed land, with other areas being slightly irrigated.

2.3 Soil survey and sampling techniques

The sample sites were randomly selected over the agricultural land in the research region, taking into account land use and soil association maps, terrain, and the variability of soil types. The gathering of field data and soil samples was conducted by using GPS technology to navigate to certain spots. A total of 150 surface soil samples (0-15 cm) were gathered from a farmer's field during the non-growing season to prevent the influence of fertilization during crop cultivation. At each primary sampling location, a 1.0 kilogram composite soil sample, which accurately represents the area, was collected and recorded in a correctly labeled sample bag. Soil samples were excluded from atypical sites such as locations with animal excrement buildup, areas with inadequate drainage, and any other locations that cannot provide representative soil samples. During the process of soil sampling, many data points were gathered from each site, including geographic information such as latitude and longitude, topography, slope, elevation, land use type, crop type, local soil name, sample depth, soil color, crop residue management, rate of previous year's fertilizer application, and fertilizer type.

2.4 Analysis of soil separates and DTPA extractable micronutrients

The soil available Fe, available Mn, available Cu, and available Zn were extracted with diethylenetriaminepentaacetic acid (DTPA), and the extracted Fe, Mn, Cu, and Zn were determined with flame atomic absorption spectrometry by Lindsay and Norvell [13].

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 [14] 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. [15]. 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

The Geostatistical Analyst tool in ArcGIS 10.5 was used to model the semivariogram and choose the most suitable semivariogram model. Prior to fitting the semivariogram models, the skewed soil parameters were normalized by using the natural logarithm to get a nearly normal distribution. The data underwent back transformation via the process of back transformation.

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

Where: N (h) is the number of pairs of points distant from each other by h. We assessed many semivariogram models in ArcGIS v 10.3.1 to determine the best match for the experimental data. An evaluation was conducted on several soil properties using the circular, spherical, tetra spherical, exponential, Gaussian, K-Bessel, J-Bessel, and stable models. The semivariogram model with the lowest nugget/sill ratio was chosen as the most suitable model for the specified soil attributes [16]. The exponential, Gaussian, spherical, and circular models provided the most accurate match for the soil parameters that were evaluated.

Exponential model:

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

Gaussian Model

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

Spherical Model

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

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 semivariogram parameters, including the nugget (C0), partial sill (C), sill (C + C0), and range (r), were computed to analyze the spatial structure of the soil variables and to be used as input for kriging interpolation.

The characteristics that define the spatial organization of a soil attribute are the range and the nugget/sill ratio, or (C0) /(C+C0). The range indicates the length of time that the correlation between the values of the soil properties is present. In general, a low ratio of (C0) /(C+C0) and a large range suggest that kriging may provide high accuracy of the attribute [17]. The criteria for categorizing the spatial dependency of variables was the nugget/sill ratio. Strong geographic reliance was defined as ratio values less than or equal to 0.25, moderate spatial dependence as values between 0.25 and 0.75, and weak spatial dependence as values more than 0.75 [17].

The un-sampled areas' various soil properties were estimated using the ordinary kriging (OK) approach. For randomly dispersed soil samples, OK is the most effective unbiased prediction approach, as recommended by Schepers et al. [18]. OK is best suited for estimating soil parameters for un-sampled places because it lessens the influence of outliers on prediction [19]. The cross-validation method was used to assess the soil maps' accuracy [20].

2.7 Principal component analysis

Principal component analysis (PCA) is a dimension reduction technique in multivariate analysis that identifies orthogonal linear recombination of correlated attributes or variables in order to characterize the primary sources of variability in the data. In lieu of a covariance matrix, a correlation matrix comprising specific soil properties was utilized as the input for the analysis, leading to the attainment of normalized PCA. Numerous principal component (PC) variables are incorporated throughout the analysis. It was postulated that principal components (PCs) that acquire high Eigen values provide the most accurate representation of the properties of the field [18]. The current investigation utilized PCs that possessed Eigen values equal to or greater than 1.0 in order to construct the management zone classes.

Results and Discussions

3.1 Descriptive statistics of selected soil properties

The descriptive statistics pertaining to specific soil properties (namely sand, silt, clay, Zn, Fe, Cu, and Mn) are displayed in Table 1. The mean values for the available micronutrients Zn, Fe, Cu, and Mn were 0.63, 3.65, 6.68, and 8.72, respectively, and ranged from 0.12 to 1.66 mg kg^{-1}, 2.06 to 6.22 mg kg^{-1}, 3.70 to 10.40 mg kg^{-1}, and 2.41 to 14.64 mg kg^{-1}. The variability pertaining to the physical properties of the soil, specifically sand, silt, and clay, spans from 9.15 to 24.06%, 24.00 to 41.55%, and 40.20 to 58.60%, respectively. The mean values for these range from 16.34, 34.00, and 49.78.

