# Spatial Variability in Soil properties, Delineation Site-Specific Management division based on soil fertility Using Fuzzy clustering in Gwalior, Madhya Pradesh, India


## ABSTRACT

Farmers who want to improve nitrogen usage efficiency (NUE) and crop yield must have access to information regarding the geographical variability and distribution of soil parameters. Fertilizer application relying on soil characteristic maps and fertilizers recommendations may help reduce fertiliser input without sacrificing crop production. The current research focused heavily to evaluating the variability of soil fertility status in Madhya Pradesh Gwalior region using geostatistical techniques. In order to do this, 150 GPS-based surface (0–15 cm) soil samples were obtained from the Gwalior region's five districts (Gwalior, Shivpuri, Datia, Guna, & Ashok Nagar) during crop harvest inside the rabi season of 2019–20. Statistics and geostatistics were used to analyse the results of the laboratory analysis. The analysis revealed that the soil samples' pH, EC, SOC, and $CaCO_3$ values, respectively, varied from 4.40 to 8.30, 0.09 to 1.03 $dSm^{-1}$, 2.0 to 10.60 $gkg^{-1}$, and 3.0 to 24.0 $gkg^{-1}$. In contrast, the amounts of N, P, K, and S that are present in soil vary from 102.0 to 356.0 kg $ha^{-1}$, 6.0 to 61.0 kg $ha^{-1}$, 114.0 to 896.0 kg $ha^{-1}$, and 5.90 to 49.20 mg $kg^{-1}$, respectively.

Through building semi-variograms and mapping the data utilizing standard kriging techniques, the information was studied using both traditional statistics and geostatistics. For soil properties, semi-variograms were created, and their geographical distributions were delineated. The Nugget/Sill (Co/Co+ C) ratio for the modelled variables revealed moderate to high spatial dependences. The best-fit models for the reported soil characteristics were exponential, spherical, and circular. The findings of this research clearly demonstrated that soil fertility quality varied significantly across the Gwalior area. This knowledge may aid in making choices about crop succession and the usage of plant nutrients to increase farmers' financial returns.



**Key words: Geo-statistical approach, NUE, Soil quality, Productivity**


## 1. Introduction

Geographical Information Systems and Remote Sensing is the requisite backbone for the planning and management in agriculture. Understanding the spatial variability and distribution of soil characteristic is essential for growers seeking to increase nutrient use efficiency and productivity. Applying fertilizer based on soil characteristics related to fertilizer recommendations can help minimize fertilizer input without yield loss. Geostatistics is a useful tool that is widely used to analyze spatial variability, interpolate between observation points, and ensure interpolated values with a certain error using a minimum number of observations (Long et al., 2014 & Cambule et al., 2014). Information about the spatial variability of soil physicochemical properties and microbiological activity is very important in the selection of crops and cultivation systems, and also broadens ideas about prevailing management practices (Weindorf and Zhu, 2010; Cao et al. al., 2011 and Liu et al., 2013). The spatial variability of pH, EC, organic matter and NPK and available micronutrients has been studied by various researchers by comparing soils and their management systems to refine and implement site-specific nutrient management (Franzen et al., 2002; and Li et al., 2011).

Soil is one of the main components of a sustainable agricultural production system and its quality is determined by its physicochemical characteristics and its nutrient supply capacity which is ultimately reflected in crop productivity. Soil quality is defined as the ability of a particular soil type to function, within ecosystems and land use boundaries, to maintain productivity, maintain environmental quality and improve plant growth and human health (Andrews et al., 2002). Soil is inherently heterogeneous as many factors contribute to its formation and the complex interactions of those factors (Maniyunda et al., 2013). According to Jha and Mohapatra, 2012; it is well known that changes in land use, long-term cultivation & mineral fertilization can cause significant variations in soil properties. Soil properties & characteristics mainly depend on the geological formation, topography and climate of the region where the land is located. Dokuchaev considers soils as independent natural bodies, each with a single morphology resulting from a unique climate arrangement, living matter, parent matter, relief, and age of the landform.The spatial variations of soil physicochemical properties have been reported as the primary source of variability in crop yields. The similar spatial patterns of soil water content, cation exchange capacity, SOC, and crop yield in the sandy soil of Poland. Understanding the spatial variability of soil physicochemical characteristics, in both its static (e.g., texture and mineralogy) and dynamic (e.g., water content, compaction, electrical conductivity, nutrient and carbon content) forms is necessary for SSSM, as it is directly contributing to variability in crop yields and quality.

