

Original Research Article

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Mapping of Spatial Pattern of Micronutrients in Soils of Harda District of Madhya Pradesh through Geo-statistical Tool in Arc GIS Environment

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ABSTRACT

Keywords

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In present study GPS based three hundred three surface (0-15 cm depth) soil samples, were collected across the district. The Zn, and Fe deficient in 79.54% and 7.92 percent soil samples and none of soil samples were found to be deficient in Cu, Mn and B. Soil pH showed significant and negative correlations with Zn, Cu, Mn and Fe. The EC had positive and significant relationship with OC and B with r values of 0.163** and 0.168**, respectively. The significant positive relationship of OC of soil with available hot water-soluble B showing value of 0.164**. The micronutrients i.e. DTPA extractable Zn and Cu, Fe and Mn showed significant positive relationship with each other. HWS B was also found positive and significantly related with Fe ($r=0.135^*$). Geo-statistical suggested that the exponential models best fitted for, Zn and B while spherical models for Cu, Mn, Fe. The nugget/sill ratios of semivariogram models for micronutrients were moderate. The having value were 0.78, 0.49, 0.44, 0.42 and 0.41 for Mn, Fe, Zn, B and Cu, respectively.

Introduction

Soil micronutrients play a major role to maintain soil health. Proportionate to primary and secondary nutrients, plants need a much smaller quantity of micronutrients. However, their importance is still great. A shortage of micronutrients can limit plant growth and crop yields. Too great a shortage could even because plant death, even with all other essential elements fully represented. An adequate attention is still necessary to pay in this area.

In Indian soils 49 percent soil are Zn deficient and over 57% soil samples are reported Zn

deficient in Madhya Pradesh by Shukla and Tiwari (2016). In Madhya Pradesh, many soils are deficient in zinc, the highest percent in Alluvial soils (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%) reported by Khamparia *et al.*, (2009). Fageria *et al.*, (2002) in their review of micronutrients in crop production, maintained that micronutrient deficiencies in crop plants are widespread worldwide. As many findings showed that micronutrients status in the soil is mostly a positively correlated with OC content but negatively correlated with soil pH

(Dibabe *et al.*, 2007). Determining soil variability and maintaining soil health is very much important for ecological modelling, environmental predictions, precise agriculture and management of natural resources (Hangsheng *et al.*, 2005; Wang, 2009). Geo-statistics is the strategy that considers spatial variance, location, estimation and distribution of samples. This study was done to investigate and map the spatial variability of micronutrients in the soil at different unsampled locations by using data at sampled locations.

Materials and Methods

Description of study area

Geographically, Harda district lies in between 21° 53' - 22° 36' North latitude and 76° 47' - 77° 30' East longitude with an area of 3330 km². It is located in the Narmada river valley and the Narmada forms the district northern boundary.

Administratively, the district divided in six blocks, Rahatgaon, Harda, Khirkiya, Hundia, Sirrali and Timarani (Fig. 1). The district feels maximum temperature up to 47 °C and minimum up to 12 °C and an average annual rainfall of 1021.84 mm. The district has varied physiographic; geology and diverse land use have resulted in diversity in soil development.

Land use

Land use map prepared by using Indian remote-sensing satellite-P6, linear imaging self-scanning satellite-III (IRS-P6, LISS-III). The satellite data has the characteristics of 23.5 m spatial resolution, four spectral channels green (0.52 µm-0.59 µm), red (0.62 µm-0.68 µm), NIR (0.77 µm-0.86 µm), and SWIR (1.55 µm -1.70 µm) and five days' temporal resolution with 141 km swath. The

major land-use/land-cover categories were identified and mapped (Fig. 1).