As a percentage, the coefficient of variation, which is calculated as the ratio of the standard deviation to the mean, is a valuable indicator of overall variability. Varied variability is categorized as low (10% CV), moderate (10-100%) CV, and high (100% CV). The CV data, which were displayed in Table 1, indicated that Zn exhibited the highest degree of variability (CV = 39.65%), followed by Mn (CV = 30.95), Cu (CV = 25.19), Fe (CV = 23.61), sand (CV = 21.86), SOC (CV = 14.00), silt (CV = 9.55%), and clay (CV = 6.78 percent).

The area's range of CV indicated varying levels of variability among the properties under investigation. While all other soil parameters shown considerable variability, the silt and clay exhibited minimal variability. Micronutrients, on the other hand, were shown to be quite varied, ranging from 23.61 to 39.65 percent.

Table 1 displays the results of soil parameters after the Kolmogorov-Smirnov (K-S) technique was used to evaluate the data's normality (P-value > 0.05). The degrees of skewness for these metrics were typical when given appropriate consideration. For a randomly distributed variable that is normally distributed, the skewness and kurtosis coefficients are 0. Data transformations are often carried out in order to lessen the impact of extreme values on spatial analysis if the data distributions are significantly different from a normal distribution [14]. Table 1 revealed, however, that the data set's skewness coefficients varied from -0.38 to 0.25 when the observed skewness coefficient values were taken into account without any data transformation. Because of their greater values of skewness and kurtosis, the soil fertility metrics available Zn, Cu, and Fe were determined to be nonnormally distributed.

Table 1Statistical summary of selected soil properties

Soil properties	Unit	Minimum	Maximum	Mean	Std. Deviation	CV	Skewness	Kurtosis
Sand	%	9.15	24.06	16.34	3.57	21.86	0.03	-0.55
Silt		24.00	41.55	34.00	3.25	9.55	-0.16	0.05
Clay		40.20	58.60	49.78	3.38	6.78	-0.38	0.23
Zn	mg kg^{-1}	0.12	1.66	0.63	0.25	39.65	**0.19**	**0.42**
Cu		2.06	6.22	3.65	0.92	25.19	**0.25**	-0.33
Fe		3.70	10.40	6.68	1.58	23.61	**0.23**	-0.76
Mn		2.41	14.64	8.72	2.70	30.95	-0.16	-0.48

Note: Zn, Fe, Cu, and Mn represent available zinc, iron, copper, and manganese in soil, respectively; SD = standard deviation; CV = coefficient of variation

3.2 Soil fertility index and soil fertility classes

The nutrient index values for soil fertility classes are categorized as follows: values below 1.67 indicate low fertility, values between 1.67 and 2.33 indicate medium fertility, and values above 2.33 indicate high fertility [2, 5, 21]. The mean nutritional index values for Zn, Cu, Fe, and Mn were determined to be 1.56, 1.97, 1.98, and 2.97, respectively (Table 2). These values indicate that Zn falls into the low fertility category, whereas Cu and Fe fall into the medium fertility category, and Mn falls into the high fertility category. Gehlot et al. [1] reported a comparable outcome in relation to the matter.

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

Available	Number of	Mean value of	Percent distribution of soil fertility

Nutrients	samples	soil index fertility	class		
			Low	Medium	High
Zn	150	1.56	44.6% (67)	54.7% (82)	0.7% (1)
Cu	150	1.97	0% (0)	0% (0)	100% (150)
Fe	150	1.98	10.6% (16)	80.7% (121)	8.7% (13)
Mn	150	2.97	0% (0)	2.7% (4)	97.3% (146)

3.2 Pearson's' correlation

A strong negative association was seen between sand and silt, sand and clay, silt and clay, silt and Cu, and Zn and Fe. Additionally, a positive correlation was detected between clay and Fe (0.204) only in the soils of the region. The correlation investigations revealed that there was no significant association between sand and Fe, silt and Fe, silt and Mn, clay and Zn, clay and Mn, Cu and Fe, and Cu and Mn. The pH of the soil was slightly alkaline in reaction and Fe, Mn, Zn and Cu are available in acidic range thus, it showed no significant correlation.However, all the other parameters exhibited a non-significant positive correlation (Table 3). The results were consistent with the previous findings of [1, 2, 5].

