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Spatial variability of available nutrients in soils of Nainpur tehsil of Mandla district of Madhya Pradesh, India using Geo-statistical approach

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Scientific information concerning spatial variability and distribution of soil properties is critical for farmers attempting to increase fertilization efficiency and crop productivity; fertilization based on maps with recommendations related to soil fertility may lead to reduced fertilizer inputs without reducing yield. In the present study, GPS based one hundred fifty surface soil samples (0-15 cm) were collected from dominant cropping system. After processing, the soil samples were analyzed for different soil characteristics in laboratory using standard procedures. The data obtain from laboratory analysis was statistically and geo-statistical interpreted. The results revealed that the 23.6, 28.30, 48.6, 13.9, 25.5 and 54.7% soil samples were found to be deficient in OC, N, P, K, S and Zn, respectively. None of the soil samples were tested low in Cu, Fe, Mn and B. Exponential model was found as the best fit for considered soil parameters whereas, spherical model was found as the best fit for Mn. The best model was used to generate the spatial distribution maps. Spatial maps showed that the soil pH, EC, organic carbon, available N, P, K, S, Zn, Cu, Fe, Mn and B spatially varied and N, P, K, S and Zn were deficient in major areas. Therefore these maps are more useful for guiding site-specific field management for agricultural production and environmental protection. In addition, reduce the losses of nutrients and could be save time and money for fertilizers.

Key words: Geo-statistical, soil types, land use, semi-variogram, kriging, nutrient status.

INTRODUCTION

Soil is the primary source of plant nutrients that control its fertility and thus yield of crops (Qu et al., 2014). Expectation of higher productivity using adequate amount of fertilizer nutrients may lead to become limiting to some micronutrients in the soil and most times due to their over mining by the crops and shortage of which often show the

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deficiency symptoms and yields are reduced. However, intensive cultivation, indiscriminate use of high analysis chemical fertilizers results deficiency of micronutrients (Singh et al., 2007). The soil must supply all the essential nutrients for desired growth of plants has contributed to a tremendous increase in yields of agricultural crops that feed the world's population (Hak-Jin et al., 2009). Ideally, application rates should be adjusted based on estimates of the requirements for optimum production at each location because there is high spatial variability of N, P, and K within individual fields (Page et al., 2005; Ruffo et al., 2005). In this context, it is necessary to evaluate the fertility status of the soil and promote the recommendations of soil test for balanced nutrition to maintain soil health. Classical statistics requires the validity of some basic hypotheses, such as the independence between observations, due to the randomness of variations from one place to another. Farmer's of the tribal areas have very little knowledge of fertility status of their fields; therefore, the desired level of productivity is not being achieved even after utilizing all inputs.

In the last few decades, geo-statistics has been used extensively to characterize the spatial variability of soil attributes due to its ability of quantifying and reducing sampling uncertainties and minimizing investigation costs (Cambule et al., 2014). Numerous studies have been conducted based on geo-statistical analysis to characterize the spatial variability of soil physical (Li et al., 2007; Weindorf and Zhu, 2010), chemical (Liu et al., 2013; Lin et al., 2009; Huang et al., 2007), and biochemical (Šnajdr et al., 2008) properties, as well as microbiological processes (Cao et al., 2011). Thus, information on spatial variability of soil nutrients is important for sustainable management of soil fertility (Fraisse et al., 1999). Hence, the present study was conducted.

MATERIALS AND METHODS

Description study area

Geographical location of study area

Mandla district is located in the east-central part of the Madhya Pradesh, India covering an area of 8771 km^2 and consists of a rugged high tableland in the eastern part of the Satpura hills. Geographically, Nainpur is located between 79°56'45.0" to 80°26'15.0" E longitudes and 22°17'31.0" to 22°37'30" N latitudes, having an area of 845.79 km^2 of the total geographical area of district.

Climate

The climate of this district is characterized by hot summer season and general dryness except in the southwest monsoon season. May is the hottest month with the mean daily minimum temperature at 41.3°C and the mean daily minimum at 24°C (Figure 1).

Land use and cropping pattern

Land use map prepared by using Indian remote-sensing satellite-P6, linear imaging self-scanning satellite-III (IRS-P6, LISS-III) satellite imagery dated January-2014, October-2013 and April-2013. The satellite data has the characteristics of 23.5 m spatial resolution, four spectral channels green (0.52 to 0.59 µ), red (0.62 to 0.68 µ), NIR (0.77 to 0.86 µ), and SWIR (1.55 to 1.70 µ) and five days temporal resolution with 141 km swath. The statistics reveals area extent of land mainly under agricultural (46.37%), followed by dense forest (19.98%), open forest (9.79%), fallow land (9.23%) waste land- dense (3.22%) and waste land open scrub (6.53%) and others etc. Based on ground truth data collected from local agriculture departments and farmers interviewed, the rice and wheat are major food grain crops. Paddy, maize, kodo, kutki, soybean are important crops during *Kharif* season and wheat, pea, gram, lentil, and mustard crops during *Rabi* season in tribal areas of Mandla district (Figure 2).

Soil types

The survey of India topographical maps (1:50000) and the map of soil as a secondary data was used from NBSSLUP Nagpur. The highest area occupied under vertisols followed by inceptisols, entisols and alfisols. These soils are fine montmorillonitic, hyperthermic and having high swell shrink potential (Table 1 and Figure 3).

Soil sampling and analysis

Sampling sites were generated using land use and soil association maps. The sites decided randomly distributed over agricultural land of the study area by considering of 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 soil samples (0 to 15 cm) were collected from farmer's field during the 2013 off season from the agricultural land. For each main sampling point, 1.0 kg of representative composite soil sample was collected and logged into properly labeled sample bag.

Laboratory analysis

Soil samples collected from the study area were dried and crushed with the help of wooden rod and passed through 2 mm sieve and then used for the determination of soil pH, electrical conductivity, organic carbon, calcium carbonate and macronutrients like N using Subbiah and Asija (1956), P using Olsen et al. (1954) and K content by adopting standard laboratory methods described in Jackson (1973) (Table 2).

Available micronutrients (Zn, Cu, Fe and Mn) were extracted by DTPA-$CaCl_2$ solution and analyzed using atomic absorption spectrophotometer (Lindsay and Norvell, 1978). Hot water soluble boron in soil was analyzed by azomethine-H method as outlined by Berger and Truog (1939). The available sulphur was extracted by 0.15% $CaCl_2$ solution and the concentration of sulphur was determined by the turbidimetric method using spectrophotometer (Chesnin and Yien, 1951).

Nutrient index calculation

The nutrient index (NI) values for available nutrients present in the soils were calculated utilizing the 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).

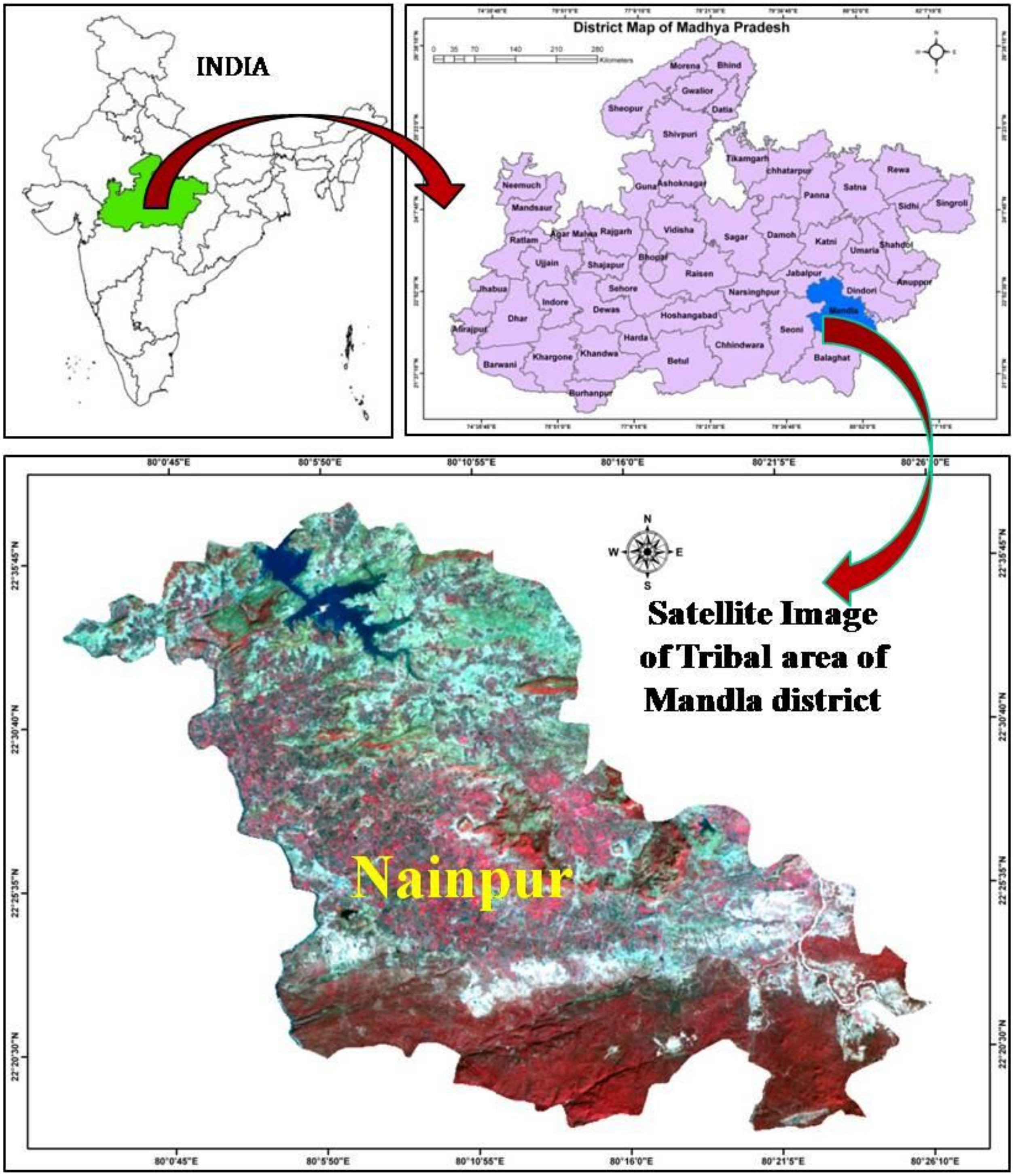


Figure 1. Location map of study area.

