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Spatial Variability of Soil Micronutrient Properties Using Geostatistical Approach and Geographic Information System Technique

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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

The distribution of soil qualities in every given area is essential for the development of management strategies that are appropriate to that site, since this promotes agricultural productivity sustainability and preserves the health of the soil.In spite of this, the current study was carried out in the Madhya Pradesh state of India to measure the spatial distribution of specific soil qualities in the soybean-wheat and soybean-chickpea belt. A total 303 geo-referenced composite surface (0-15cm) soil

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samples were collected across the study area. These samples were analyzed for different soil properties viz: pH, soil organic carbon (SOC), Calcium carbonate (CaCO3) the DTPA extractable Zn, Cu, Mn and Fe. The main goals of the study were to: (i) use geo-statistical methods to assess the spatial variability of soil available micronutrients, such as extractable zinc (Zn), copper (Cu), manganese (Mn), iron (Fe), and boron (B), at a regional scale; (ii) use ordinary kriging to develop maps of soil micronutrient distribution; and (iii) evaluate the relationships between micronutrient availability and several soil properties. It was revealed that 79.54% and 7.92% of the soil samples had shortages in accessible zinc and iron, respectively, but no soil sample had deficiencies in copper, magnesium, or zinc and sulphur. The concentrations of extractable Zn, Cu, Mn, and Fe, with the exception of B, exhibited substantial negative relationships with the pH of the soil. The EC had positive and significant relationship with SOC and B, respectively. The significant positive relationship of SOC of soil with available hot water-soluble B respectively. The soil micronutrients were showed significant positive relationship with each other. HWS B was also shown to be positive and statistically significant. In this study, spherical models were best suited for Cu, Mn, and Fe, whereas exponential models were best fitted for Zn and B. The semivariogram models for Zn, Fe, Cu, Mn, and B's nugget/sill ratios There was a documented moderate regional dependence for extractable Zn, Cu, Mn, Fe, and B for Mn.

Keywords: Geo-statistics; semi-variogram; precision farming; micronutrients; kriging.

1. INTRODUCTION

The environment and agriculture system both depend heavily on soil. The health of the soil is largely dependent on soil micronutrients. In comparison to major and secondary nutrients, plants require a significantly smaller amount of micronutrients. However, their importance is still great. Micronutrient deficiency can affect plant growth and crop output. Even if all other required elements are completely represented, a severe deficit could induce plant death. There is still a need to give this topic sufficient attention.

The state of MP is the leader in the production of soybeans in a Vertisol, yet its productivity of 1109 kg ha-1 is being hampered by a lack of some vital nutrients [1]. According to Shukla and Tiwari [2], nearly 60% of soil samples in Madhya Pradesh have been found to be zinc deficient, while 49% of Indian soils are zinc deficient. “Several soil types in Madhya Pradesh have zinc deficiencies; alluvial soils have the largest percentage of deficiencies (86%) followed by mixed red and black soils (68%), red and yellow soils (62%), medium black soils (61%), deep black soils (35%), and skeletal soils (31%)”, according to Khamparia et al. [3]. According to Fageria et al. [4], there is a global prevalence of micronutrient deficits in crop plants, as per their review on micronutrients in crop production. “Various studies have demonstrated that the status of micronutrients in the soil is primarily positively connected with organic carbon content, but negatively correlated with soil pH” [5]. Ecological modelling, environmental forecasts, precision agriculture, and natural resource management all heavily depend on identifying soil variability and preserving soil health (Wang, 2009). Spatial variance, location, estimation, and sample distribution are all considered in the geo-statistics approach. In order to predict micronutrients in the soil in various unsampled areas using data from sampled locations, this study looked into and mapped the spatial variability of the soil [6-9].

Geostatistical methods are a powerful tool for modeling soil spatial behavior, thereby facilitates the prediction of soil values for unknown locations [10]. To find the average degree of dissimilarity between values in the vicinity and locations not sampled, an experimental variogram is typically utilised [11]. According to Tula et al. (2017), correlations at different distances can therefore be established to determine values for un-sampled places. Spatial variability of soil properties is assessed adequately by geostatistical methods [12]; Shukla et al. 2015; [13]; 2018 for site-specific nutrient management [14]; Tripathi et al. 2019 and physical properties [15,16] under the different production system and varied soils of India. However, the information regarding the spatial variability of soil micronutrients in the soybean-wheat production system in Vertisols of India is entirely missing.

2. MATERIALS AND METHODS

Geographically speaking, the 3330 square kilometre Harda district is situated between 21°

53' and 22° 36' north latitude and 76° 47' and 77° 30' east longitude.It is situated in the valley of the Narmada River, which also serves as the district's northern border. The administrative blocks that comprise the district are Timarani, Harda, Khirkiya, Hundia, Sirrali, and Rahatgaon (Fig. 1). The district has an average annual rainfall of 1021.84 mm with maximum and lowest temperatures of up to 47 °Cand 12 °C, respectively. The region's subtropical climate range, diversified land use patterns, and varied physiographic and geological features all contribute to the diversity of soil development in the area.