Table 3 Pearson's correlation coefficients for selected soil properties

Corr.	Sand	Silt	Clay	Zn	Cu	Fe	Mn
Sand	1.00						
Silt	**-0.520****	1.00					
Clay	**-0.535****	**-0.407****	1.00				
Zn	0.06	0.03	-0.13	1.00			
Cu	0.03	**-0.163***	0.13	0.06	1.00		

Fe	-0.16	-0.03	**0.204***	**-0.195***	-0.02	1.00	
Mn	0.09	-0.06	-0.02	0.11	-0.05	0.09	1.00

3.3 Spatial variability analysis

Semivariograms were computed and optimal models were found to characterize the spatial patterns of various soil characteristics. The semivariogram analysis findings are shown in Table 4 and Figure 3. The majority of soil characteristics were best represented by exponential models, with the exception of AP, SOC, EC, Zn, and Mn. Gaussian, circular, and Hole Effect models were used to suit these specific values, respectively. Multiple authors have documented comparable findings, with the majority of soil parameters exhibiting the greatest match with spherical models [9, 22]. The findings revealed that soil properties exhibited spatial autocorrelation, which was influenced by various structural factors including proximity to water bodies, parent material, mangrove ecosystem characteristics, and water table depth. Additionally, human-induced factors such as soil crop management practices, fertilizer application, and prevalent farming systems in the study area also played a role in determining the spatial correlation of soil properties [23]. The nugget/sill ratio was examined for several soil characteristics (Table 4). The relationship between the amount of nugget and sill provides insight into the regional correlation of soil parameters [17, 24]. The research used criteria that closely resembled those documented by Gehlot et al. [17]. A low ratio (25%) indicates that a significant portion of variation is attributed to geographical factors, suggesting a strong spatial correlation of the variable. If the ratio falls between the range of 25 to 75%, the variable exhibits a moderate level of dependency. Otherwise, the variable has a weak spatial dependence. The current research observed a significant geographical correlation between soil Zn and Fe, which may be ascribed to the combined influence of closeness to the sea shore and the presence of a mangrove environment. Other soil parameters investigated exhibited a moderate level of spatial dependency, perhaps attributed to variations in soil fertilization and cultivation techniques, as well as the influence of robust hydrological processes in the area, characterized by the presence of several rivers and creeks. Jiang et al. [9] and Ausari et al. [2] found comparable findings. Furthermore, the presence of a substantial Mn nugget in the studied region may be explained by ecological processes, including natural disturbances within the mangrove ecosystem, variations in hydrology, nutrient cycling, and interactions between living and non-living components at a local level. Figure 2 displays spatial distribution maps for all soil parameters. The majority of soil nutrients exhibited elevated levels inside the mangrove forest and its surrounding area, whereas lower levels of soil nutrients and SOC were seen in other regions of the research area, which are mostly rice farmed fields (Fig. 2). The nitrogen content in mangrove forests was boosted by the addition of leaf litter and the promotion of biological processes. Conversely, agricultural soils in cultivated rice fields had low nutrient levels due to the use of very little or no inorganic fertilizer and the inconsistent management practices. The maps offer precise data on nutrient content, enabling the implementation of site-specific nutrient management and variable-rate fertilizer application technology. This, in turn, maximizes rice yield and increases farmers' income by reducing input costs, while also promoting the use of 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
Sand	None	Exponential	4.94	13.19	5952.06	0.37	Moderate
Silt	None	Exponential	4.59	13.30	7052.04	0.35	Moderate
Clay	None	Exponential	3.89	12.80	9567.10	0.30	Moderate
Zn	None	Hole Effect	0.01	0.06	353.52	0.23	Strong
Cu	None	Exponential	0.65	0.89	21535.77	0.73	Moderate
Mn	None	Hole Effect	5.55	7.08	370.78	0.78	Weak
Fe	Log	Exponential	0.02	0.07	7452.06	0.25	Strong