$$NI = [(NL \times 1) + (NM \times 2) + (NH \times 3)]/NT$$

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

Statistical and geo-statistical analysis

It is necessary to check whether the available contents of N, P, K and S and micronutrients in soil samples are approximately normally distributed or not because Kriging assumes the normal distribution for each estimated variable. A normal distribution was estimating based on skewness values and the variable datasets

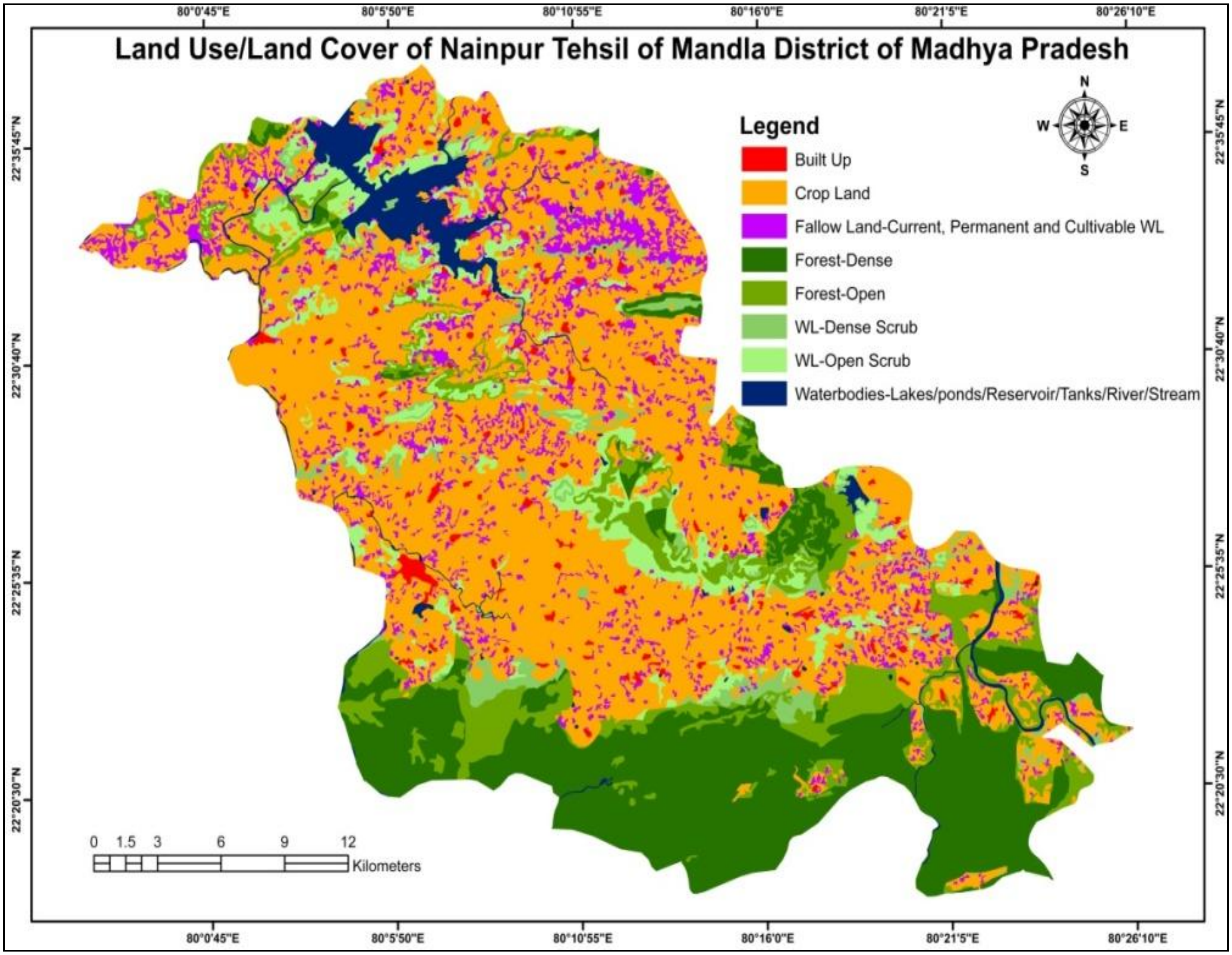


Figure 2. Land use/land cover of study area.

having a skewness ranging between -1 and 1 were considered normally distributed. For non-datasets, a logarithmic transformation was performed to achieve a normal distribution for use in the next step of the statistical analysis.

Geo-statistical methods were used to analyze the spatial correlation structures of the available contents of N, P, K and S and micronutrients in soil and spatially estimate their values at unsampled locations using geo-statistical tool in GIS 9.3.1 software. The spatial dependency of selected soil parameters was analyzed using semi-variogram analyses with normalized data. Semi variogam analyses have been proven as an excellent approach to exploring the structure of spatial variogram in agricultural soils.

The above phenomena is the best accomplished studying the semivariogram (Warrick et al., 1986) which is a plot of semi-variance that characterizes the rate of change of a mapped variable with respect to distance. Semi-variogram $y(h)$ is computed as half the average squared difference between the soil properties of data pairs. The structure of spatial variability was analyzed through semi-variograms (Figure 4). A semi variogram was calculated for each soil property. The semi variance γ(h) is estimated as:

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

where N(h) is the number of data pairs within a given class of distance and direction, z(xi) is the value of the variable at the location xi and z(xi + h) is the value of the variable at a lag of h from the location xi.

An experimental semi-variogram was calculated using the measured data. Next, this was generally fitted with a theoretical model, such as Exponential, spherical and Gaussian models (Goovaerts, 1999). Choice of the best-fitted model was based on the lowest residual sum of square (RSS) and the largest coefficient of determination (R^2). The model provided information about the spatial structure as well as the input parameters (that is, nugget, sill and range) for the Kriging interpolation. Nugget is the variance at distance zero, sill is the semi- variance value at which the Semi-variogram reaches the upper bound after its initial increase, and range is a value (x axis) at which one variable becomes spatially independent.

Table 1. Soil associations in Nainpur tehsil of Mandla district.

Code	ASS1	ASS2	Area(km^2)
9	Loamy mixed hyperthermic, Typic Ustochrepts	Loamy mixed hyperthermic, Lithic Ustorthents	62.65
23	Loamy skeletal mixed hyperthermic Lithic Ustochrepts	Loamy mixed hyperthermic, Lithic Ustorthents	19.70
28	Loamy mixed hyperthermic Lithic Ustochrepts	Fine mixed hyperthermic, Typic Ustochrepts	16.05
54	Fine montmorilonitic hyperthermic Vertic Ustochrepts	Fine montmorilonitic hyperthermic Typic Haplusterts	2.80
58	Loamy mixed hyperthermic, Lithic Ustorthents	Clayey mixed hyperthermic, Typic Ustochrepts	17.40
60	Fine montmorilonitic hyperthermic Typic Haplusterts	Fine montmorilonitic hyperthermic Vertic Ustochrepts	130.82
81	Fine montmorilonitic hyperthermic Typic Haplusterts	Fine montmorilonitic hyperthermic Chromic Haplustrets	280.01
85	Fine montmorilonitic hyperthermic Chromic Haplusterts	Fine montmorilonitic hyperthermic Typic Ustochrepts	23.79
97	Fine Loamy Kaolinitic hyperthermic Typic Ustochrepts	Fine Loamy Kaolinitic hyperthermicTypic Haplustalfs	201.94
101	Fine Loamy Kaolinitic hyperthermicTypic Haplustalfs	Fine Loamy Kaolinitic hyperthermicTypic Ustochrepts	70.23
109	Loamy mixed hyperthermic, Lithic Ustohrepts	Fine mixed hyperthermic, Typic Ustochrepts	17.87
122	Fine mixed isohyperthermic Typic Haplusterts	Fine mixed isohyperthermic Typic Ustropepts	15.90