At the field, catchment, and regional sizes, geostatistical is a potent technique for estimating spatial variability of soil characteristics and soil nutrients. Geo-statistics is the most confident, strongest, and broadest approach for interpolation, considering geographic variance, location, and sample distribution. Geostatistical approaches interpolate using mathematical and statistical functions, and their foundation is statistical data. Based on autocorrelation and the spatial organisation of observed points, Kriging interpolation predicts unknown points (Cambardella et al., 1994. Kriging interpolation may identify soil property-related spatial characteristics. Numerous research employ geo-statistics to map geographical variability and soil properties (Jian-Bing et al. 2008, Zhang and Grath, 2011).

The goal of this study was to look at the geographical variability of certain physico-chemical parameters in the soybean-wheat belt of Madhya Pradesh. Soil health, plant nutrient management, erosion, and water stability are only some of the outcomes of assessing soil's spatial variability using geo-statistical techniques in a wide range of geographic and ecological contexts (Rosemary et al., 2017). In order to make appropriate management planning for sustaining the productivity of crop lands, spatial distribution maps of key soil properties are needed. particle size distribution viz: pH, EC, Soil organic carbon, available P, K, and micronutrients are important soil properties that direct the decision of soil management for sustainable crop production. Therefore, the results on spatial characteristics of key soil properties are useful for near future management decision of producers and for improving soil nutrient management. Fertilization based on maps with recommendations related to soil fertility may also lead to reduced fertilizer inputs without reducing yield (Jalali, 2007). This study aimed at determining and mapping the key soil physical and chemical properties of dominant Soybean – Wheat belt of central India using geo-statistical techniques to support near-future management decisions.

The cluster algorithm is an efficient way to identify solution points with heterogeneous data sets. With multiple comparisons using cluster analysis, it is possible to identify a subregion within areas with similar characteristics. Aaron and others. (2004) used crop yield data while Fleming et al. employed fuzzy soil characteristics. Various authors have identified management zones using principal component analysis and fuzzy clustering technique based on soil parameters (Davatgar et al., 2012; Xin-Zhang et al., 2009).

**Material and Methods**

## 2.1 Site details

Gwalior division is an administrative subdivision of Madhya Pradesh as well as rich in natural resources which covers these five districts is Ashoknagar, Datia, Guna, Gwalior and Shivpuri. The area of Gwalior division is spread between 24° 10'N to 26°48'N latitude to76°31'E to79°15'E longitude and the elevation ranges from 160 to 529 m above mean sea level. The region is semi-arid characterized by black less fertile soil, average annual rainfall of 500 to 800 mm/year, and winter temperatures that sometimes drop below 5 degrees Celsius. The division falls in the gird Agro- climatic zone of Madhya Pradesh. The soil moisture regime observed is Ustic. The topography extends from west to east direction with medium slope gradient of 0- 6 per cent. Agriculture is the main occupation of the people in this division and the major crops are rice, wheat, pulses, millets, potato and seasonal vegetables. GPS based one hundred fifty (150) surface soil samples were collected scientifically from different location across the Gwalior division.