2.1 Cropping Pattern and Land Use

Land use types were extracted from Landsat- 8 and classified in four classes: water, agriculture, forest, built-up area. Landsat 8 satellite has two sensors: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). OLI will collect images using nine spectral bands in different wavelengths of visible, near-infrared, and shortwave light to observe a 185 kilometer (115 miles) wide swath of the Earth in 15-30 meter resolution, encompassing large portions of the Earth's geography while offering enough detail to distinguish features like as metropolitan centre, farms, forests, and other land uses As shown in below Table 1 Processing parameters for Landsat 8 Satellite standard data products.

The digital map of soil, satellite images, and topographical maps of India (1:50000) were used as secondary data sources from the internet. Arc GIS 10.8 was utilized for image analysis. The physical features identified from the imagery were verified in the field using the information gathered from this process.

The significant land-use/land-cover map categories were identified and mapped (Fig. 2). Maps show that the majority of the area, 2082.20 sq km, is occupied by cultivated land, making up 62.52% of the total area. Based on data gathered from each survey site and the local agriculture department, the predominant current cropping system is one based on soybeans, specifically soybean-wheat, soybean-wheat-summer mungbean, soybean-chickpea, and soybean-fallow.

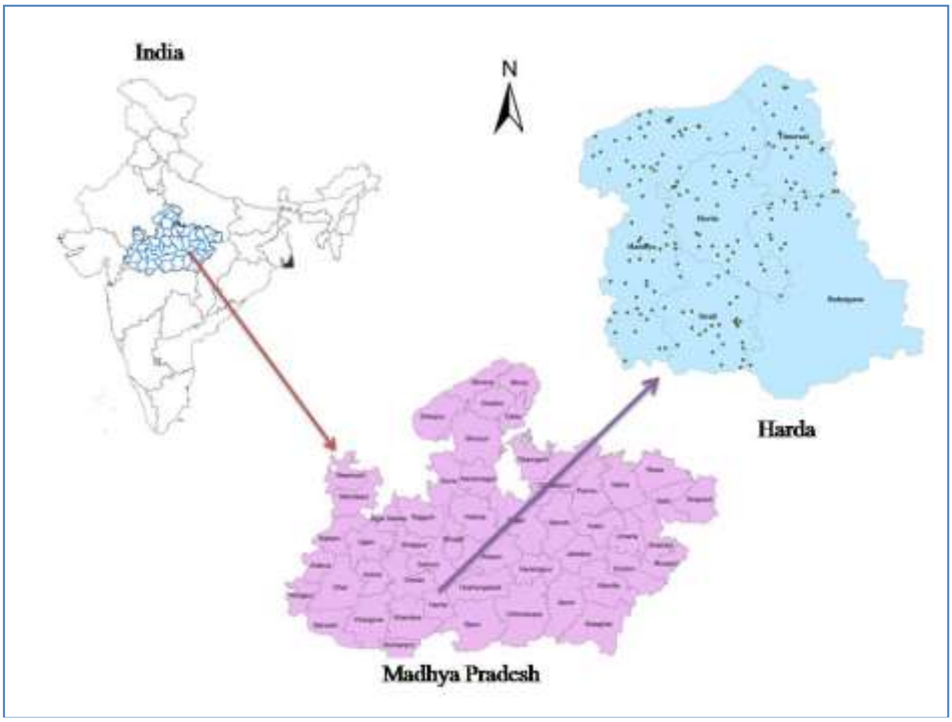

Fig. 1. Location map of study area

Table 1. Landsat -8 Satellite data characteristics parameters

Product Type	**Level 1T (terrain corrected)**
Data type	16-bit unsigned integer
Output format	GeoTIFF

Pixel size	15 meters/30 meters/100 meters (panchromatic/multispectral/thermal)
Map projection	UTM (PolarStereographic for Antarctica)
Datum	WGS 84
Orientation	North-up(map)
Resampling	Cubic convolution
Accuracy	OLI: 12 meters circular error, 90 percent confidenceTIRS:41meterscir cularerror,90percentconfiden ce

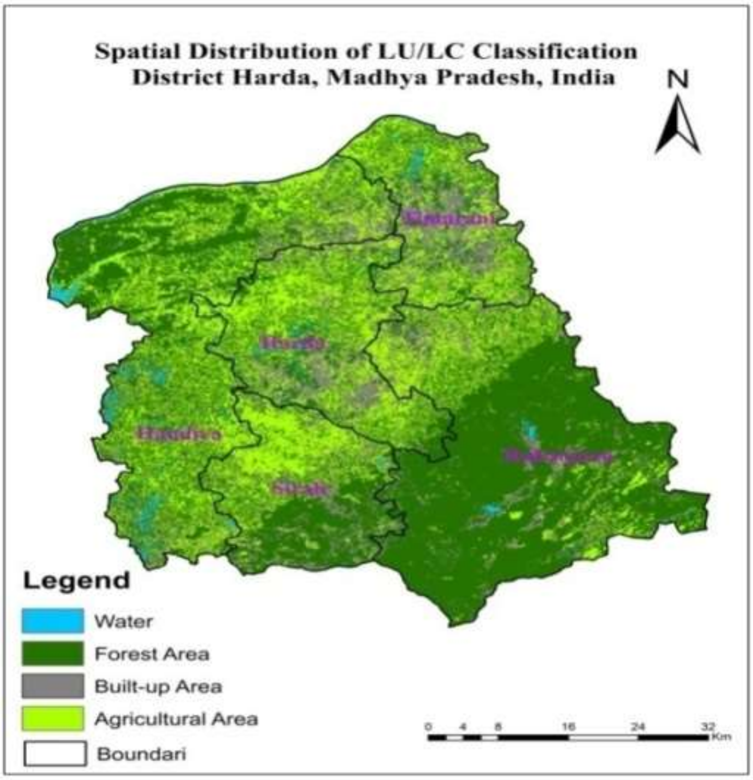

Fig. 2. Classification of land-use/land-cove in major class in Harda District, M.P