From the maps, it is evident that the major area is occupied 2082.20 sq km, which was accounted to 62.52% by cultivated land. On interview basis of information obtained from every sampling site and local agriculture department, the soybean based cropping pattern is predominant viz., soybean-wheat, soybean-wheat-summer mungbean, soybean-chickpea and soybean-fallow. Sugarcane and horticultural crop/orchards-spices crop/vegetables were also observed. The forest was classified in two categories; dense 20.0% (666.0 sq km) and 6.96% (231.90 sq km).

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 wasteland in four categories i.e., gullied/ravenous land 0.05 % (1.82 sq km), sandy area-riverine, 0.10 % (3.17sq km), dense scrub 1.28 % (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.

Soil survey and sampling techniques

Considering of cropping system and soil association maps, topography and heterogeneity of the soil type, the site for collecting of Jabalpur were divided GPS based three hundred three surface soil samples (0-15 cm) and field data were collected from farmer's field during the off season to avoid the effect of fertilization during crop cultivation. 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.

Soil analysis

The soil samples were air dried and crushed with wooden pestle and mortar and sieved through 2 mm sieve was determined using the pH meter with a soil: water ratio of 1: 2.5 and supernatant of same was used for electrical conductivity determination with the help of conductivity-meter. The organic carbon in soil was determined using Nelson and Sommers (1982) and calcium carbonate content in soils carried out using rapid back titration described method as Jackson (1973). Available micronutrients were extracted with diethylene triamine pentaacetic acid (DTPA), were determined with Flame Atomic Absorption Spectrometry as described by Lindsay and Norvell (1978). Hot water soluble boron in soil was analyzed by Azomethine-H method as outlined by Berger and Truog (1939).

NI calculated as per formula suggested by Parker *et al.*, (1951) and classified this index as low (<1.67), medium (1.67 to 2.33) and high (>2.33). $NI = [(NI \times 1) + (Nm \times 2) + (Nh \times 3)] / Nt$,

Where: NI, Nm and Nh are the number of soil samples falling in low, medium and high categories for nutrient status and are given weightage of 1, 2 and 3, respectively. Nt is the total number of samples.

Statistical and geo-statistical analysis

Geo-statistics is a powerful tool for determining the spatial variability (Jian-Bing *et al.*, 2008). ArcGIS 10.1 software was used for statistical and geo-statistical analysis of the data. Semivariogram analysis was done to calculate the nugget to sill ratio, which indicates the degree of spatial dependence by using uniform interval to establish the range of spatiality. According to criteria given by Attar *et al.*, (2012) spatial dependence is

classified in to weak (ratio >75%), moderate (ratio 25-75%) and strongly spatial dependent (ratio <25%). Because Kriging assumes the normal distribution for each estimated variable, it is necessary to check whether the available contents of micronutrients (Zn, Cu, Fe, Mn and B) in soil samples are approximately normally distributed or not. A normal distribution was estimating based on skewness values and the variable datasets having a skewness ranged between -1 to 1 were considered normally distributed (Ortiz *et al.*, 2010). For non-datasets, a logarithmic transformation was performed to achieve a normal distribution for use in the next step of the statistical analysis.

Among the geostatistical techniques, Kriging is a linear interpolation procedure that provides a best linear unbiased estimation for quantities, which vary in space. The semi-variogram analyses were carried out before application of ordinary kriging interpolation as the semi-variogram model determines the interpolation function (Goovaerts, 1997) as given below.

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

Where N (h) is the total number of data pairs separated by a distance h, Z represents the measured value for soil property, and x is the position of soil samples.

Several standard models are available to fit the different semi-variogram functions were evaluated to select the best fit with the data, e.g., spherical, exponential, Gaussian, linear and power models (Wang, 1999).

The spherical function is:

$$y(h) = C_0 + C \left[\frac{3h}{2a} - \frac{1}{2} \left(\frac{h}{a} \right)^3 \right] \quad 0 < h \leq a$$

$$y(h) = C_0 + C \quad h > a$$

Where C_0 is the nugget variance ($h = 0$), C is the structural variance and the spatial range.