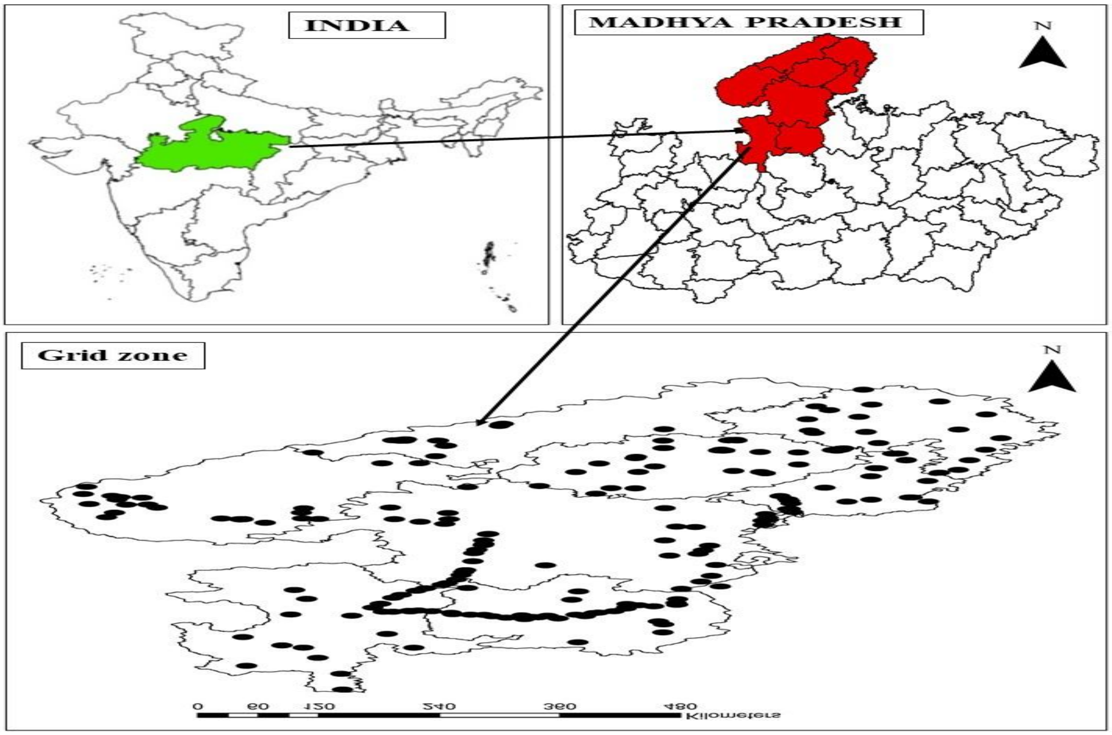



**Fig. 1. Location map of study area**

**2.2 Soil survey and sampling techniques:**

Based on land use and soil association maps, geography, and soil heterogeneity, the research area's agricultural land was randomly sampled. GPS locations were used to gather field data and soil samples. To prevent fertilising during crop cultivation, 150 surface soil samples (0-15 cm) were gathered from farmers' fields during the off-season. Each major sampling station received 1.0 kg of typical composite soil sample in a labeled sample bag. Animal faces accumulation sites, poorly drained locations, and other unrepresentative soil samples were avoided. Latitude, longitude, topography, slope, elevation, land use type, crop type, local soil name, sample depth, soil colour, crop residue management, rate of previous year fertiliser application, and type were gathered from each site during soil sampling (fig.-1).

**2.3 Analysis of soil physicochemical properties and DTPA extractable micronutrients**

The soil pH was measured both in a soil–water suspension (1:2.5). The electrical conductivity (EC) was determined from the soil–water suspension (1:2.5). the soil organic carbon (SOC) in soil was determined using the method as described by Walkley and Black (1934).The calcium carbonate in the soil was carried out using a rapid back titration method as described by Jackson (1973).and available N of the soil samples were analyzed by standard procedures. Phosphorus (Bray P, $NH_4F$ + HCl) and potassium ($NH_4OAc$), the methods outlined by Bray and Kurtz (1945) and Black (1965) were adopted, respectively. The available sulphur (S) was extracted by 0.15 per cent $CaCl_2$ solution and the concentration of sulphur was determined by the turbidimetric method using Spectrophotometer (Chesnin and Yien, 1951). Phyto available iron (Fe), zinc (Zn), copper (Cu) and manganese (Mn)contents of soil were determined using DTPA extraction technique(Lindsay and Norvell, 1978) followed by analysis using atomic absorption spectrophotometer. Hot water-soluble boron in soil was analyzed by azomethine-H method as outlined by Berger and Truog (1939).

### *2.4 Descriptive statistics*

The soil parameters were estimated using descriptive statistics of the soil data. SPSS 21.0 programme calculated soil parameter minimum, maximum, mean, standard deviation, coefficient of variation, and skewness values. According to Webster (2001), soil data with positive or negative skewness deviates most from normalcy. Consequently, parameter distributions with skewness are likewise considered normal. For variables lacking normal distributions, those with positive or negative skewness values larger than 0.5 were square root transformed, while those with values greater than 1.0 were log transformed. 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., (1998). A Pearson correlation matrix among all the soil variables was also generated to investigate the association between the variables and Microsoft Excel.

### *2.5 Geostatistical analysis*

Arc GIS 10.3.1 statistical analyzer was used for semivariogram modeling and selecting the best semivariogram model. Before fitting the semivariogram models, the asymmetric soil properties were converted to a semi-normal distribution using the natural logarithm. The data was re-transformed using the inverse transformation.

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

Where: N (h) is the number of pairs of points distant from each other by h.

Several semivariogram models were evaluated to best fit with the experimental data in the ArcGIS v 10.3. 1 The circular, spherical, tetra spherical, exponential, Gaussian, K-Bessel, J-Bessel, and stable model were evaluated for different soil parameters. A semivariogram model with the lowest value of nugget/sill ratio was selected as the best fit model for the given soil properties.The exponential, Gaussian, spherical, and circular models were best fitted for the studied soil properties.