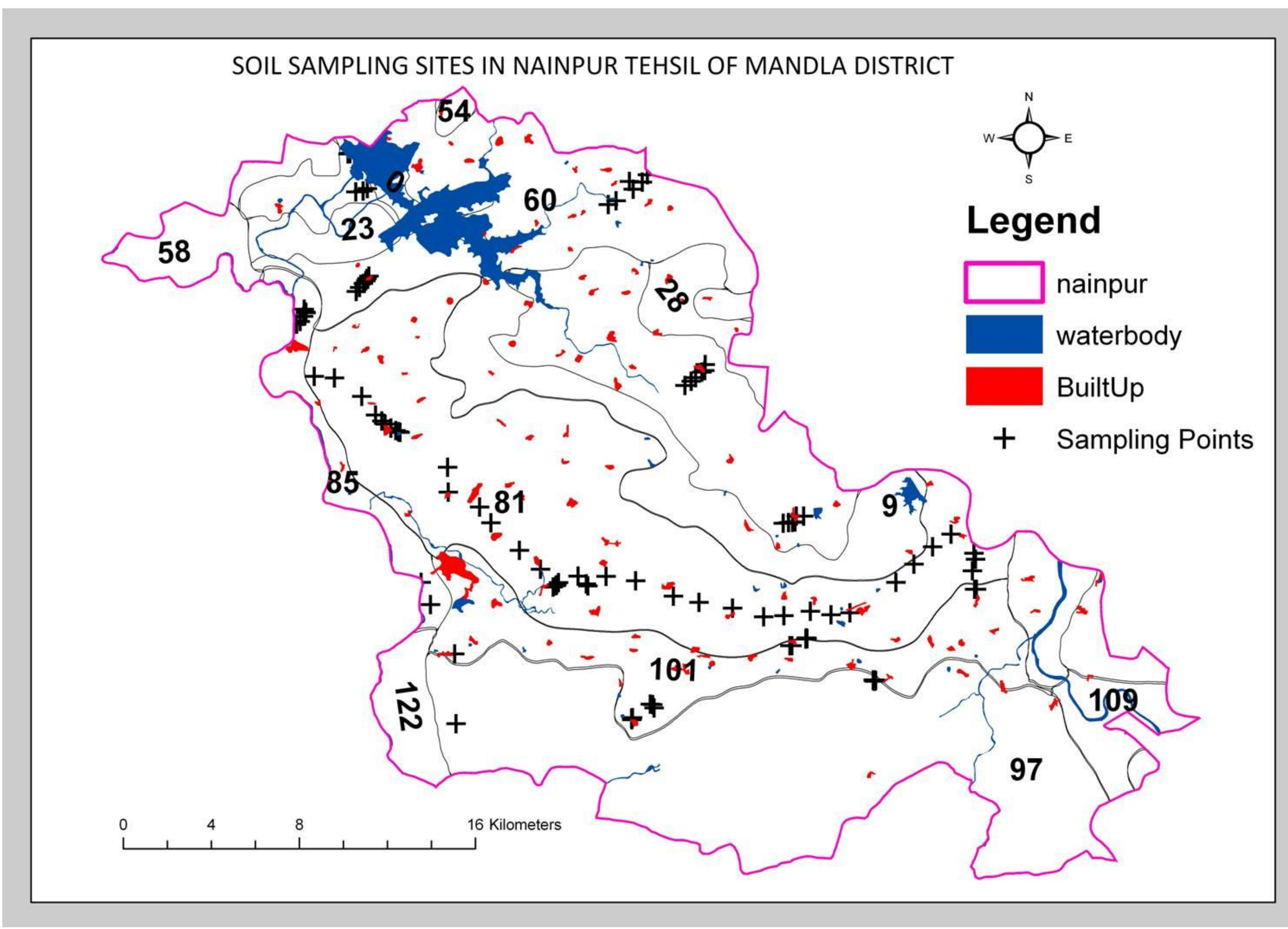
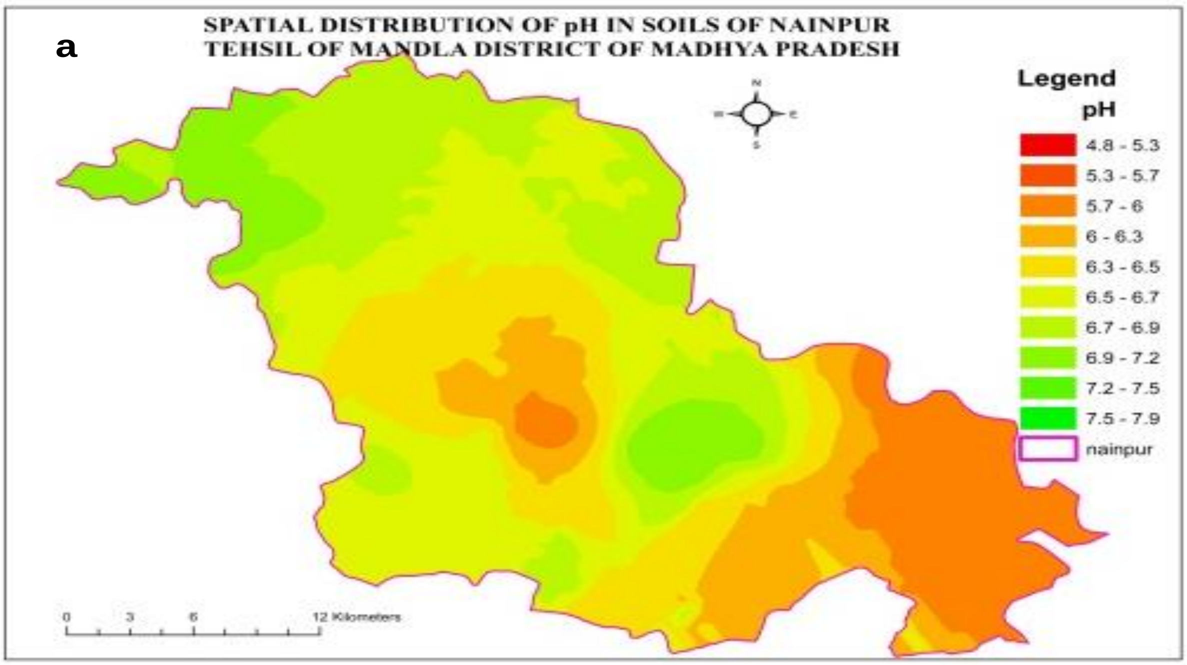
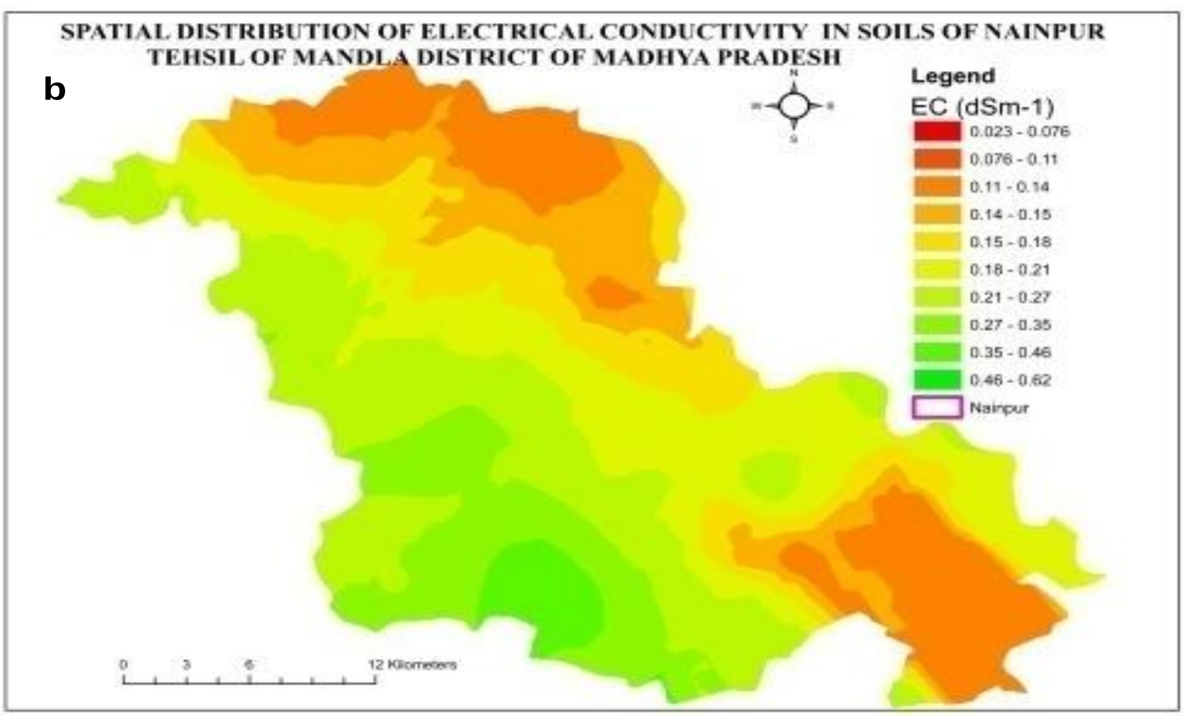