In the research area, land uses included sugarcane and horticultural crops, orchards, spices, crops, and vegetables. The classified image and area statistics were interpreted, and the forest was divided into two categories: dense (20.0%, or 666.0 sq km) and 6.96%, or 231.90 sq km), open. Other land use categories are built-up (52.83 sq km) which accounted by 1.59 percent represented to Harda city and some village’s settlements. Water bodies were occupied (68.25 sq km) and 2.05% of TGA. The classified data showed the wasteland in four categories i.e., gullied/ravenous land 0.05 % (1.82 sq km), sandy area-riverine,0.10 % (3.17sq km), dense scrub1.28 % (42.72 sq km) and open scrub 1.80 % (59.89 sq km) and minimum area covered by mining 0.01 % (0.17 sq km) of the total geographical area. The elevation, slope, contour, and hillshead map is compound topographic index were selected as the independent variables (Fig. 3), whereas the values of spatial components at each scale were dependent variables.

2.2 Techniques for Surveying and Sampling Soil

The study area's agricultural land was used to determine the randomly distributed sampling locations, which took into account topography, soil heterogeneity, and maps showing soil associations with land use. The GPS was used to navigate those points and collect field data and soil samples. In order to prevent the effects of fertilizing during crop cultivation, 303 surface soil samples (0–15 cm) were taken from farmer's fields during the off-season. A representative composite soil sample of 1.0 kg was obtained from each primary sampling location and logged into a properly labelled sample bag. Soil samples were not taken from uncommon areas such as animal dung accumulation sites, poorly drained areas, or any other areas where representative soil samples could not be obtained. The topography, slope, elevation, land use type, crop type, local soil name, sampling depth, color, crop residue management, rate of previous year's fertilizer application, and type of soil were all determined throughout the soil sampling process for each site.

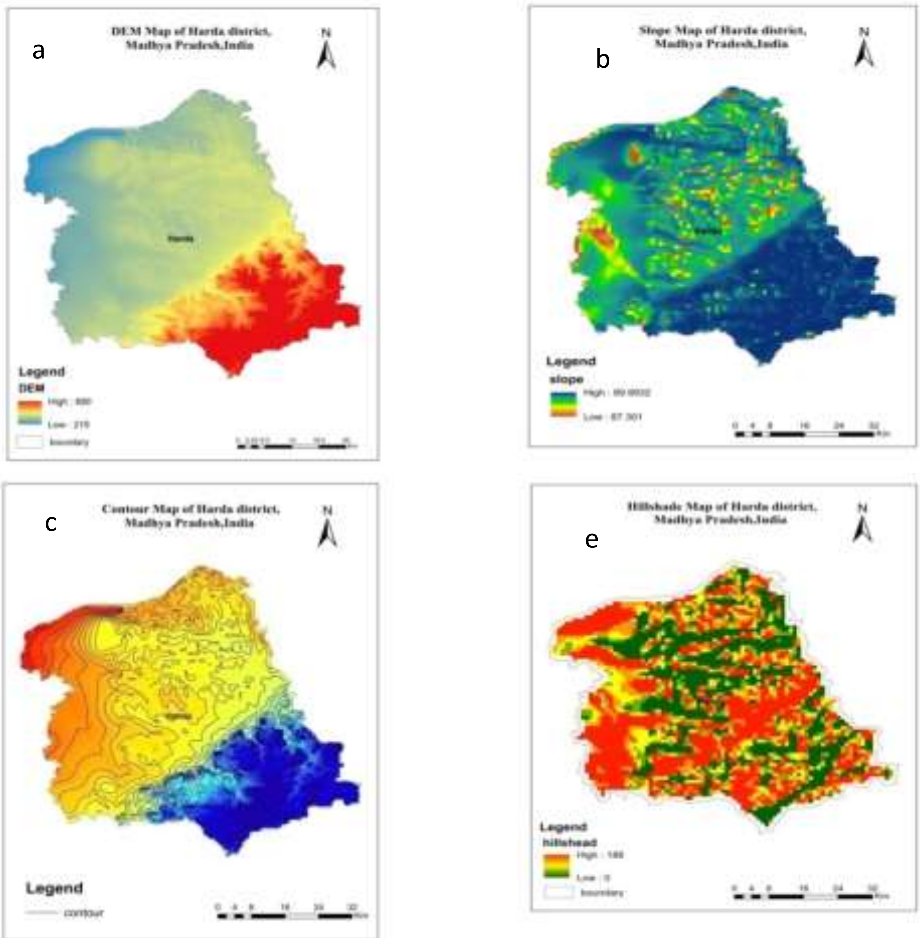

Fig. 3. Factors affecting the spatial variability of soil micronutrients: (a) elevation, (b) slope, (c) contour, (d) hillshead