**Exponential model:**

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

Where

h = lag distance,

$C_0$ = nugget variance,

C = structural variance (partial sill) and

r = range

The parameters of the semivariogram, which offer information on the spatial structure of the provided soil variables and also serve as input for the kriging interpolation, were computed. These parameters include the nugget (C0), partial sill (C), sill (C+ C0), and range (r).

The characteristics that describe the spatial organisation of a soil property are the mass/threshold ratio, also known as (C0)/(C + C0), and extension. The distance across which the values of the various soil properties relate to one another is defined by the range. The low value of (C0)/(C + C0) and the typically large range suggest that kriging may be used to obtain high accuracy of the feature (Cambardella et al. 1994). The term "ecosystem" refers to a group of people who work in the construction industry. The term "ecosystem" refers to a group of people who work in the construction industry (Cambardella et al. 1994). The ordinary kriging (OK) approach was carried out in order to estimate a variety of soil properties at the places that had not been tested. According to the findings of Schepers et al. (2004), OK is the most accurate and objective approach of prediction for soil samples that have been randomly dispersed. Since OK also lessens the influence of outliers on prediction, it is the method that is most suited for estimating soil parameters at places that have not been sampled. A method called cross-validation was used to determine how accurate the soil maps were (Davis 1987). Mean absolute error (MAE), mean squared error (MSE), and prediction goodness (G) are the three metrics that were used in this investigation. Mean absolute error assesses prediction accuracy, whereas mean squared error indicates prediction efficacy. The mean absolute error (MAE) is calculated by adding together all of the differences between the observed and anticipated values (Voltz & Webster 1990).

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

Where z1 is the anticipated value at point i. The SML measurement doesn't reveal inaccuracy, hence MSE is computed.

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

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.

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

where z is the sample mean. The term "ecosystem" refers to a group of people who work in the construction industry. The correctness of the interpolated maps of the investigated soil parameters was confirmed using G-values. Negative values and values close to zero-G show that the mean catchment scale accurately or even better than sampling estimates forecasts values in un sampled places.

### 2.6 Principal component analysis

Principal component analysis (PCA) is a method of multivariate analysis that uses features or related variables and identifies orthogonal linear regressions of features those summaries the main sources of data variability. PCA is a technique that reduces the number of dimensions in which the analysis is performed. As a consequence of using a correlation matrix that was comprised of the chosen soil attributes as the input to the analysis rather than the covariance matrix, a normalized principal component analysis was produced. The study consisted of a significant number of principal component variables (PC variables). It has been postulated that the principal components (PC) that have high Eigen values are the ones that are best able to describe the characteristics of the field. To create the management domain classes in the present research, PCs with eigenvalues of less than 1.0 were chosen.

### 2.7 Fuzzy cluster algorithm

The term "ecosystem" refers to a group of people who work in the construction industry. Fuzzy cluster analysis quantitatively reduces within-group variation and maximises between-group variance to create homogenous groupings. The term "ecosystem" refers to a group of people who work in the construction industry (Brown, 1998). Fuzzy c-mean, an unsupervised continuous classification approach (De Gruijter and Mc Bratney, 1988), was utilised to split the field into 2-8 clusters using FuzME software developed at the Australian Center for Precision Agriculture (Minasny and McBratney, 2006). According to Xin-Zhang et al., we determined that eight clusters were the maximum number of viable applications for management zones. An iterative procedure that began with a random set of cluster means was used to select who would be included in each cluster. The average that was closest to each observation was given to it. Based on the distance between the observation and the cluster mean, the new means were computed for each cluster. Euclidean distance was utilised to compute the distance of data points from their cluster midpoints based on the result of covariance and statistical independence. The following parameters were utilised in the FuzME programme: maximum number of iterations = 300, stopping criteria = 0.0001, minimum number of zones = 2, maximum number of zones = 8, and exponent fuzzy = 1.5. (McBratney and Moore, 1985), and the normalised classified entropy (NCE), have been utilised as indications of the ideal cluster number in the following ways:

$$FPI = 1 - \frac{c}{c-1}\left[1 - \frac{\sum_{i=1}^{c}\sum_{k=1}^{n}(\mu_{ik})^2}{n}\right]$$

$$NCE = \frac{n}{n-c}\left[-\frac{\sum_{k=1}^{n}\sum_{i=1}^{c}\mu_{ik}\log_a(\mu_{ik})}{n}\right]$$

where c is the number of clusters and n is the number of observations, μik is the fuzzy membership and log is the natural logarithm. FPI measures the amount of blur created by a specified number of classes. ICS values can range from 0 to 1. Values close to 0 indicate distinct classes with little member sharing, and values close to 1 indicate no distinct classes with a large amount of member sharing. The NCE is a rough calculation of the chaos that would result from adding up the number of classes. When the index is the lowest, signifying the smallest membership share (FPI) and greatest organisation size clusters (NCE), the method calculates the best number of clusters for each determined index (FPI and NCE). In addition, analysis of variance was utilised to show the variation amongst MZs. SAS 9.2 was used to compile the descriptive statistics. Geostatistical mapping and analysis were carried out using ArcGIS 10. FuzME software (Minasny and Mc Bratney, 2006) was utilised to develop the c-means fuzzy clustering algorithm.