Exponential model was fitted to the empirical semivariograms. The exponential model that fitted to experimental semivariograms is defined below (Burgess and Webster, 1980) as:

$$y(h) = C_0 + C_1 \left[1 - \exp\left(-\frac{h}{a}\right) \right]$$

Where, C_0 is the nugget, C_1 is the partial sill, and a is the range of spatial dependence to reach the sill ($C_0 + C_1$). The nugget/sill ratio, i.e. $C_0/(C_0 + C_1)$ and the range are the parameters which 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 $C_0/(C_0 + C_1)$ and a high range generally indicates that high precision of the property can be obtained by kriging. 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 (Cambardella *et al.*, 1994).

Prediction accuracy of semivariogram models was evaluated by mean square error (MSE). Among two evaluation indices used in this study, mean absolute error (MAE) and measure the accuracy of prediction, whereas goodness of prediction (G) measure the effectiveness of prediction.

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

Where, n is the number of observation for each case, $z(x_i, y_i)$ is the observed soil parameter, $z^*(x_i, y_i)$ is the estimated soil

parameter, and (x_i, y_i) are sampling coordinates. Using the geospatial parameters of the best fitted exponential semivariogram model, interpolation was made through ordinary kriging (Goovaerts, 1997).

The MAE measure, however, does not reveal the magnitude of error that might occur at any point and hence MSE was calculated,

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

Where z is the sample means If $G = 100$, it indicates perfect prediction, while negative values indicate that the predictions are less reliable than using sample mean as the predictors

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

Squaring the difference at any point gives an indication of the magnitude, e.g. small MSE values indicate more accurate estimation, point-by-point. The G measure gives an indication of how effective a prediction might be, relative to that which could have been derived from using the sample mean alone (Agterberg, 1984).

Results and Discussion

Soil characteristics

The descriptive statistics on soil characteristics are presented in table 2 showed the pH, EC, OC and $CaCO_3$ varied from 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 7.61, 0.20 dSm^{-1} , 5.32 $g\ kg^{-1}$ and 37.35 $g\ kg^{-1}$, respectively. The Zn, Cu, Fe, Mn and B varied from 0.02-2.50, 0.78-7.84, 1.91-35.34, 2.93-35.18 and 0.5-2.9 $mg\ kg^{-1}$ with mean

values of 0.49, 2.16, 10.05, 18.19 and 1.33 mg kg⁻¹, respectively in the district as a whole (Table 1).

Considering CV <10% as low, 10 to 100% as moderate, >100% as high variability, result revealed that the CaCO₃ had the largest variation (CV = 83.40 percent) followed by EC (CV = 60.00 percent), OC (CV =24.06) and pH had least variability (CV = 6.70 percent). Among the micronutrients, the Zn was found to be highly variable (CV = 77.55 percent), followed by Fe (CV=60.30 percent), Cu (CV= 54.17 percent) and Mn (CV = 48.16 percent) while the hot water soluble B only 39.85 percent variability.

The pH had low variability and all other soil properties showed moderate variability. The micronutrients with CV ranged from 39.85–77.55 per cent. Further, it was observed from the table 2 that the skewness coefficients of the data set ranged from -0.45 to 3.70 revealed the value of skewness and kurtosis was higher for EC, CaCO₃ and Zn, Cu, Fe, Mn and B. Hence, these variables are largely deviated from normal distribution.

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 and kriged maps the spatial analysis results in the form of maps were showed in figure Zn(3a), Cu(3b), Fe(3c), Mn (3d) and B (3e) (Table 3). The kriged map of spatial variability of soil nutrient could be used as a basis for consideration in variable rate fertilization, especially for Zn and Fe in order to supply the optimum requirements for plant growth that can be optimized crop production. In case of Cu, all soil samples

were in high category and none of soil samples were found to be deficient and medium category. Data further indicate that the NI value was found to be low 1.26, for Zn, respectively and in whole district, high nutrient index value of 2.38, 2.66, 2.98 and 3.00 for Fe, B, Mn and Cu, respectively.