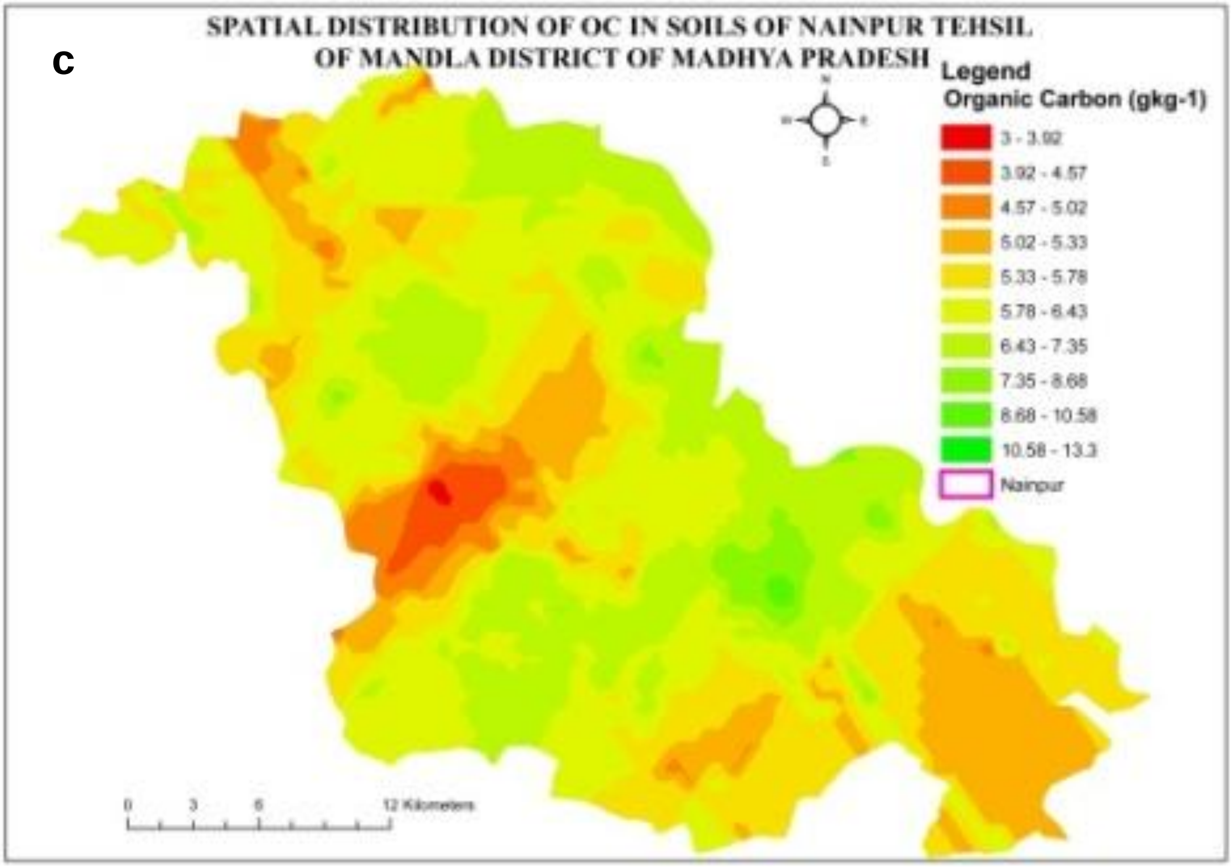
Figure 3. Sampling sites distribution under different soil associations of Nainpur tehsil of Mandla district of M.P.

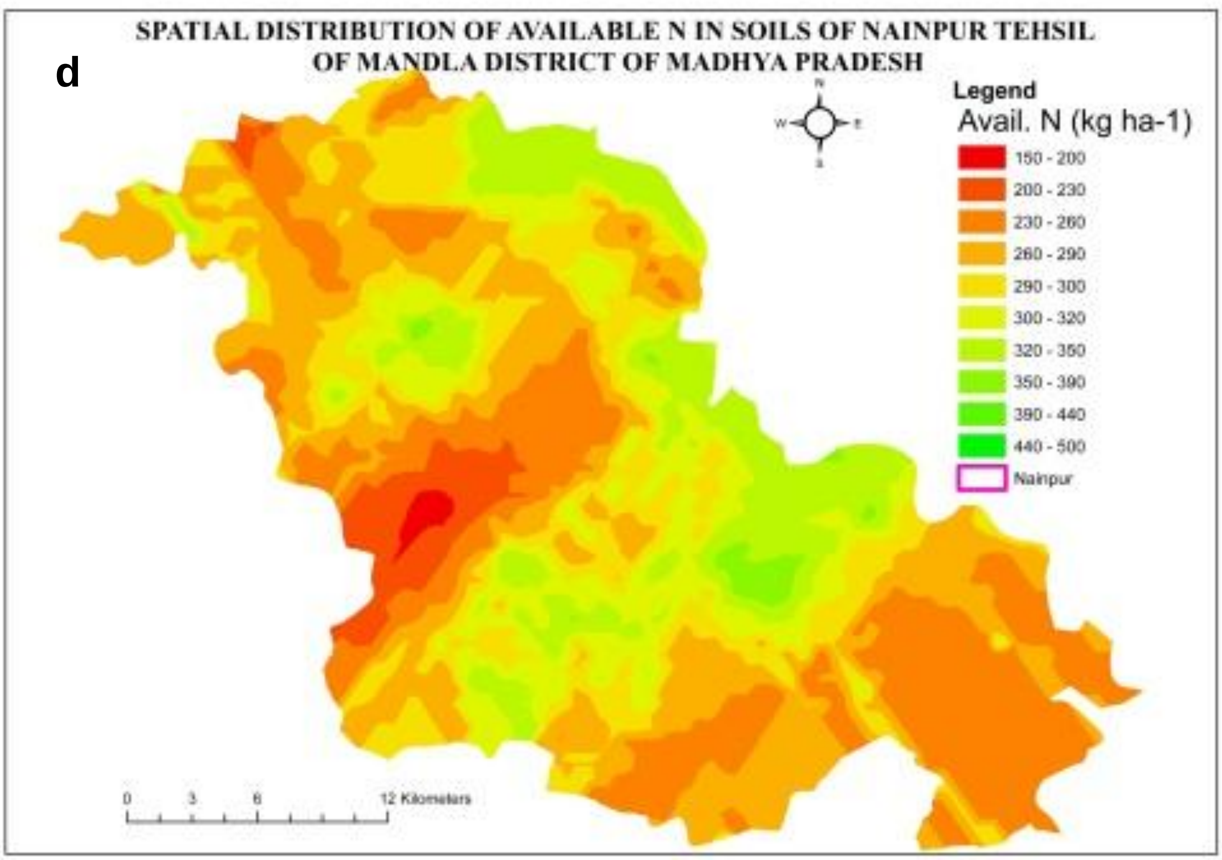
Table 2. The critical limits of micronutrients (mg kg^{-1}) were used for various categories (low, medium and high) as suggested by Singh et al., (2007).

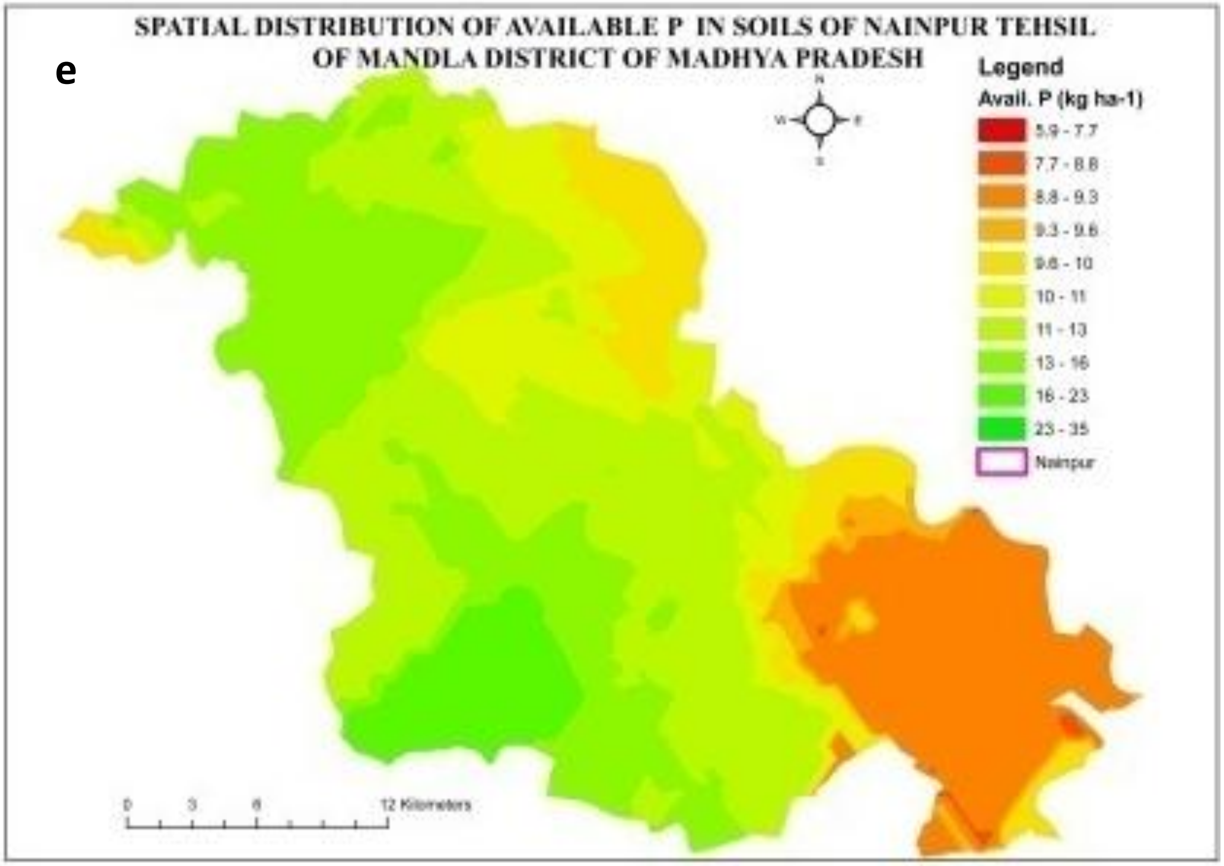
Micronutrients	Low	Medium	High
Zn	<0.6	0.6-1.2	>1.2
Cu	<0.2	0.2-0.4	> 0.4
Fe	< 4.5	4.5-9.0	>9.0
Mn	<2.0	2.0-4.0	>4.0
B	<0.1	0.1-0.60	>0.60