## 2. Results

Descriptive statistics of physical and chemical properties of soil samples are the datasets are summarized in table 2. The variability of attributes within study area was interpreted using the coefficient of variation (CV). which is the ratio of the standard deviation to mean, expressed, as a percentage is a useful measure of overall variability. The values of coefficient of variation for all the variables observed was very different ranging from 6.65% (pH) to 61.95% (Av-P). Since pH had least variability (CV = 6.65 %). Since pH represents the log scale was due to transformed measurement of hydrogen ion concentration. which could be as a result of the uniform conditions in the area such as little changes in slope and its direction leading to a uniformity of soil in the area the range of CV for the area suggested

different degrees of heterogeneity among the properties studied. The soil properties with high variability in terms of coefficient of variation are Av- P similarly result Silt & Clay, EC, Macroaggregates and Av-K (C.V. = >35%), MWD, soil organic carbon, Microaggregate, Water stable aggregates, silt and clay were all moderately variable (C.V. = 34–15%) while PWP, Sand, FC and pH were the least variability (C.V. = <15%) according to the guidelines provided by Wilding (1987) and Warrick, (1998), for the variability of soil properties.
Skewness values of soil properties varied from -019 (Microaggregates) to 1.44 (EC) for different soil proprieties revealed that some soil properties were not normally distributed. This variation and non-normal distribution of soil properties in the large positive values of skewness revealed that some soil properties were not normally distributed.Skewness values of soil properties were in good agreement and indicated that few soil properties have negative values viz. pH, clay, PWP, WSA and Micro aggregates. High positive skewness values (≥1.0) of EC, Silt + Clay and Av-P in studied are as may be due to these variations in chemical properties are mostly related to the different soil management practices including in the study area, variation in fertilizer application, parent material on which the soil is formed, irrigation water quality and other crop management practices.

The descriptive statistics of soil attributes are presented in table 2 the soil pH, EC, SOC, Av-P and Av-K, Sand, Silt, Clay, water content at field capacity and permanent wilting point, MWD, Water Stability Aggregate (WSA), Micro aggregate and silt & Clay, The soil properties data sets obtained from soil analysis were evaluated using minimum, maximum and mean parameters of study area varied from 5.97 to 8.56, 0.04 to 0.47 dSm$^{-1}$, 0.15-1.26%, 1.87 – 62.94kg ha$^{-1}$ and 62.16 – 987.11kg ha$^{-1}$, 33.21 to 66.96%, 9.28 to 37.72%, 13.04 to 46.72%, 21.06 to 42.04%, 10.36 to 26.10%, 0.33 to 1.53 mm, 18.42 to 86.27%, 5.32 to 66.93%, 15.57 to 87.56% and 0.89 to 35.53% respectively. The standard deviation values of soil attributes presented in table 1 with the value of SD viz: 0.51, 0.08, 0.19, 13.34, 163.69, 5.61, 3.81, 5.49, 3.77, 2.75, 0.25, 11.92, 13.35, 13.04 and 7.60respectively in the whole study area.

***2.1 Physico-chemical properties, in soils of Gwalior division***

Data pertaining to physico-chemical properties and fertility status of soil in Gwalior division are accessible (table 2) as whole the pH, electric conductivity (EC), soil organic carbon (SOC) and $CaCO_3$content in the soil were varied from 4.80 to 8.30, 0.09 to 1.03dS m$^{-1}$, 2.0 to 10.60 g kg$^{-1}$ and 3.0 to 24 g kg$^{-1}$ with mean values of 7.36, 0.34 dS m$^{-1}$,5.62 g kg$^{-1}$ and 10.12 g kg$^{-1}$, respectively.