Correlation matrix

Pearson's' correlation matrix data showed that the pH of soil had significant negative relationship with Zn, Cu, Fe and Mn. The EC had positive and significant relationship with OC and B with r values of 0.163**and 0.168**, respectively. The significant positive relationship of OC of soil with available hot water soluble B was observed by showing values of 0.164** respectively. Micronutrient showed significantly positively related with each other. Results were supported by Katyal and Sharma (1991, Rajakumar *et al.*, (1996), Chinchmalatpure *et al.*, (2006) (Table 4).

Spatial variability assessment using GIS

The spherical and exponential were best fitted models for with low MSE values. The nugget (an indication of micro-variability) was highest for Zn, Mn, which is ascribed to the fact that the selected sampling distance could not capture the spatial dependence well. The moderate spatial dependence showed values table 5 with the having nugget/sill ratio values 0.78, 0.49, 0.44, 0.42 and 0.41 for Mn, Fe, Zn, B and Cu respectively moderate spatial dependence.

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 (Lopez-Granados *et al.*, 2002). The different range soils might be due to combined effect of parent material, climate and adoption of different land management. Several authors reported range values of 2.5–9.1 km for Zn, 3.30–28 km for Cu (Behera *et al.*, 2012), 0.7–66 km for Mn and 2.7–5.2 km for Fe (Behera and Shukla, 2014) in some acid soils of India. Information on the range in semi-variogram of Zn, Cu, Mn Fe and B acts as a guide in future soil sampling designs in similar areas. The sampling interval should

be less than half the semivariogram range (Kerry and Oliver, 2004). It is therefore recommended that for ensuing studies aimed at characterizing spatial dependency of Zn, Cu, Mn Fe and B in similar areas, soil sampling should be done at distances shorter than the range found in this study.

Cultivation of high yielding varieties of different crops coupled with non-inclusion of micronutrients in fertilizer scheduling also contributed to spatial variability of micronutrients (Shukla *et al.*, 2015).

Table.1 Critical limits of soil characteristics

Parameters	Zn	Cu	Fe	Mn	B
Low	<0.60	<0.20	< 4.50	<1.0	<0.50
Medium	0.61-1.20	0.21-0.40	4.51-9.0	1.0-4.0	0.51-1.00
High	>1.20	> 0.40	>9.0	>4.0	>1.00

Table.2 Statistical summary of soil characteristics (n = 303)

Soil characteristics	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
CaCO ₃ g kg ⁻¹	5.00	115.00	37.35	31.15	0.83	-0.45	83.40
DTPA-Zn mg kg ⁻¹	0.02	2.50	0.49	0.38	2.84	9.97	77.55
DTPA-Cu mg kg ⁻¹	0.78	7.84	2.16	1.17	2.13	5.72	54.17
DTPA-Fe mg kg ⁻¹	1.91	35.34	10.05	6.06	1.93	4.29	60.30
DTPA-Mn mg kg ⁻¹	2.93	35.18	18.19	8.76	0.15	-1.27	48.16
HWS-B mg kg ⁻¹	0.5	2.9	1.33	0.53	0.77	0.22	39.85

Table.3 Status of micronutrient in soil of Harda district (n=303)