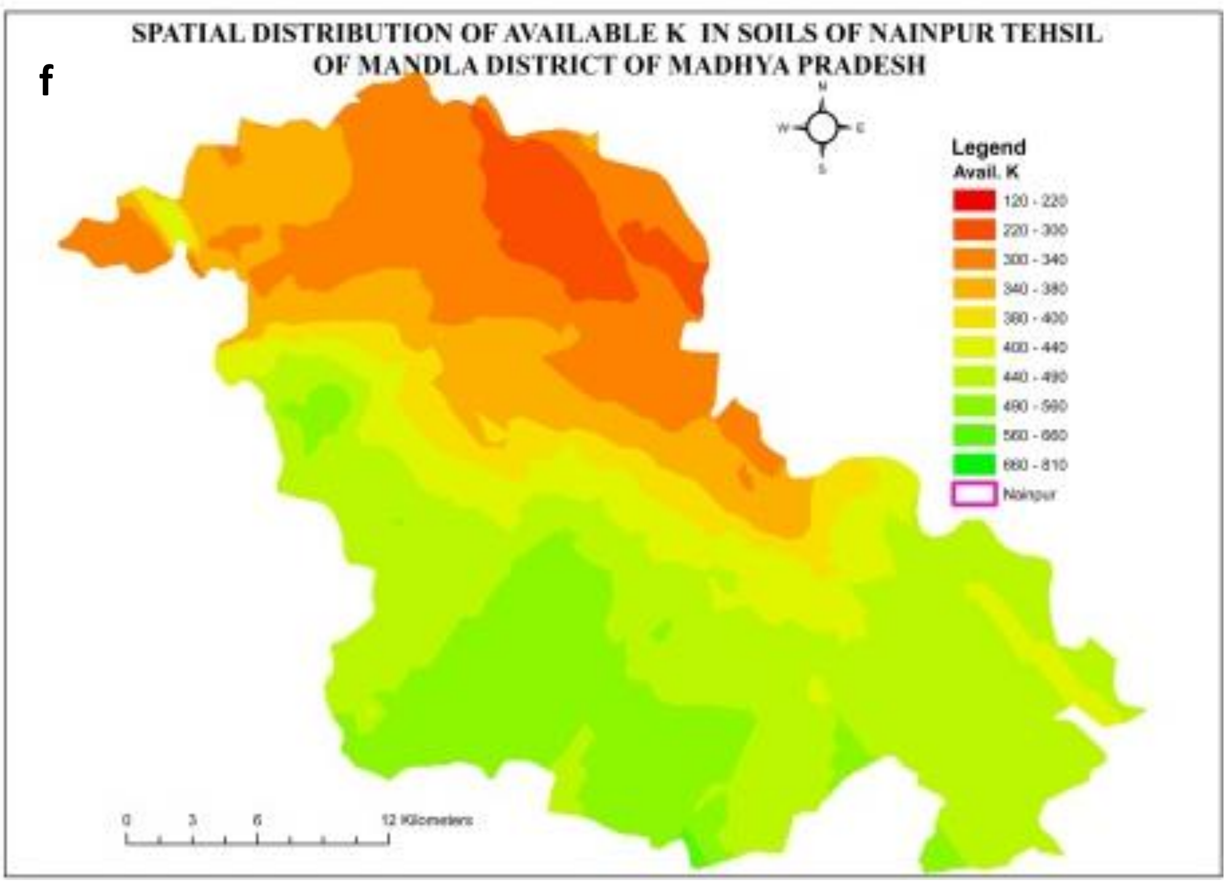


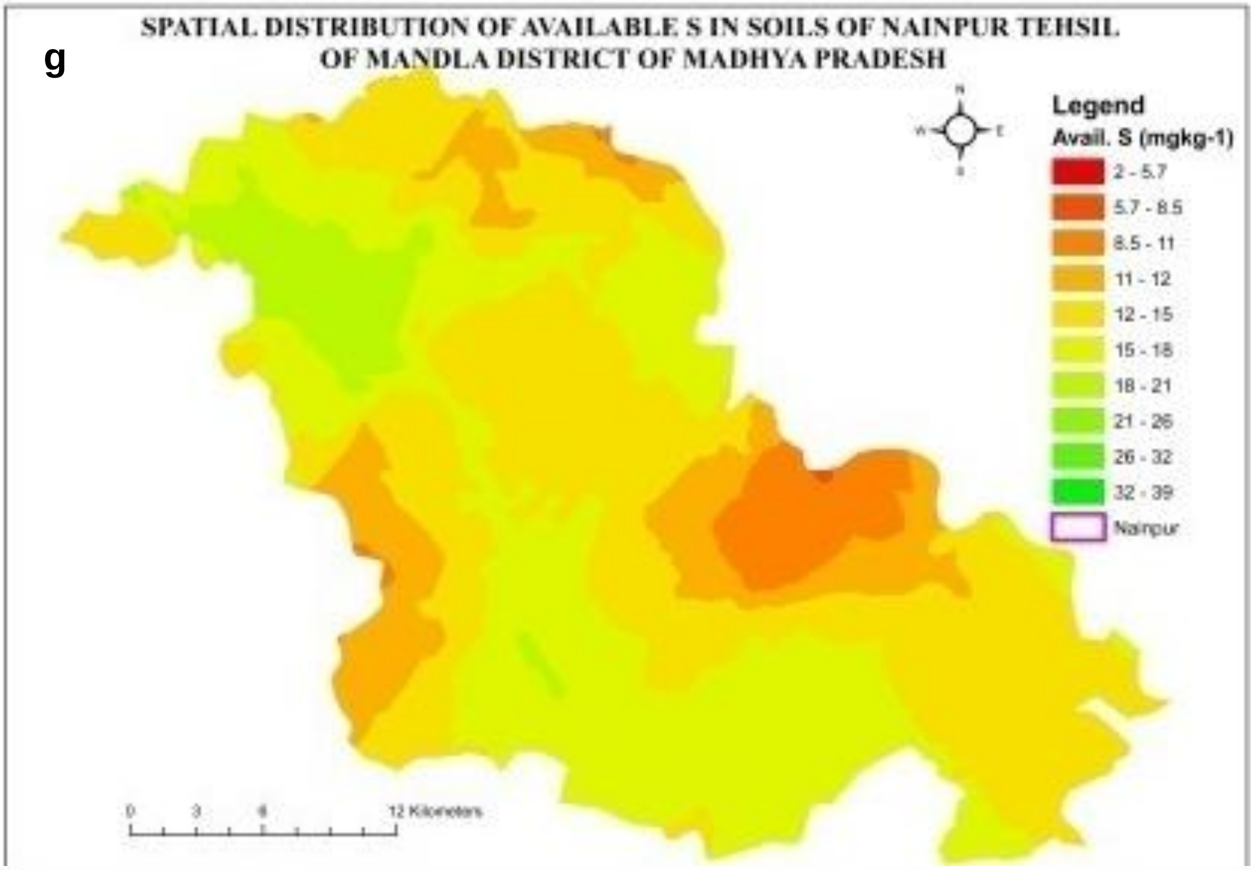


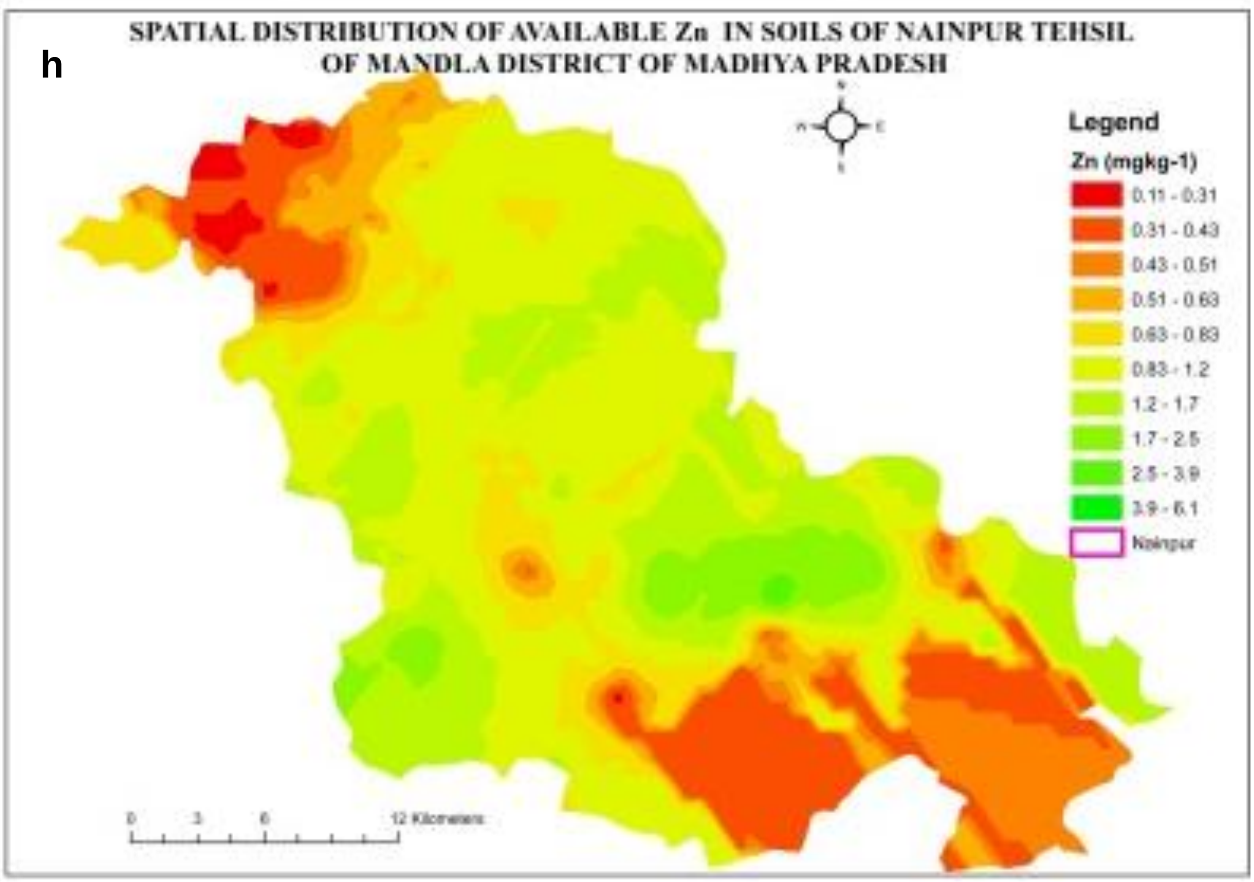

c
SPATIAL DISTRIBUTION OF OC IN SOILS OF NAINPUR TEHSIL
OF MANDLA DISTRICT OF MADHYA PRADESH
Legend
Organic Carbon (gkg-1)
3 - 3.92
3.92 - 4.57
4.57 - 5.02
5.02 - 5.33
5.33 - 5.78
5.78 - 6.43
6.43 - 7.35
7.35 - 8.68
8.68 - 10.58
10.58 - 13.3
Nainpur
0 3 6 12 Kilometers