2.3 Soil Analysis

Prior to being crushed using a wooden pestle and mortar and sieved through a 2 mm sieve, the soil samples were allowed to air dry. Several properties were determined using the material that went through the sieve. With a soil: water ratio of 1:2.5, pH was measured using a pH meter, and the supernatant of that mixture was utilized to measure electrical conductivity using a conductivity meter. The soil organic carbon in soil was determined using Nelson and Sommers [17] and calcium carbonate content in soils carried out using rapid back titration described method as Jackson [18]. Available micronutrients (Zn, Cu, Fe, and Mn) were extracted with diethylene triamine penta-acetic acid (DTPA), and their concentrations were measured by flame atomic absorption spectrometer (AAS) [19]. Hot water-soluble boron in soil was analyzed by azomethine-H method as outlined by Berger and Truog [20].

The values of the nutrient index (NI) for available nutrients in the soils were calculated utilizing the formula suggested by Parker et al. [21] and classified this index as low (<1.67), medium (1.67 to 2.33) and high (>2.33).

NI= [(Nl x 1) + (Nm x 2) + (Nh x 3)]/Nt,

Where Nl, Nm, and Nh are the number of soil samples that fall into the low, medium, and high nutrient status categories, and are weighted 1, 2, and 3 respectively. Nt is the total number of samples.

2.4 Data Analysis

The soil variables were primarily analyzed for various statistical parameters through classical statistics. The central tendency and dispersion parameters were obtained for variability analysis. These

The statistical parameters were mean, standard deviation (SD), coefficient of variation (CV), skewness, and kurtosis. A Pearson correlation matrix among all the soil variables was also generated to investigate the association between the variables. Before the geostatistical analysis, data of all the soil variables were tested for normality using Kolmogorov-Smirnov (K-S) and skewness. All the general statistical parameters for the soil variables were obtained using the SPSS statistical software.

2.5 Geostatistical Analysis

The spatial pattern and variability of any soil property can be studied using geostatistical analysis. The concept of geostatistical approaches is broadly based on the regionalized variable theory, which mentioned that variables in an area have both random and spatial properties. They give a collection of statistical methods for adding geographical coordinates of observations in data processing, allowing for spatial pattern description and modelling, and prediction (kriging) at unsampled locations, and assessment of the associated uncertainty [22]; Ruth and Lennartz 2008. The spatial dependence and variation of the quantities, z(xi) was studied with the help of semivariogram (γ(h)) that was

calculated from the following equation:

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

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 root mean square error (RMSE) (eq.2) was selected as the best fit model for the given soil properties [8]. The exponential, Gaussian, spherical, and circular models were best fitted for the studied soil properties.

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

Exponential model:

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

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 specifies the distance over which the soil property values are connected. “A low value of (C0) /(C+C0) and a high range generally indicate that high precision of the property can be obtained by kriging” [23]. “To identify the geographical dependence of variables, the nugget/sill ratio was used. Strong spatial reliance was defined as a ratio less than or equal to 0.25, moderate spatial dependence between 0.25 and 0.75, and weak spatial dependence larger than 0.75” [23].

The ordinary kriging (OK) method was performed to estimate different soil parameters at the un-sampled locations. As suggested by Schepers et al. [24] 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 [25]. “Accuracy of the soil maps was evaluated through cross-validation approach” [26]. “The accuracy of prediction is measured by mean absolute error (MAE) and mean squared error (MSE), whereas the efficiency of prediction is measured by goodness of prediction (G) (Utset et al. 2000). MAE is a measure of the sum of the residuals (e.g., predicted minus observed)” (Voltz & Webster 1990).

$$MAE = \frac{1}{N}\sum_{i=1}^{N} z(x_i) - \hat{z}\,(x_i)$$

Where z1 the predicted value at location i. Small MAE values indicate less error. The MAE measure, however, does not reveal the magnitude of error that might occur at any point, and hence MSE will be calculated.

$$MSE = \frac{1}{N}\sum_{i=1}^{N} [z(x_i) - \hat{z}\,(x_i)]^2$$

“The smaller value of MSE indicates a more accurate estimation. The G measure indicates how effective a prediction might be relative to that which could have been derived from using the sample mean alone” [27].

$$G = \left[1 - \frac{\sum_{i=1}^{N}\left[Z(x_i) - \hat{Z}\,(x_i)\right]^2}{\sum_{i=1}^{N}[Z\,(x_i) - \bar{Z})^2}\right] \times 100$$

Where z is the sample mean. G is one of the methods used for accuracies of interpolated maps Tesfahunegn et al. [28]. Accuracies of interpolated maps of studied soil properties were checked by G values. According to Parfitt et al. [29], “positive G values indicate that the map obtained by interpolating data from the samples is more accurate than average. Negative and close to zero-G values suggest that the catchment-scale average predicts the values at unsampled locations as accurately as or even better than the sampling estimates”.