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

Table.4 Pearson’s correlation coefficients

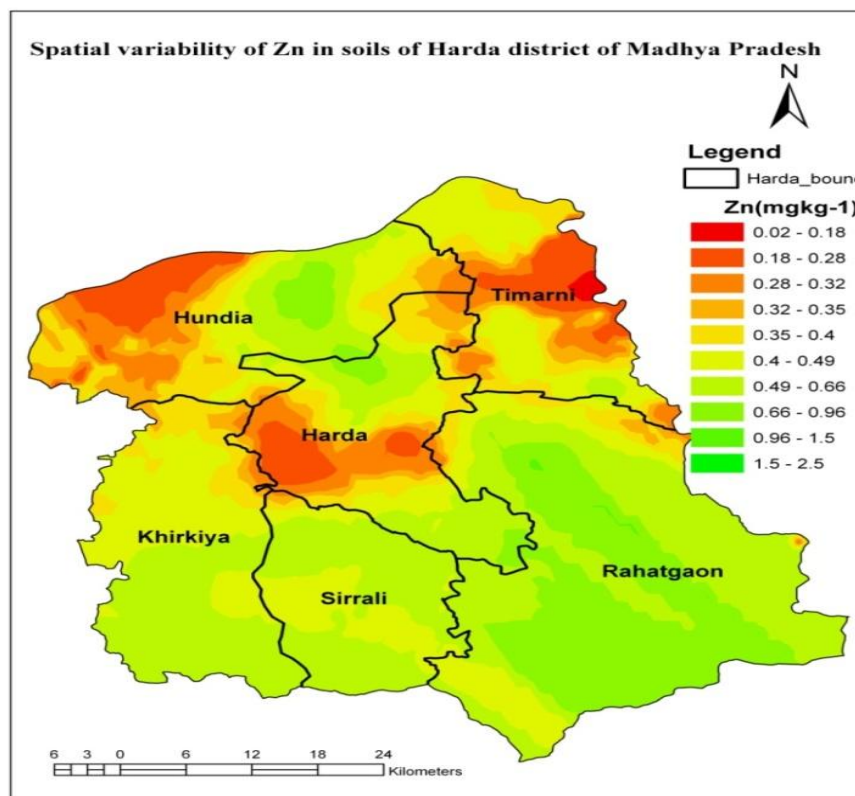
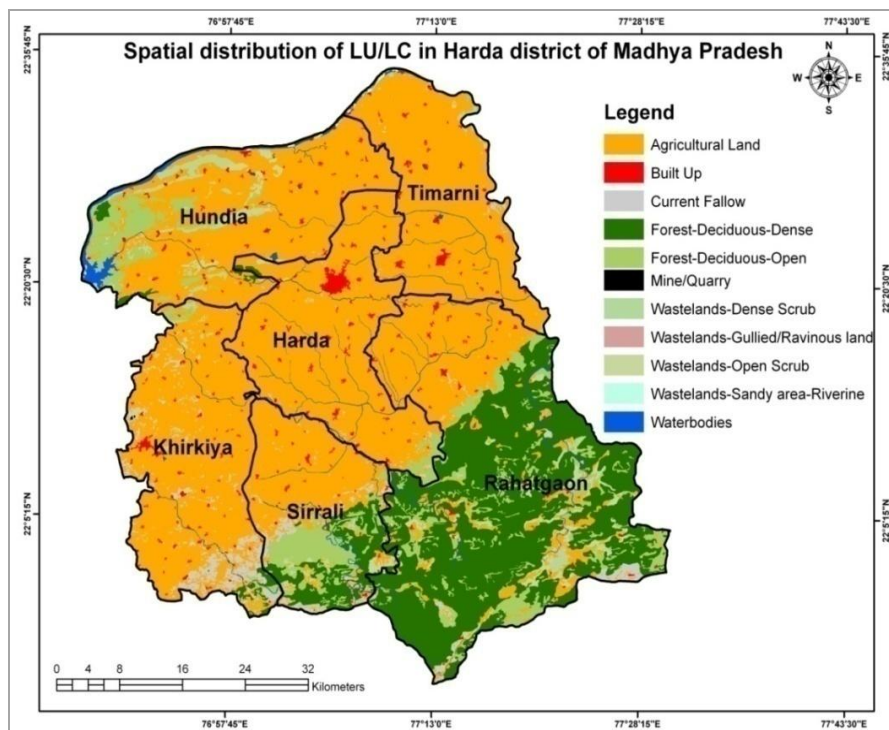
parameters	Physico-chemical properties				Micro nutrients			
	pH	EC	OC	CaCO ₃	Zn	Cu	Fe	Mn
EC	0.153**	1						
OC	0.138*	0.163**	1					
CaCO ₃	0.017	0.059	-0.013	1				
Zn	-0.144*	0.024	0.087	0.049	1			
Cu	-0.251**	-0.007	0.071	-0.076	0.317**	1		
Fe	-0.476**	-0.082	0.058	0.065	0.385**	0.611**	1	
Mn	-0.473**	0.001	0.013	0.011	0.263**	0.453**	0.663**	1
HWS-B	-0.024	0.168**	0.164**	0.077	0.033	-0.031	0.135*	0.026