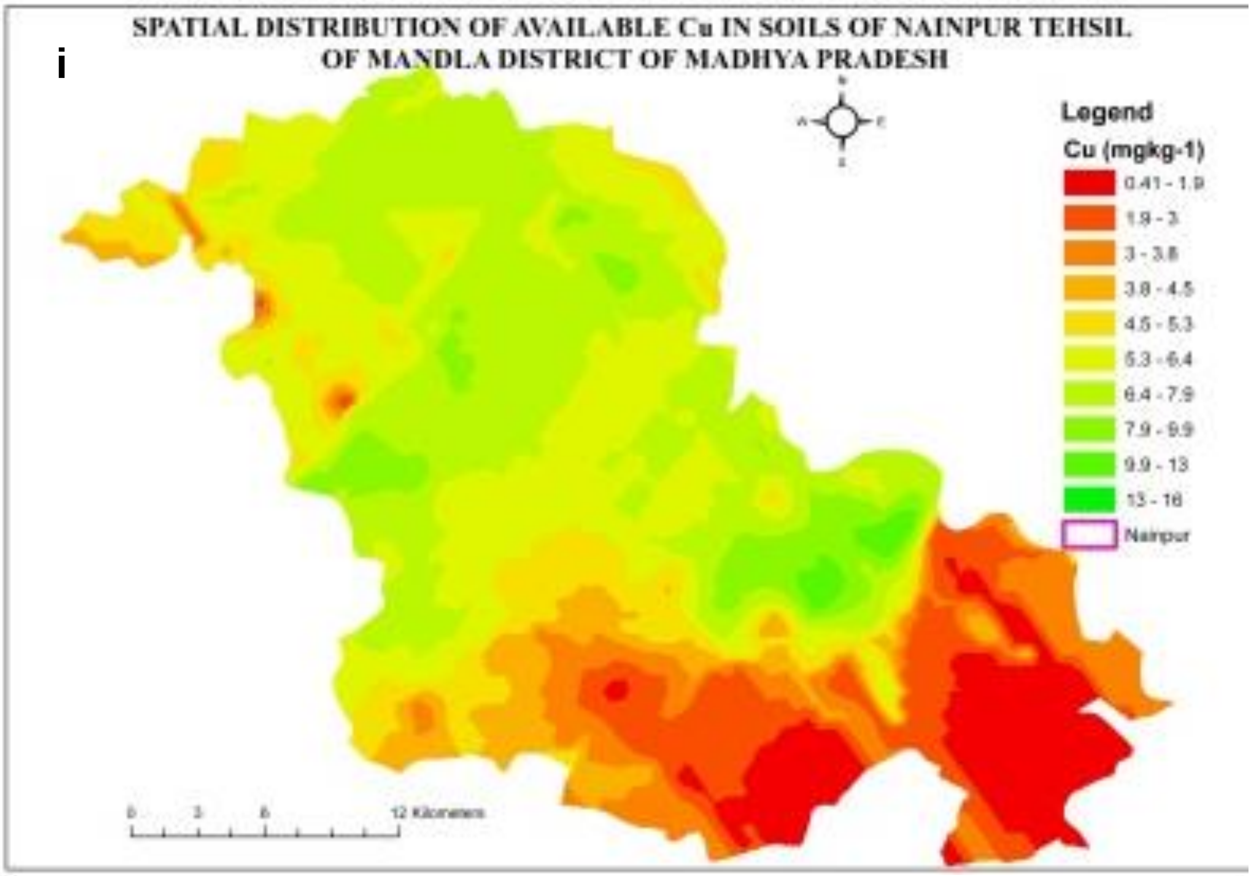

d
SPATIAL DISTRIBUTION OF AVAILABLE N IN SOILS OF NAINPUR TEHSIL
OF MANDLA DISTRICT OF MADHYA PRADESH
Legend
Avail. N (kg ha-1)
150 - 200
200 - 230
230 - 260
260 - 290
290 - 300
300 - 320
320 - 350
350 - 390
390 - 440
440 - 500
Nainpur
0 3 6 12 Kilometers

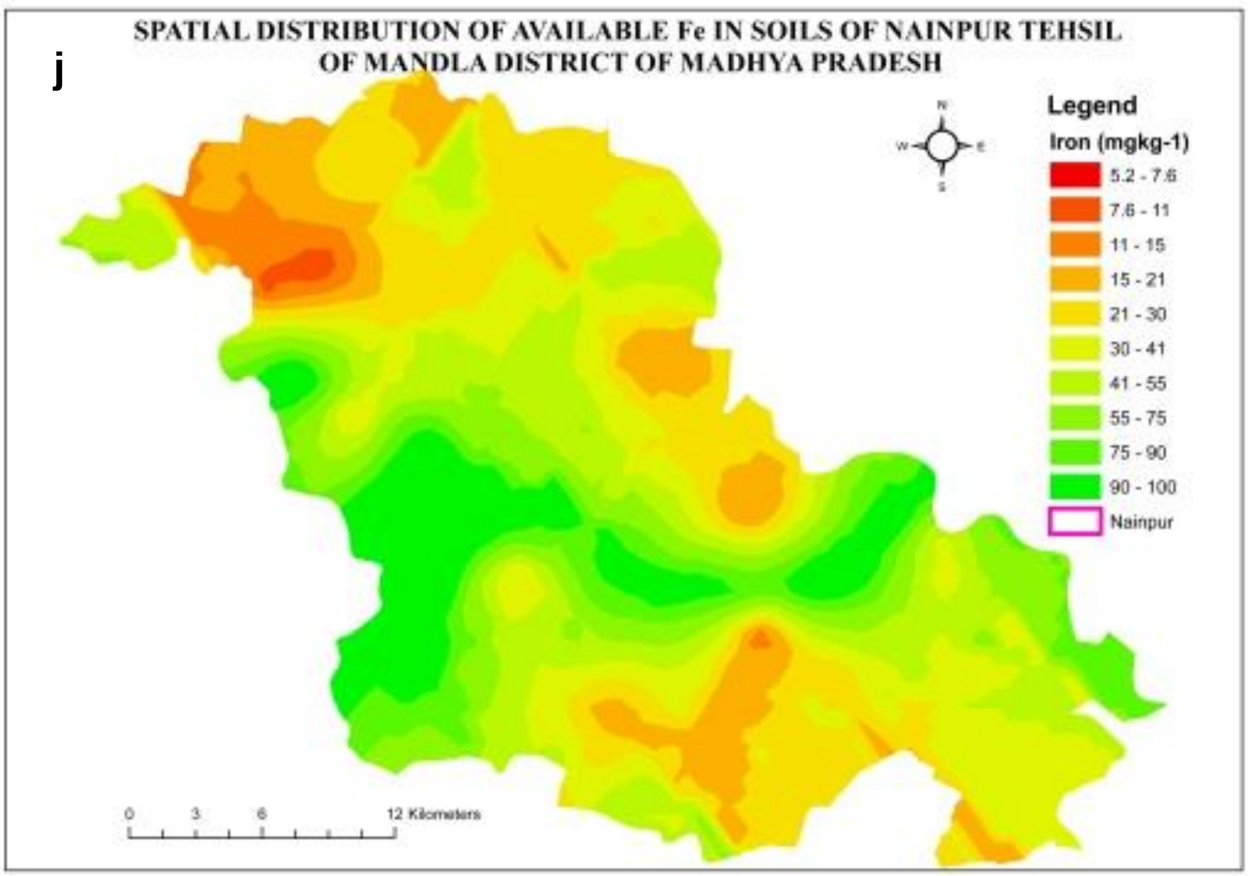

SPATIAL DISTRIBUTION OF AVAILABLE P IN SOILS OF NAINPUR TEHSIL OF MANDLA DISTRICT OF MADHYA PRADESH
e
Legend
Avail. P (kg ha-1)
5.9 - 7.7
7.7 - 8.8
8.8 - 9.3
9.3 - 9.6
9.6 - 10
10 - 11
11 - 13
13 - 16
16 - 23
23 - 35
Nainpur
0 3 6 12 Kilometers