3. RESULTS AND DISCUSSION

3.1 Soil Properties Descriptive Statistics Field

Table 2 displays descriptive statistics (DTPA) on a subset of soil parameters, including pH, EC, OC, CaCO3, Zn, Fe, Cu, Mn, and B. The data indicates that the values of pH, EC, SOC, and CaCO3 changed as 6.42-8.90, 0.09-0.98 dSm^{-1}, 2.35 -10.16 g kg^{-1} and 5.0-115 g kg^{-1} with the mean values of 7.6, 0.2 dSm^{-1}, 5.32 g kg^{-1} and 37.4 g kg^{-1}, respectively. The extractable DTPA of soil micronutrients i.e., Zn, Cu, Fe, Mn and hot water soluble B varied from 0.02 to 2.5, 0.78 to 7.84, 1.91 to 35.34, 2.93 to 35.18 and 0.5 to 2.9 mg kg^{-1} with values ofmean2.16 ,0.49, 18.19 ,10.05 and 1.33 mg kg^{-1}, in the district overall, respectively.

The coefficient of variation, which is the ratio of standard deviation to mean presented as a percentage, is a useful indicator of overall variability. According to Table 2, when defining CV 10% as low, 10 to 100 percent as moderate, and >100 percent as high variability, the CaCO3 had the highest variability (CV = 83.40 percent), followed by EC (CV = 60.00 percent), SOC (CV = 24.06), and pH (CV = 6.70 percent). Zn was discovered to be the most variable of the DTPA extractable micronutrients (CV = 77.55%), followed by Fe (CV = 60.30%), Cu (CV = 54.17 %t), and Mn (CV = 48.16 %). The hot water-soluble B had the lowest variability (CV = 39.85%).

The characteristic's range and standard deviation varied from 0.89 to 0.12 (EC), respectively.Various levels of heterogeneity among the properties under study were indicated by the range of CV in the area.Only the pH varied little, whereas the other soil characteristics varied much.However, it was shown that micronutrients varied somewhat, ranging from 18.62 to 71.19 percent.Micronutrients had a similar outcome, with a CV ranging from 39.85 to 77.55 percent.

Further analysis of the Table 2 showed that the skewness and kurtosis values were greater for EC, CaCO3, and DTPA extractable Zn, Cu, Fe, Mn, and B. The skewness coefficients of the data set ranged from -0.35 to 3.7. As a result, these variables diverge significantly from the normally distributed set.

Results were related to index of nutrient availability as shown in Table 3 indicate The Zn and Fe deficiency was observed in 79.54% and 7.92% soil samples and none of soil samples were found deficient in Cu, Mn and B. The percent soil samples were found medium in respect of Zn, Fe, Mn and B by 15.18, 46.53, 2.31 and 34.32%. The 5.28%, 100%, 45.54%, 97.69% and 65.68% soil samples were fall in high in case of Zn, Cu, Fe, Mn and B, respectively. In case of Cu, all soil samples were in high category and none of soil samples were found to be deficient and medium category. Further data show that the district-wide nutrient index values were 2.38, 2.57, 2.66, 2.98, and 3 for Fe, B, Mn, and Cu, respectively, whereas the NI value for Zn was found to be low at 1.26..

3.2 Pearson's' Correlation of Zn, Cu, Mn, Fe and HWS-B with Selected Soil Properties

The Pearson's' correlation matrix in Table 4a showed that the pH of soil had significant negative relationship with micronutrients i.e., Zn, Cu, Fe and Mn. These results were supported by Rajakumar et al. (1996), Chinchmalatpure et al. [30] Katyal and Sharma [31] who reported negative significant correlation between micronutrients and soil pH Except B in soil the correlation coefficient (r) obtained between hot water-soluble Boron and soil pH was -0.024. The result was negative non-significant. This result was supported by Abid et al. (2002) and Kumar and Singh (2003). In addition, the EC had positive and significant relationship with SOC and B with r values of 0.163**and 0.168**, respectively. By displaying values of 0.164**, respectively, the substantial positive association between the soil's SOC and the hot water soluble B that is readily available was observed. The micronutrients i. e. DTPA extractable Zn and Cu, Fe and Mn showed significant positive relationship with each other. HWS B was likewise discovered to have a positive and substantial relationship (r=0.135*) with DTPA extractable Fe.