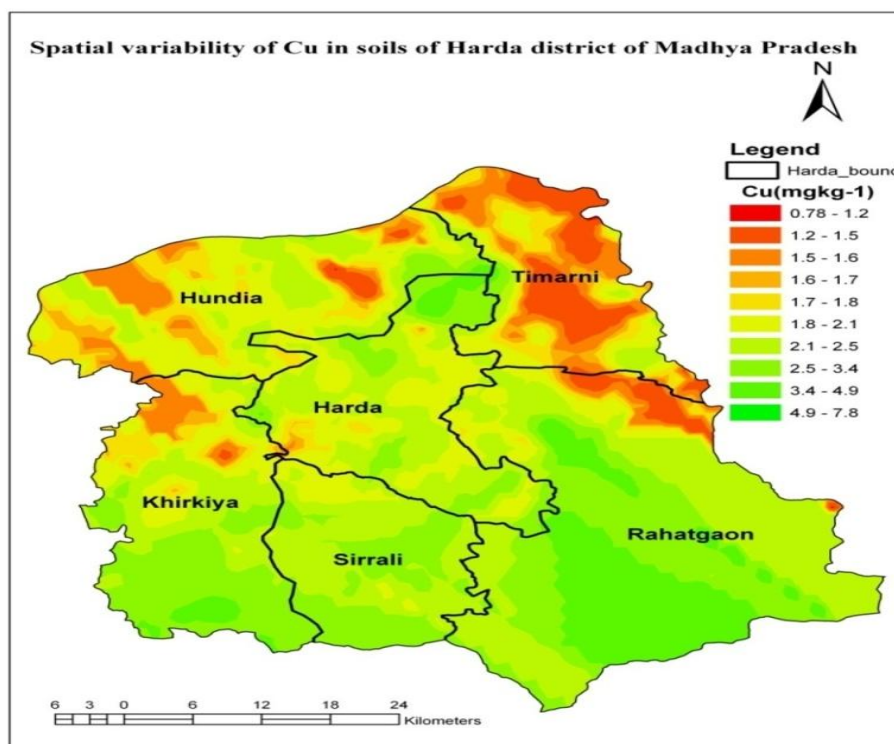
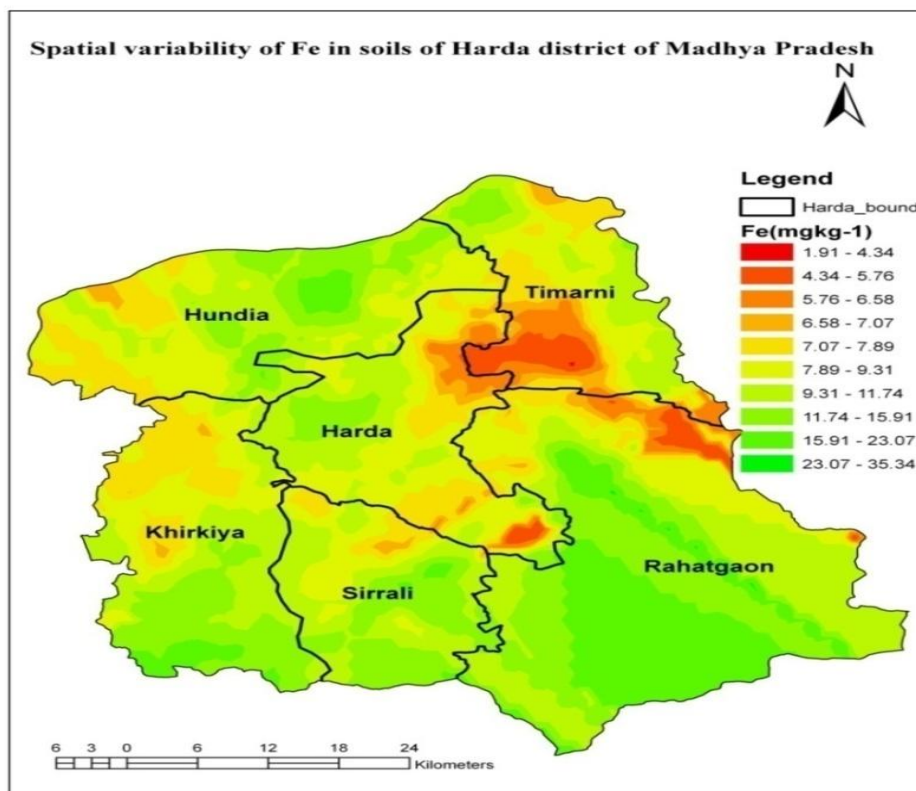
Table.5 Theoretical model parameters fitted to experimental semi-variograms for the studied micronutrients