SPATIAL DISTRIBUTION OF AVAILABLE K IN SOILS OF NAINPUR TEHSIL OF MANDLA DISTRICT OF MADHYA PRADESH
f
Legend
Avail. K
120 - 220
220 - 300
300 - 340
340 - 380
380 - 400
400 - 440
440 - 490
490 - 560
560 - 660
660 - 810
Nainpur
0 3 6 12 Kilometers


g
SPATIAL DISTRIBUTION OF AVAILABLE S IN SOILS OF NAINPUR TEHSIL OF MANDLA DISTRICT OF MADHYA PRADESH
Legend
Avail. S (mgkg-1)
2 - 5.7
5.7 - 8.5
8.5 - 11
11 - 12
12 - 15
15 - 18
18 - 21
21 - 26
26 - 32
32 - 39
Nainpur
0 3 6 12 Kilometers


h
SPATIAL DISTRIBUTION OF AVAILABLE Zn IN SOILS OF NAINPUR TEHSIL OF MANDLA DISTRICT OF MADHYA PRADESH
Legend
Zn (mgkg-1)
0.11 - 0.31
0.31 - 0.43
0.43 - 0.51
0.51 - 0.63
0.63 - 0.83
0.83 - 1.2
1.2 - 1.7
1.7 - 2.5
2.5 - 3.9
3.9 - 6.1
Nainpur
0 3 6 12 Kilometers


SPATIAL DISTRIBUTION OF AVAILABLE Cu IN SOILS OF NAINPUR TEHSIL
OF MANDLA DISTRICT OF MADHYA PRADESH
i
Legend
Cu (mgkg-1)
0.41 - 1.9
1.9 - 3
3 - 3.8
3.8 - 4.5
4.5 - 5.3
5.3 - 6.4
6.4 - 7.9
7.9 - 9.9
9.9 - 13
13 - 16
Nainpur
0 3 6 12 Kilometers


SPATIAL DISTRIBUTION OF AVAILABLE Fe IN SOILS OF NAINPUR TEHSIL
OF MANDLA DISTRICT OF MADHYA PRADESH
j
N
W
E
S
Legend
Iron (mgkg-1)
5.2 - 7.6
7.6 - 11
11 - 15
15 - 21
21 - 30
30 - 41
41 - 55
55 - 75
75 - 90
90 - 100
Nainpur
0 3 6 12 Kilometers

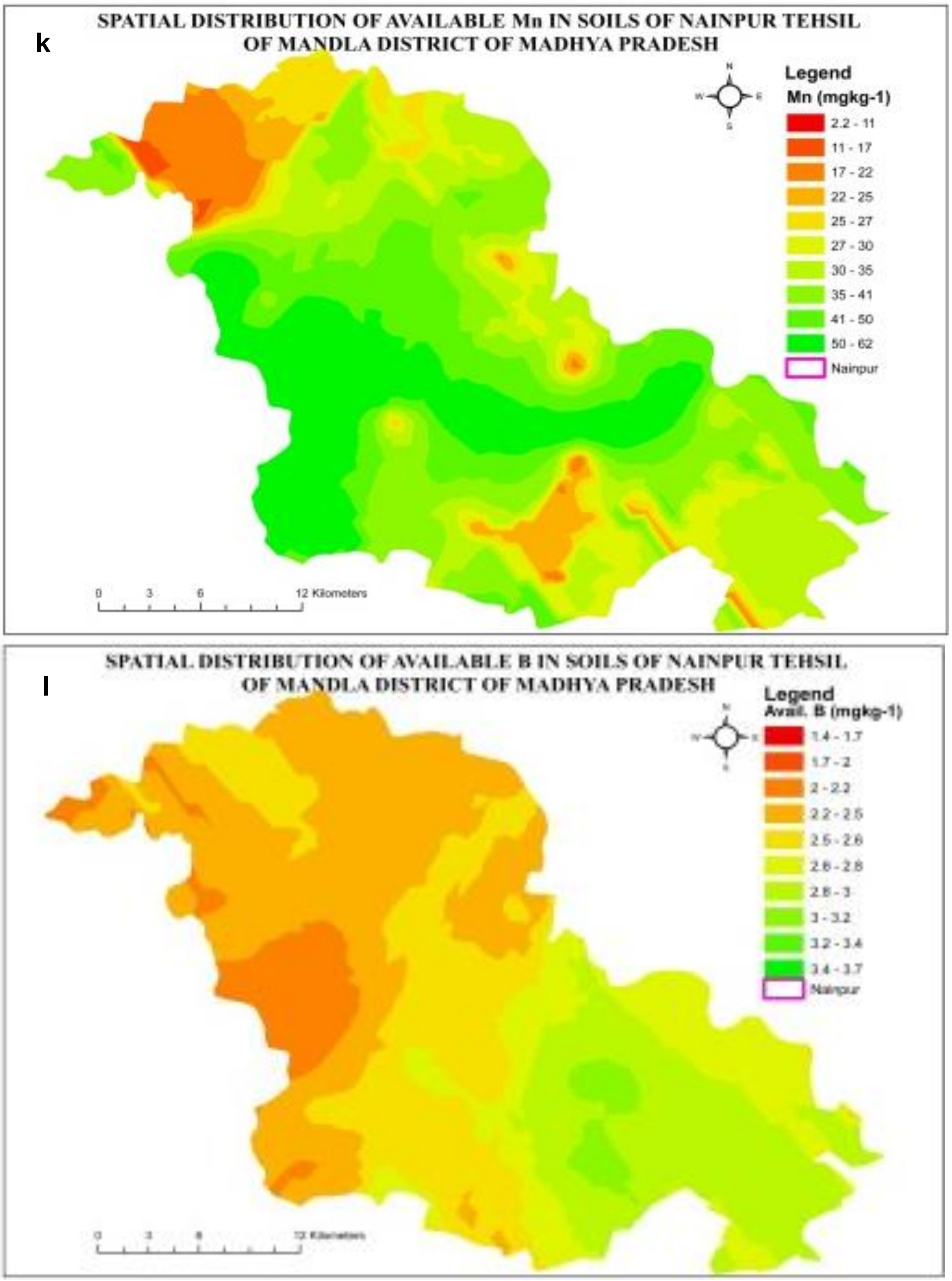


Figure 4. Kriged maps showing spatial variability of pH (a), EC (b), OC (c), AN (d), AP (e), AK (f), AS (g), Zn(h),Cu(i), Fe(j), Mn (k) and B (l).

The nugget to sill ratio was used to define different classes of spatial dependence for the soil properties (Emadi et al., 2008; Zuo et al., 2008). Nugget/sill ratio of 25%, 25 to 75% and >75% were classified as having strong, moderate and weak spatial dependence, respectively, according to Cambardella et al. (1994). Ordinary Kriging was used for the spatial interpolation because it is best at providing an unbiased prediction for specific unsampled locations and minimizing the influence of outliers (Tesfahunegn et al., 2011; Kavianpoor et al., 2012).

Evaluation criteria

Accuracy of the soil maps was evaluated through cross-validation approach (Davis et al., 1987; Santra et al., 2008). Among three evaluation indices used in this study, mean absolute error (MAE), and mean squared error (MSE) measure the accuracy of pre effectiveness of prediction. MAE is a measure of the sum of the residuals (e.g. predicted minus observed)(Voltz and Webster, 1990).

$$\text{MAE} \quad = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left[\left|z(x_i) - \hat{z}(x_i)\right|\right]$$

where zˆ(xi) is the predicted value at location i. small MAE values indicate few errors. The MAE measure, however, does not reveal the magnitude of error that might occur at any point and hence MSE will be calculated,

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

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).

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

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

RESULTS AND DISCUSSION

Descriptive statistics of soil properties

The mean values for pH, EC, OC content were 6.58, 0.21 dSm^{-1} and 6.30 g kg^{-1} with a range of 4.8 to 7.90, 0.02 to 0.60 dS m^{-1} and 3.0 to 13.30 g kg^{-1}, respectively. The available N, P, and K varied from 150 to 500 kg ha^{-1}, 5.88 to 34.89 kg ha^{-1} and 122.08 to 807.52 kg ha^{-1} with mean value of 299.43 kg ha^{-1}, 12.31 kg ha^{-1} and 405.30 kg ha^{-1}, respectively. The S varied from 2.04 to 39.0 mg kg^{-1} with a mean value of 14.69 mg kg^{-1}. The available micronutrients Zn, Cu, Fe, Mn and B varied from 0.11 to 6.08, 0.41 to 16.35, 5.15 to 101.20, 2.24 to 61.80 mg kg^{-1} and 1.40 to 3.72 with mean values of 0.83, 4.81, 40.81, 35.29 and 2.54 mg kg^{-1}, respectively (Table 3).

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. According Hillel (1980) and Yang and Yang (2005), there are three classes about coefficient of variation of soil nutrients (C.V.), weak variation (C.V. <0.1), medium variation (C.V. = 0.1–1.0), strong variation (C.V. > 1.0). The EC had the largest variation (CV = 50.12%) followed by OC (CV = 27.83%) while pH was found least variable (CV = 8.71%). The macronutrients are, NPK, the available P had the highest variability (CV=49.21%) and followed by avail. K (CV = 35.75%) whereas N had the lowest variability (CV= 27.00). The S was found to be moderately variable (CV = 56.84%). Among the micronutrients, the Zn was found to be highly variable (CV = 98.80%), followed by Fe (CV = 86.22%), Cu (CV =60.55 percent) and Mn (CV = 52.57 percent) while B was found least variable (CV= 25.75%). The range of CV for the area suggested different degrees of heterogeneity among the properties studied. All the macronutrients were found to be moderately variable with ranging from 27.00 to 49.21%. All the micronutrients were highly variable with CV ranging from 25.57 to 98.80%. Among the soil fertility parameters, $CaCO_3$, Zn, Cu and Fe were found not normally distributed due to higher value of skewness and kurtosis.