3.3 Spatial Distribution of DTPA Extractable Zn, Cu, Mn Fe and HWS- B

For each of the five micronutrients, the exponential model suited the data the best, showing low RMSE and MSE values (Table 4b).The reason why Zn and Mn had the largest nugget (a measure of micro-variability) is because the chosen sampling distance was unable to adequately capture the spatial dependence.Indicating a moderate geographical dependence for Zn, Cu, Fe, Mn, and B, the nugget/sill ratio values for Mn, Fe, Zn, B, and Cu were 0.53, 0.46, 0.44, 0.44, and 0.43, respectively. This is attributed to inherent soil properties (such as soil pH, EC, SOC and soil mineralogy) as well as management factors including fertilization. Samples separated by distances lower than the range are spatially related, whereas those separated by a distance greater than the range are considered not to be spatially related. A large range indicates the value of measured soil property to be influenced by natural and anthropogenic ranges [32]. The different range values for Zn, Cu, Mn Fe and B in these soils might be due to combined effect of parent material, climate and adoption of different land management [33-37]. A number of authors published range values in various acid soils of India, which are consistent with the current study: 17711.63 m for Zn, 4302.543 m for Cu (Behera et al., 2012), 5523.347 m for Mn, and 5068.235 m for Fe [38]. Future soil sample designs in comparable locations are guided by the information on the range in the semi-variogram of Zn, Cu, Mn, Fe, and B. According to Kerry and Oliver [39], the sampling interval needs to be smaller than half the range of the semivariogram. Therefore, it is advised that soil sampling be done at distances shorter than the range found in this study for future research targeted at describing spatial dependency of Zn, Cu, Mn Fe, and B in comparable areas.

Table 4c shows the evaluation indices resulting from cross-validation of surface maps of soil properties. The MAE of pH, OC, and Zn was found to be lower than those of other soil variables. The G value was more than 0 for all soil characteristics, indicating that spatial prediction using semivariogram parameters is better than assuming the property value for every unsampled location equals the mean of observed values. This also shows that semivariogram parameters obtained from fitting of experimental semivariogram values were reasonable to describe the spatial variation of all the studied soil properties. Experimental semi-variograms and their fitted models for a. Zn, b. Cu, c. Mn d. Fe, and e. B as shown Fig. 4.

"The distribution pattern of the five micronutrients in soils of the studied region was rather similar (Fig. 5), which corroborates our finding of significant and positive correlations among Zn, Cu, Mn Fe and B in these soils. Furthermore, anthropogenic activities like cultivation of high yielding varieties of different crops coupled with non-inclusion of micronutrients in fertilizer scheduling also contributed to spatial variability of micronutrients" [9].

Table 2. Micronutrients (Zn, Cu, Mn, Fe, and B) that can be extracted using DTPA and a statistical description of a few selected soil parameters

Soil properties	Unit	Minimum	Maximum	Mean	S.D.	Skewness	Kurtosis	CV (%)
pH		6.40	8.90	7.61	0.51	-0.45	-0.48	6.70
EC	dSm-1	0.09	0.98	0.20	0.12	3.70	17.39	60.00
SOC	g kg^{-1}	2.35	10.16	5.32	1.28	0.13	0.26	24.06
CaCO3		5.00	115.00	37.35	31.15	0.83	-0.45	83.40
DTPA-Zn		0.02	2.50	0.49	0.38	2.84	9.97	77.55
DTPA-Cu		0.78	7.84	2.16	1.17	2.13	5.72	54.17
DTPA-Mn	mg kg^{-1}	2.93	35.18	18.19	8.76	0.15	-1.27	48.16
DTPA-Fe		1.91	35.34	10.05	6.06	1.93	4.29	60.30
HWS-B		0.5	2.9	1.33	0.53	0.77	0.22	39.85

Abbreviations: n=number of soil samples, EC = electrical conductivity, SOC = soil organic carbon, CaCO3 = calcium carbonate, DTPA-Zn = diethylene triamine penta acetic acid extractable zinc, DTPA-Cu= diethylene triamine penta acetic acid extractable copper, DTPA-Mn = diethylene triamine penta acetic acid extractable manganese, DTPA-Fe = diethylene triamine penta acetic acid extractable iron, SD = standard deviation, CV = coefficient of variation

Table 3. An indicator of the nutrients available in the Harda district soils

Fertility Variables	Percent samples			NI	NI class
	Low	Medium	High		
DTPA-Zn	79.54	15.18	5.28	1.26	Low
DTPA-Cu	0.00	0.00	100	3.00	High
DTPA-Mn	0.00	2.31	97.69	2.98	High
DTPA-Fe	7.92	46.53	45.54	2.38	High
HWS-B	0.00	34.32	65.68	2.66	High

Table 4a. Pearson's correlation coefficients for DTPA extractable Zn, Cu, Mn and Fe and selected soil properties

	Physico-chemical properties				Micro nutrients				
	pH	EC	SOC	$CaCO_3$	Zn	Cu	Fe	Mn	B
EC	**0.153****	1							
SOC	**0.138***	**0.163****	1						
$CaCO_3$	0.017	0.059	-0.013	1					
Zn	**-0.144***	0.024	0.087	0.049	1				

Cu	**-0.251****	-0.007	0.071	-0.076	**0.317****	1			
Fe	**-0.476****	-0.082	0.058	0.065	**0.385****	**0.611****	1		
Mn	**-0.473****	0.001	0.013	0.011	**0.263****	**0.453****	**0.663****	1	
B	-0.024	**0.168****	**0.164****	0.077	0.033	-0.031	**0.135***	0.026	1

*** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed)*

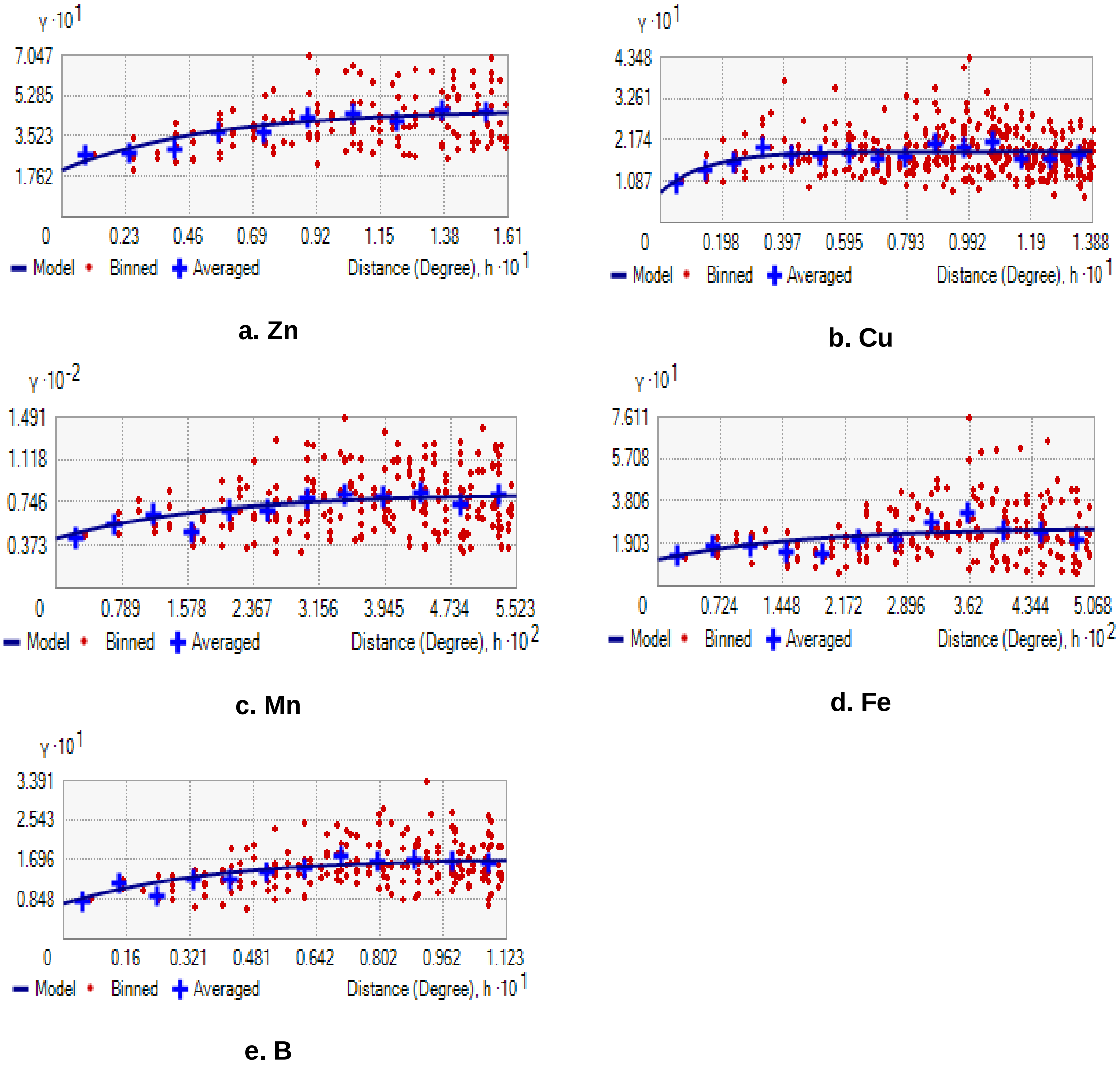

Fig. 4. The Zn, Cu, Mn, Fe, and B semi-variograms from experiments and their fitted models

Table 4b. Theoretical model parameters fitted to experimental semi-variograms for the studied micronutrients

Soil micronutrients	Distribution	Model	Range (m)	Nugget (C_0)	Partial Sill (C_1)	Sill (C_0+C_1)	Nugget/Sill	Spatial dependence
DTPA- Zn	Log	Exponential	17711.63	0.21	0.26	0.47	0.44	Moderate
DTPA- Cu	Log	Exponential	4302.543	0.08	0.11	0.19	0.43	Moderate
DTPA- Mn	Square root	Exponential	5523.347	43.40	38.91	82.31	0.53	Moderate
DTPA- Fe	Log	Exponential	5068.235	0.12	0.14	0.26	0.46	Moderate
HWS- B	Log	Exponential	11228.02	0.08	0.10	0.17	0.44	Moderate

Abbreviations: DTPA-Zn = diethylene triamine penta acetic acid extractable zinc, DTPA-Cu = diethylene triamine penta acetic acid extractable copper, DTPA-Mn = diethylene triamine penta acetic acid extractable manganese, DTPA-Fe = diethylene triamine penta acetic acid extractable iron, HWS-B=Hot water-solubleboron