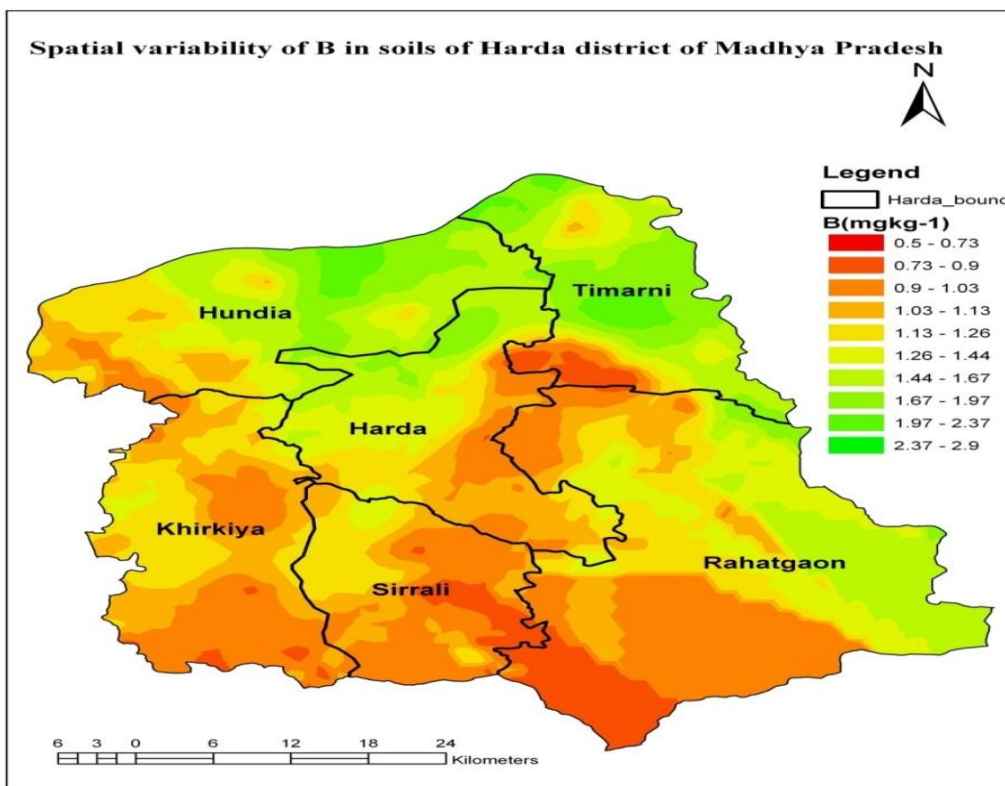
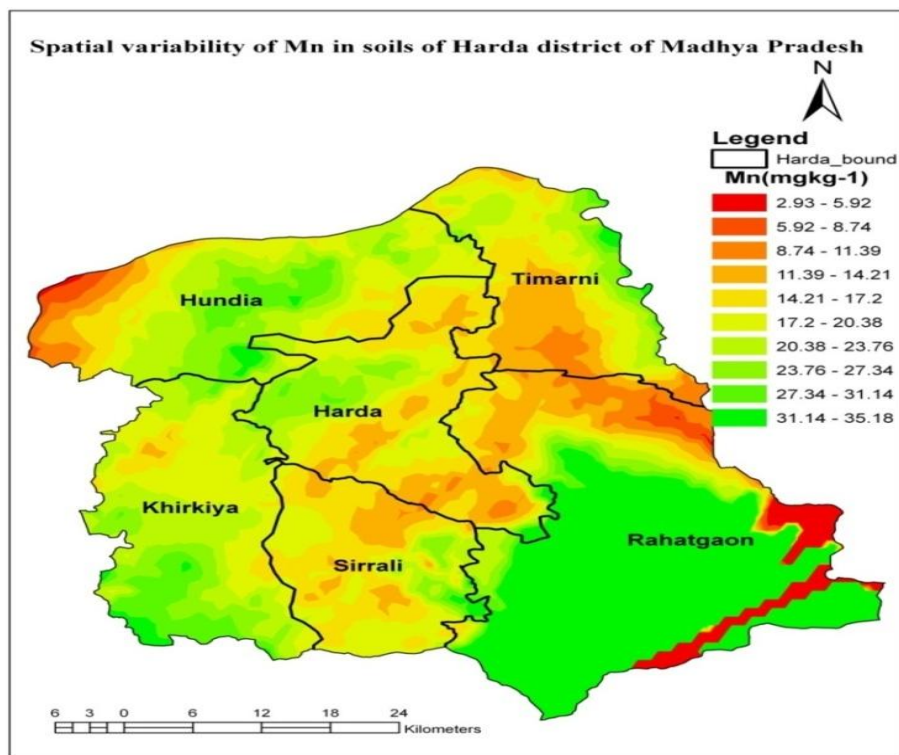
Micronutrients	Model	Range(m)	Nugget (C ₀)	Partial Sill (C ₁)	Sill (C ₀ +C ₁)	Nugget/Sill	MAE	G
Zn	Exponential	17622.70	0.22	0.28	0.49	0.44	0.00	10.59
Fe	Spherical	3960.50	0.12	0.12	0.24	0.49	0.00	27.25
Cu	Spherical	3772.74	0.08	0.11	0.19	0.41	0.12	33.56
Mn	Spherical	4019.87	0.22	0.06	0.28	0.78	0.59	9.14
B	Exponential	8974.11	0.07	0.10	0.17	0.42	0.01	28.90

Figure.1 Location map of study area









It is concluded that the soils of Harda district were found neutral to alkaline in soil reaction, safe in electrical conductivity, low to medium in organic carbon content and non-calcareous to slightly calcareous in nature. The result of this study suggested that the exponential models best fitted for, Zn and B while spherical model for Cu, Mn, Fe. The nugget/sill ratios of semivariogram models for Zn, Fe, Cu, Mn and B falls between 38% and 75%, which exhibit moderate spatial dependency. Correlation results also that soil pH had a negative significant relationship with available micronutrients. OC exhibited significant positive correlation with micronutrients advised to apply organic matter to their field to supply nutrients. The spatial variability map of soil characteristics showed that the micronutrient mainly Zn and Fe are deficient so far the Zn and Fe fertilizers in the area to be recommended for increasing productivity and sustainability.

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