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

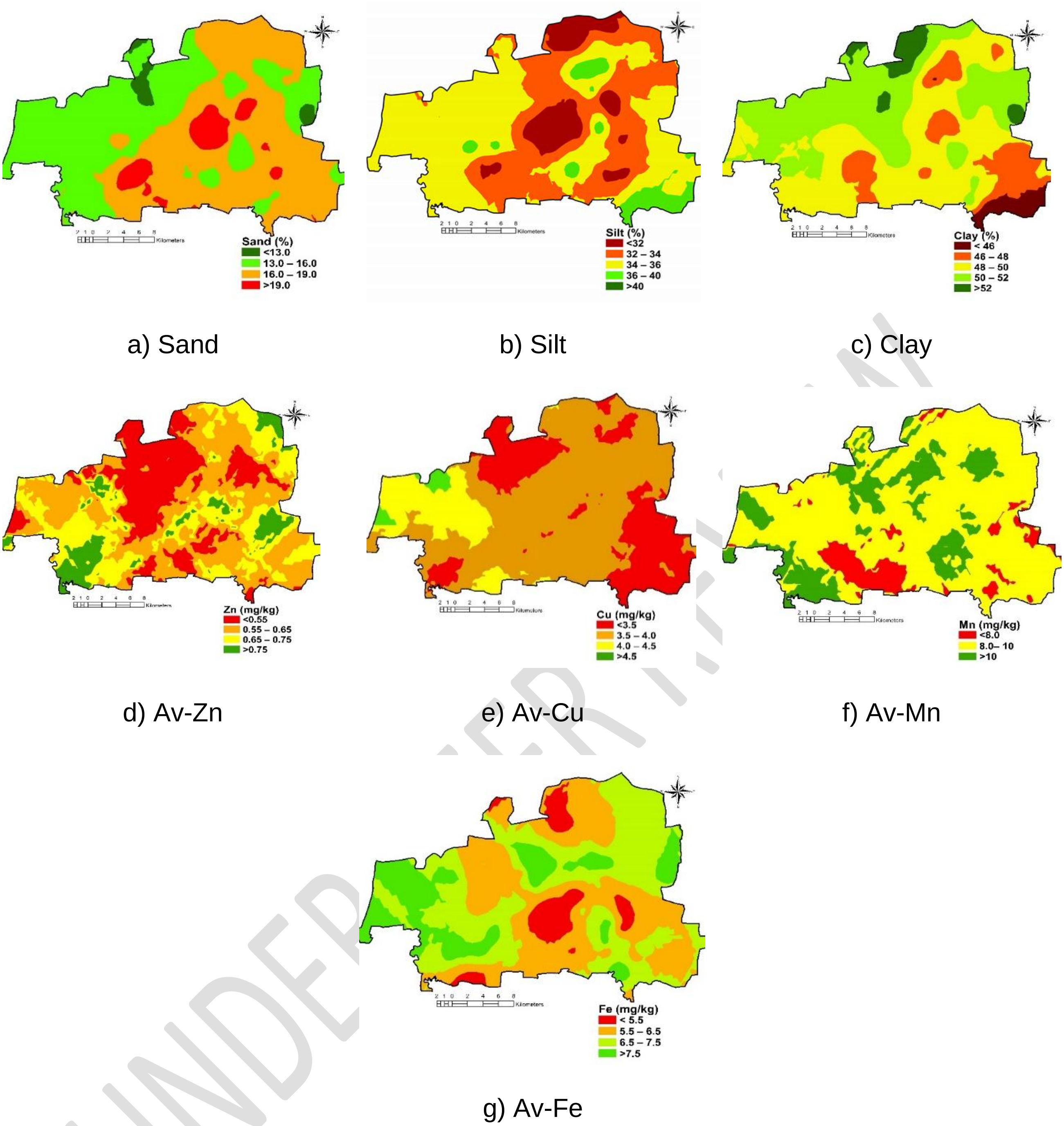
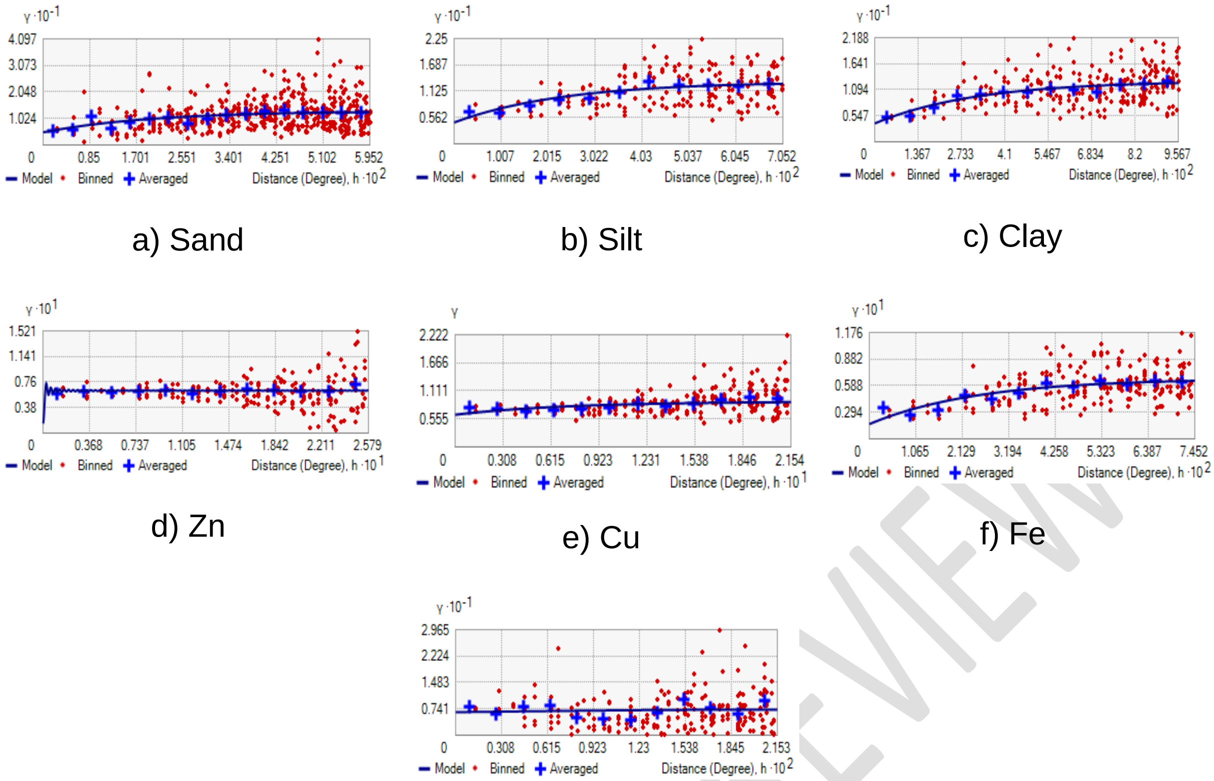