Soil nutrient status

It is evident from the data presented in Table 4 that soil organic carbon content was found to be low in 23.6% and only 2% soil samples were medium and rest of soil samples were high (74.5%). It indicates that majority of these soils were low to moderately high in organic carbon content. On the basis of the ratings suggested by Subbiah and Asija (1956), the available N was found to be low (28.30%), medium (1.9%) and high (74.5%) in soil samples. It may be due low organic matter content of soil as well as rapid loss of applied N in soil. On the basis of the limits suggested by Muhr et al. (1963), the available phosphorus content was found to be low 48.6% in soil samples, none of the samples were found in medium and rest of soil samples were fall in high category (51.4%). The low amount of available P may be due to application of lower doses of P fertilizer, fixation of P on clay minerals or $CaCO_3$ surfaces with the time elapsed between fertilizer application and crop uptake. It may also be due low organic matter content of soil (Sanyal et al., 2015).

According to Muhr et al. (1963), the available potassium content was found to be low in 13.9 soil samples, high in 86.1% soil samples and non of soil samples were found in medium. For these soils available micronutrients status using critical limit as given in Table 4 for DTPA-extractable Zn content was found to be deficient in 54.7%, medium in 26.4% and high in 18.9% soil samples. The data showed the DTPA extractable Fe

Table 3. Statistical overview for physico-chemical properties and macro and micronutrients of soils of study area (N=150).

Parameter	Min	Max	Range	Mean	SD	β	Skewness	CV%
pH	4.8	7.9	3.1	6.58	0.57	0.02	-0.39	8.71
EC	0.02	0.62	0.6	0.21	0.11	4.32	1.75	50.12
OC	3	13.3	10.3	6.3	1.75	1.1	0.59	27.83
N	150	500	350	299.43	80.84	-0.71	0.2	27.0
P	5.88	34.89	29.01	12.31	6.06	5.36	2.31	49.21
K	122.08	807.52	685.44	405.3	144.9	0.78	0.67	35.75
S	2.04	39	36.96	14.69	8.35	0.51	0.91	56.84
Zn	0.11	6.08	5.97	0.83	0.82	**16.26**	3.35	98.8
Cu	0.41	16.35	15.94	4.81	2.91	2.97	1.34	60.55
Fe	5.15	101.2	96.05	40.81	35.19	-1.43	0.64	86.22
Mn	2.24	61.8	59.56	35.29	18.55	-1.23	0.3	52.57
B	1.4	3.72	2.32	2.54	0.65	-0.86	0.24	25.57

Table 4. Nutrient status and NI of soils of Nainpur tehsil of Mandla district (N=150).

Nutrients		Per cent samples under different categories			NI	NI class
		Low	Medium	High		
OC		23.6	1.9	74.5	2.51	High
Available	N	28.3	1.9	69.8	2.42	High
macronutrients	P	48.6	0	51.4	2.03	Medium
	K	13.9	0	86.1	2.72	High
S		25.5	0	74.5	2.49	High
Micronutrients	Zn	54.7	26.4	18.9	1.64	Low
	Cu	0	0	100	3.00	High
	Fe	0	87.7	12.3	2.88	High
	Mn	0.0	0.9	99.1	2.99	High
	B	0	0	100	3.00	High

content was found medium in 87.7% soil samples and none of the soil samples were tested low in Cu, Fe, Mn and B content, respectively. All soil samples were found insufficient in case of Cu content. The present study result was supported by Athokpam et al. (2013). Considering soil nutrient index suggested by Parker et al. (1951) (Table 4), soils of Nainpur were found of high status in respect of all fertility status except medium P while low fertility status in case of Zn.

Spatial variability maps preparation using geo-statistical approach

It was necessary to normalize the data prior to the geo-statistical analysis because of high skewness (Table 3) and the presence of outliers. Logarithmic transformations were selected to normalize the dataset. 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 (Webster and Oliver, 2001).

$$f(x) = \ln(x) \quad \lambda=0,$$

where f(x) is the transformed value and x is the value to be transformed. For a given data set (x_1, x_2,…..xn), the parameter is estimated based on the assumption that the transformed values (y_1,y_2,…..y_n) are normally distributed. When λ = 0, the transformed becomes the logarithmic transformation.

The logarithmic transformation resulted in smaller skewness and kurtosis for $CaCO_3$, Zn, Cu and Fe and the transformed data passed the normality test. Log-transformed data were used in the spatial analysis (Table 5).

Geo-statistical analysis

Ordinary Kriging was chosen to create the spatial distribution maps of soil fertility parameters, with the

Table 5. Skewness and kurtosis values for the original and transformed data.

Parameters	Original data		Log transformed data	
	Skewness	β	Skewness	β
$CaCO_3$	1.35	1.11	.095	2.40
Zn	3.35	16.26	0.12	2.96
Cu	1.34	2.97	-0.79	3.85
Fe	0.64	-1.43	0.14	1.59

Table 6. Characteristic of calculated semi-variogram of spatial data sets.

Soil property	Range (m)	Nugget (C_0)	Partial Sill (C)	Sill (C_0+C)	NS ratio	Spatial dependence
pH	12950.9	0.14	0.25	0.39	0.36	Moderate
EC	18880.1	0.00	0.01	0.01	0.38	Moderate
OC	2376.58	0.79	3.70	4.49	0.18	Strong
ln $CaCO_3$	3793.05	0.10934	0.15	0.26	0.42	Moderate
N	2575.95	3597.50	3178.40	6775.90	0.53	Moderate
P	11538	30.14	9.79	39.93	0.75	Moderate
K	15094	11578.00	12098.00	23676.00	0.49	Moderate
S	18470.3	53.84	20.32	74.15	0.73	Moderate
lnZn	3611.75	0.07	0.55	0.62	0.12	Strong
lnCu	3349.73	0.11	0.55	0.66	0.16	Strong
lnFe	5797.27	0.22	0.71	0.93	0.24	Strong
B	22774.9	0.28	0.22	0.50	0.56	Moderate
Mn	5443.27	80.188	272.71	352.90	0.23	Strong

maximum search radius being set to the autocorrelation range of the corresponding variable. The best model for fitting on experimental variogram was selected based on less RSS value. The exponential model was selected from standard models that are available to fit experimental semi-variograms based on more favorable weighted residual mean squares, and visual fit to the data at short lags. Wasiullah et al. (2010) and Gore et al. (2012) reported the spherical model for Mn. Therefore, the authors recognized the exponential and spherical model to be suitable for estimation of soil properties. The results supported by Ferreira et al. (2015) who reported exponential model is best for most of soil properties. Similar result reported by Eltaib et al. (2002), Nayanaka et al. (2010) and Cao et al. (2011) in case of soil organic carbon (Table 6).

In this study, no apparent anisotropy was found for any studied variable through experimental variograms. So, all experimental variograms were in isotropic form and ratio of nugget variance to sill expressed in percentages (C_0/C+C_0) can be regarded as a criterion for classifying the spatial dependence of the soil parameters. If this ratio is less than 25%, then the variable has strong spatial dependence (Shi et al., 2005) 25% and 75%, and higher than 75% correspond to moderate, and weak spatial dependencies, respectively. The OC, Zn, Cu, Fe and Mn showed strong spatial dependence and the values between 25 and 75% have moderate spatial dependence as shown in table, pH, EC, $CaCO_3$, N, P, K, S and B have moderate spatial structure. According to Cambardella et al. (1994), these spatial auto dependencies may be attributed to both intrinsic factors such as other soil properties and extrinsic factors such as human activities (Table 7).

The mean absolute error (MAE) was found to be zero for pH, EC, OC, P, S, Zn, Cu, Fe and Mn. The highest mean squared error (MSE) was observed for K followed by N, Fe, $CaCO_3$, Mn, S, P, Cu, OC, Zn, pH and EC. The performance of the interpolation technique was considered in term of the G value nutrients that showed positive. The goodness of fit (G) values was positive and highest G value was observed for Fe followed by Mn, EC, pH, Cu, Zn. The G values for B and P were negative. The spatial distribution of P could be related to geology, especially parent material of the study area (Wang et al., 2009). Among the micronutrients, available Zn was spatially correlated for a shorter distance and at a distance less than the range, measured soil property of two samples become more alike with decreasing distance between them (Eltaib et al., 2002). Spatial dependence of DTPA extractable Zn, Fe, Cu and Mn were also reported by Nayak et al. (2006).

Table 7. Evaluation performance of Krigged map of soil properties through cross-validation.

Soil property	MAE	MSE	G
pH	0.0	0	35.52
EC	0.0	0	39.86
OC	0.1	3	7.04
ln $CaCO_3$	-2.2	170	14.39
N	3.4	5965	7.84
P	-0.1	38	-4.32
K	-2.3	17550	15.23
S	-0.1	65	5.22
lnZn	-0.1	1	23.34
lnCu	0.2	6	29.52
lnFe	0.6	314	74.43
B	-0.01	0.42	-5.88
Mn	-1.1	99	70.84

Conclusions

On the basis of laboratory data, soil fertility assessment in respect to available macro and micro nutrients have been drawn in terms of nutrient indexing (Low, medium and high). The available N, P, K and S were high, medium, high respectively and micro-nutrients, that is, Zn was low and rest of that were sufficient in their status. It was concluded that it is applicable to investigate the spatial variability of soil properties. Exponential model was found as the best fit of all the parameters except Mn. The spherical model was found as the best fit for Mn. Based on prediction maps, it was realized that all nutrients has no toxic status and that the application of fertilizer will improve crop yields. Hence, study area requires phosphatic and zinc fertilizers for better crop growth and productivity of crops. The spatial variability maps on nutrient status generated geo-statistical techniques will be helpful for the farmers or researchers for the location specific correction of nutrient deficiency. These maps are very much helpful for guiding the farmers to decide the amount and kind of nutrient they can apply for in terms of optimum/economic returns, as the nutrient management will be different for areas having deficiency of one or more nutrients than those having sufficient nutrients.

Conflict of Interest

The authors have not declared any conflict of interest.

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