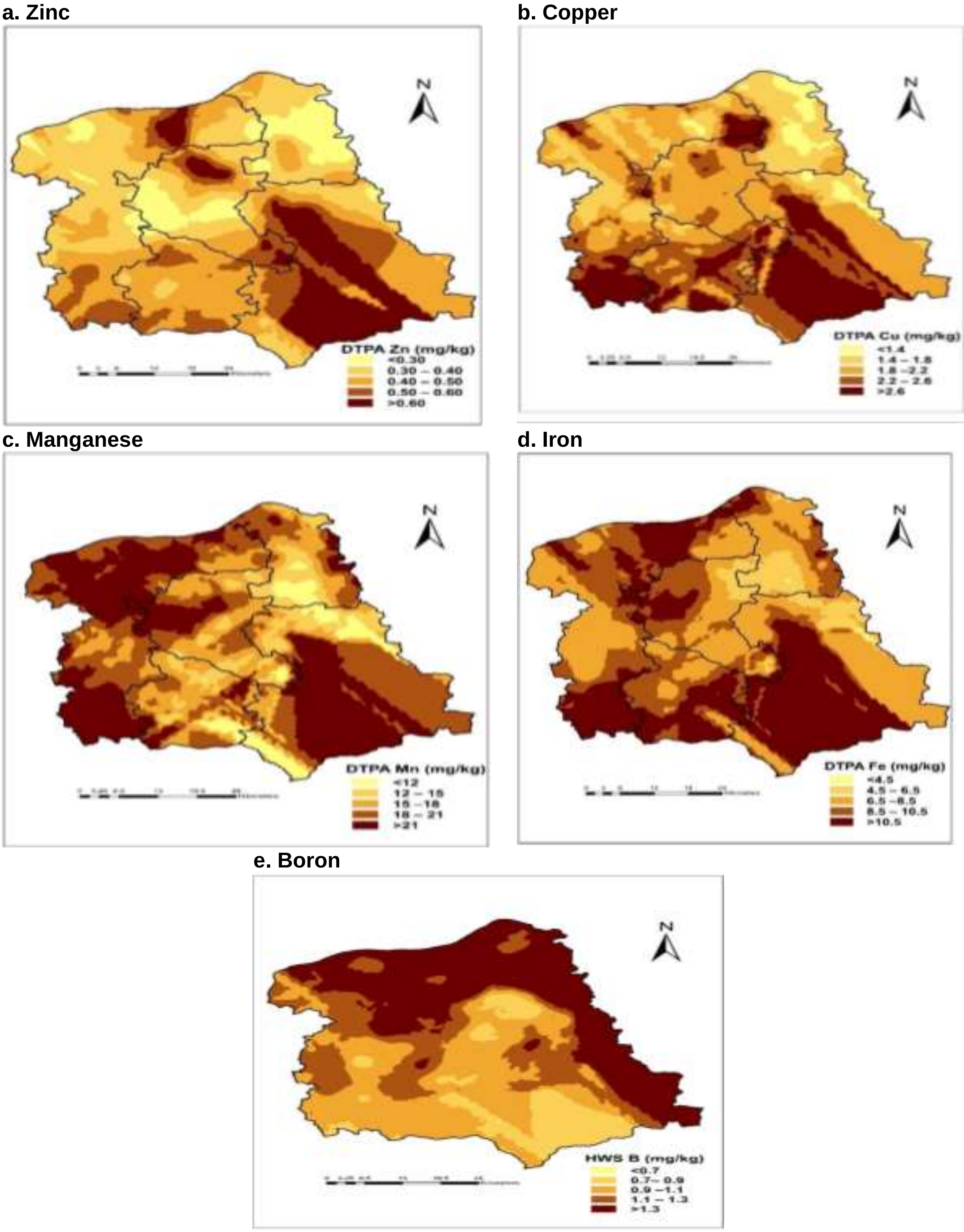

Fig. 5. Distribution maps of DTPA extractable a. zinc (Zn), b. copper (Cu), c. manganese (Mn) and d. iron (Fe) and HWS e. Boron (B) concentrations in the soil generated by ordinary kriging

Table 4c. Evaluation performance of kriged map of soil properties through cross-validation

	Mean absolute error	Mean square error	Goodness of prediction	RMSE
DTPA- Zn	0.00		10.59	0.37
DTPA- Cu	0.00	0.97	28.52	0.98
DTPA- Mn	0.08	62.07	18.84	7.88
DTPA- Fe	0.14	23.32	36.34	4.83
HWS- B	0.01	0.19	32.45	4.83

Abbreviations: RMSE = Root mean square error

4. CONCLUSION

Land use map was prepared by using Landset-8 satellite imagery. The current study revealed a wide variation in measured soil properties and available micronutrients of the region. The soils of Harda district of Madhya Pradesh were found neutral to alkaline in soil reaction, safe in electrical conductivity, low to medium in organic carbon content and non-calcareous to calcareous in nature. The result of this study suggested that the exponential models were the best fitted model for studied soil parameters.

The nugget/sill ratio of semivariogram models for available micronutrients falls between 43% and 53% which exhibit moderate spatial dependency. The correlation analysis revealed a negative correlation of soil pH with available micronutrient, whereas significant positive correlation was obtained with soil organic carbon, EC and B. However, micronutrients were significant positive correlation with each other's.

Different distribution patterns were shown in the kriged surface maps of the soil characteristics. The micronutrient distribution maps indicate that the region lacks sufficient amounts of zinc, iron, and boric acid. 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.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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