**Table 2. Descriptive statistics of soil fertility status of Gwalior division**

| parameters | Unit | Minimum | Maximum | Mean | Std. Deviation | CV | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| **pH** | | 4.80 | 8.30 | 7.36 | 0.66 | 8.96 | -1.74 | 2.86 |
| **EC** | $dSm^{-1}$ | 0.09 | 1.03 | 0.34 | 0.15 | 43.60 | 1.18 | 2.51 |
| **OC** | gm $kg^{-1}$ | 2.00 | 10.60 | 5.62 | 1.94 | 34.51 | 0.79 | 0.12 |
| **$CaCO_3$** | | 3.00 | 24.00 | 10.12 | 4.47 | 44.17 | 0.82 | 0.69 |
| **N** | kg $ha^{-1}$ | 102.00 | 356.00 | 227.79 | 51.56 | 22.63 | 0.22 | -0.36 |
| **P** | | 6.00 | 61.00 | 24.92 | 14.20 | 57.00 | 0.53 | -1.08 |
| **K** | | 114.00 | 896.00 | 343.13 | 172.37 | 50.23 | 1.58 | 2.23 |
| **S** | mg $kg^{-1}$ | 5.90 | 49.20 | 17.55 | 8.94 | 50.95 | 1.12 | 1.30 |
| **Cu** | | 0.69 | 7.30 | 1.93 | 1.06 | 54.81 | 2.39 | 8.05 |
| **Zn** | | 0.10 | 3.19 | 1.00 | 0.58 | 58.42 | 1.20 | 1.55 |
| **Fe** | | 1.90 | 25.30 | 9.91 | 5.71 | 57.63 | 0.95 | 0.12 |
| **Mn** | | 1.40 | 44.00 | 13.17 | 7.97 | 60.49 | 1.34 | 2.55 |
| **B** | | 0.05 | 4.43 | 1.86 | 1.14 | 61.10 | 0.23 | -0.93 |



Available N, P, K and S content in the soils of Gwalior division ranged from 102.0 to 356.0 kg $ha^{-1}$, 6.0 to 61.0 kg $ha^{-1}$, 114.0 to 896.0 kg $ha^{-1}$ and 5.90 to 49.20 mg $kg^{-1}$ with mean value of 227.79 kg $ha^{-1}$, 24.92 kg $ha^{-1}$, 343.13 kg $ha^{-1}$ and 17.55 mg $kg^{-1}$, respectively. This may be due to organic S constitutes the major share of total S present in soil. Zn, Cu, Fe, Mn and B contents in soil varied from 0.10 to 3.19, 0.69 to 7.30, 1.90 to 25.30, 1.40 to 44.0 and 0.05 to 4.43 mg $kg^{-1}$ with mean values of 1.0, 1.93, 9.91, 13.17 and 1.86 mg $kg^{-1}$, respectively.

## 3. Discussion

### 4.1 *Physico-chemical properties and nutrients content in soils of Gwalior division*

#### *4.1.1 pH*

Soil pH play very important role as it control the physical condition and availability of nutrients of soil to a great extent. It indicates the $H^+$ and $OH^-$ ions activities, presence of exchangeable bases such as Mg, Ca and Na+ and also gives hold of hydroxyl ions over hydrogen ions. The pH value of division varied from 4.80 to 8.30 with the mean value of 7.36. It had coefficient of variation 8.96 per cent.

The study of division are clearly shows soil pH that the maximum area falling under the slightly acidic to alkaline nature of soil. Under low to medium rainfall conditions, accumulation of bases especially sodium takes place being the primary reason for alkaline soil pH (Ram, 1998). Higher pH values were also recorded in degraded vertisols in Purna valley region by Balpande *et al.* (1996), Tripathi and Najif *et al.* (2006). Similar results for the soil of MP and MH were also reported by Shilpa *et al.* (2007), Singh *et al*. (2009) and Sharma *et al.* (2015).

The pH showed significantly positive correlation with available EC (r=0.270**), $CaCO_3$ (r=0.211**), P (r=0.242**), K (r=0.242**) Cu (r=0.130**) but negative significant relationship with Fe (r=-0.479**) and Mn (r=-0.247**). Similar results were reported by Yadav et al. (2018), Singh et al. (2017), Babel (1998), Sharma (2005) and Singh *et al.* (2009).

### *4.1.2 Electrical conductivity (EC)*

An examination of data indicated that the EC of soils of division varied from 0.09 to 1.03 $dsm^{-1}$ with the mean value of 0.34 $dSm^{-1}$, respectively. Highest EC soils were found in Gwalior district and lowest value in Shivpuri district of division.