Fig. 2 Distribution maps soil physical properties and available micronutrients in the soil generated by ordinary kriging.



a) Sand b) Silt c) Clay

d) Zn e) Cu f) Fe

g) Mn

Fig. 3. Experimental semi-variograms and their fitted models for a) sand, b) silt, c) clay, d) Zn, e) Cu, f) Fe and g) Mn

3.3. Principal component analysis

The seven soil factors examined in this research shown a strong correlation. Principal component analysis (PCA) was used to consolidate and summarize the variation in the 07 variables. Only principal components with eigenvalues above 1 and a cumulative contribution rate over 60% were retained. Based on this criteria, only the first three main components were included in the final analysis, explaining 60.27% of the overall variability (Table 5). Fig. 3 displays the maps for the three personal computers (PCs). The eigenvalues corresponding to these three principal components were denoted as N1, indicating that a principal component accounts for a greater amount of variance than an individual characteristic [5]. The second main component (PC 2) accounted for an extra 13.33% of the overall variation and was mostly influenced by the presence of sand. PC 3 accounted for an extra 12.33% of the overall variation and was mostly influenced by Cu. To summarize, the principal component analysis combined the 07 variables into three main components, which explained most of the total geographic variability in these qualities.

Table 5. Principal component analysis of soil separates and micronutrients

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
Sand	-0.439	0.558	0.626	-0.124	0.023	-0.189	0.016
Silt	0.159	-0.853	0.119	0.266	0.172	-0.062	0.080
Clay	0.359	0.268	-0.770	-0.111	-0.149	0.281	-0.108
Zn	-0.190	-0.213	0.288	-0.265	-0.370	0.537	0.256
Cu	0.206	0.280	0.036	-0.368	-0.292	0.179	-0.299
Fe	0.346	0.237	-0.357	0.246	0.085	-0.210	0.313
Mn	0.010	0.255	0.160	0.334	-0.005	0.416	0.613

Conclusion

This study found significant variations in soil properties and micronutrient levels across the region. Various models, including exponential, spherical, gaussian, and circular, were deemed suitable for characterizing the soil attributes. Micronutrient semivariogram models showed moderate spatial dependence, with nugget/sill ratios between 43% and 53%. Strong positive relationships were observed among micronutrients. Analysis of 150 soil samples revealed medium levels of DTPA-extractable zinc and iron, high levels of copper and manganese, and a moderate to low status of organic carbon, which exhibited a positive association with accessible nitrogen. About 44.6% of samples were deficient in zinc, and 10.6% in iron. Distribution maps indicated deficiencies in zinc, iron, and boron, essential micronutrients. These maps can guide sustainable soil management strategies, including tailored micronutrient-based fertilizer recommendations for optimal production in the area.

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