The EC of soil exhibited 43.60 per cent CV, which was moderate variability. Such variation in EC values in the division may be due to different soil operations including variation in fertilizer application and other crop management practices under different land use systems (Srinivasrao *et al.*, 2014). Also similar results were recorded by Yadav *et al*. (2018) and Singh *et al*. (2017)

### *4.1.3 Soil organic carbon*

The organic carbon of soils of five districts of division recorded to range between 2.0 to 10.60 with the mean value of 5.62 kg $ha^{-1}$. The results clearly showed whole zone had moderate variability in soil organic carbon. Similar results also reported by Yadav *et* al. (2018) in the soils of Alirajpur district of Madhya Pradesh, Singh *et* al. (2017) in soils of Bhind district and Yadav (2005) in soils of Nagore district.

The lower content of OC in soils was due to higher temperature which influence rapid rate of OM oxidation. Similar results were reported by Nazif *et al.* (2006). The degradation of organic matter taken place rapidly with cover lower vegetation. Sharma *et al.* (2008) also found similar Amritsar district. The large variability of organic carbon among districts is due to in the land use pattern (Mahesh Kumar, 2019).

### *4.2 Status and spatial distribution macronutrients in soils of Gwalior division*

#### *4.2.1 Available nitrogen*

Available nitrogen content in soils of Gwalior division (Ashok Nagar, Shivpuri, Guna, Datia and Gwalior districts) ranged from 102.0 to 256.0 kg $ha^{-1}$ with the average value of 227.79 kg $ha^{-1}$. It was also found that variability in available N content in soil of Gwalior division is 22.63 per cent. The available N showed positive relationship with available EC (r=0.171**), OC (r=0.832**), K (r=0.388**), Cu (r=0.195*), Zn (r=0.207**) and Fe (r=0.199*). The results are clearly showed the increase OC in the soil also increases available N, K and micronutrients. The positive relationship between available N and Organic carbon due to the mineralization of SOM in the soil. Similar study was noticed by Verma *et al*. (1980), Kanthaliya and Bhatt (1991) and Meena *et al*. (2006). The available nitrogen content in soil generally depends on altitude, rainfall and temperature and application of FYM, fertilizer schedule of previous crop and soil management practices *etc*. (Ashok Kumar, 2000). Positive relationship between OC and available nitrogen confirm that organic matter is chief source of available nitrogen. Sharma *et al*. (2008) and Kumar *et al.* (2009) also found the similar results.

#### *4.2.2 Available phosphorus*

Available phosphorus content in soils of Gird zone division varied from 6.0 to 61.0kg $ha^{-1}$ with the mean value of 24.92 kg $ha^{-1}$. It had variability in available P content in soil of division are 57.0 per cent, the highest variability was seen in Ashok Nagar district. The available P showed positive significant relationship with pH (r=0.242**) negative significant relationship with Cu, Mn, Zn and Fe. The results are clearly showed the antagonistic relation with available P and DTPA- Zn, Cu, Mn,Fe. Similar findings were reported by Yadav et al. (2018), Singh et al. (2017), Kumar and Seth (1983), Singh & Sharma (1984), Kameriya (1995), Meena et al. (2006), Sharma et al. (2008) & Kumar et al.(2013).

#### *4.2.3 Available potassium*

Available potassium content in soils of Gwalior division (Ashok Nagar, Shivpuri, Guna, Datia and Gwalior districts) ranged from 114.0 to 896.0 kg $ha^{-1}$ with mean value of 343.13 kg $ha^{-1}$. In the study of different districts of division variability of higher showed in Datia district. The available K showed positive relationship with pH (r=0.242**), OC (r=0.464**), $CaCO_3$ (r=0.211**) and N (r=0.388**). The results are clearly showed that the increases to Available K in soils also increases Available N. Kumar et al. (2014), Ravikumar and Somashekar (2014), Singh et al. (2017), Yadav et al. (2018) also reported similar findings.

### *4.2.4 Available sulphur*

Available sulphur content in soils of division (Ashok Nagar, Shivpuri, Guna, Datia and Gwalior districts) ranged from 5.90 to 49.20 kg $ha^{-1}$ with the average value of 17.55 kg $ha^{-1}$. It was also found that CV in available S content in soil of division are 8.94 per cent. Reported similarresult by Yadav et al. (2018), Singh et al. (2017), Kumar and Seth (1983), Singh & Sharma (1984), Kameriya (1995), Meena et al. (2006), Sharma et al. (2008) & Kumar et al.(2013).

### *4.3 Micronutrient status*

The micronutrients (Cu, Zn, Fe, Mn and B) status in soil of Gwalior division is presented below.

### *4.3.1 DTPA extractable Copper*

The DTPA extractable Copper constitutes in soils of division was ranged between 0.69 to 7.30 mg $kg^{-1}$ and average value was 1.93 mg $kg^{-1}$. It was found that moderate variability in DTPA extractable Cu content in soil of Gwalior division. The DTPA-extractable Cu showed positive relationship with N (r=0.195*), S (r=0.169*), Zn (r=0.215**) and Fe (r=0.374**) and negative relationship with P (r=0.193*). Copper is a very important constituent of several enzymes like: amine, oxidase, super oxide dismutase and plasto-cyanin, it also acts as an activator for several enzymes. Copper essential for maintaining hormonal activities $N_2$ fixation and oxidation reduction reactions. Similar findings also recommended by Singh (2010).

### *4.3.2 DTPA extractable Zn*

DTPA extractable Zn content in soils of Gwalior division was ranged between from 0.10 to 3.19 mg $kg^{-1}$ with the mean value of 1.0 mg $kg^{-1}$. It had variability in DTPA extractable Zn content in soil of division is 58.42 per cent. The minimum variability show in soils of Guna district. The DTPA-extractable Zn was significant negative correlation with available P (r= -0.197*). Similar results reported by Gupta (1995), Jena *et al.* (2008), Mathur *et al.* (2006) and Kumar *et al.* (2009).

### *4.3.3 DTPA- Fe*

The DTPA extractable Iron content in soils of division varied from 1.90 to 25.30 mg $kg^{-1}$ with a mean value of 9.91 mg $kg^{-1}$.The soil pH and EC affects the availability of iron content in soil. In surface soil DTPA iron content has no regular pattern of distribution (Nayak *et al*., 2002). This type of variation in DTPA Fe content may be due to the cropping pattern and soil management practices adopted by farmers. Similar results were also reported by, Sharma *et al.*, 2003 and Meena *et al*., 2006.

### *4.3.4 DTPA- Manganese*

In the study area of division, the available Mn was found sufficient in samples analyzed. This may be due to nature of parent material and neutral pH of soil as mentioned in the findings by Meena *et al.* (2006). Similar observations were also analyzed by Singh *et al.* (2009) in Ghazipur district of Uttar Pradesh and Singh (2010) in Neemrana panchayat samiti of Alwar district. Such results were also reported by Kumar (2003), Gupta (2003) and Sharma *et al.* (2003). The DTPA extractable Mn content in soils of division was ranged between from 1.40 to 44.0 mg $kg^{-1}$ with the mean value of 13.17 mg $kg^{-1}$. The DTPA-extractable Mn was showed positively relationship with the Zn (r=0.266**) and Fe (r=0.238**). Similar relationship between DTPA Cu and Fe, OC and $CaCO_3$ was also reported by Jena *et al.* (2008), Thakre *et al.* (2013); Noor *et al.* (2013); Zhang *et al.* (2014); Singh *et al.* (2017), and Yadav *et al.* (2018).

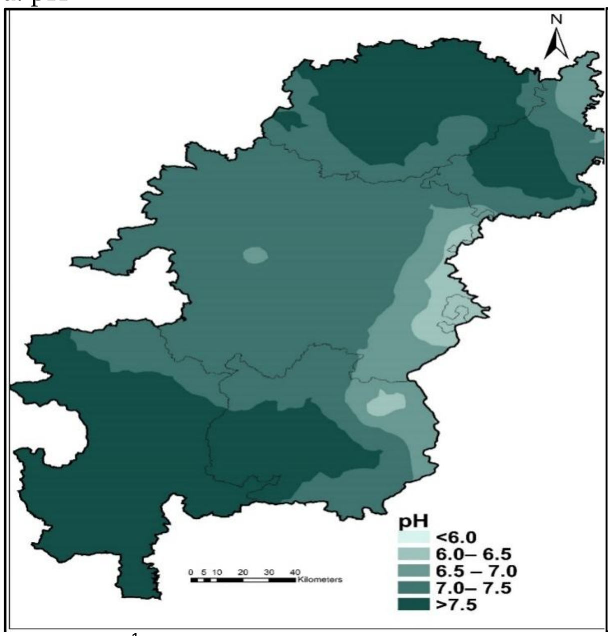
### *4.3.5 Hot water soluble Boron*

The hot water soluble B contents in soils of Gwalior division (Ashok Nagar, Shivpuri, Guna, Datia and Gwalior districts) was had ranged between 0.05 to 4.43 mg $kg^{-1}$ with the mean value of 1.86 mg $kg^{-1}$. The increase Available-S in the soil also the availability of boron increase. The results reported by Thakre *et al.* (2013); Noor *et al.* (2013); Zhang *et al.* (2014); Singh *et al.* (2017), and Yadav *et al.* (2018).

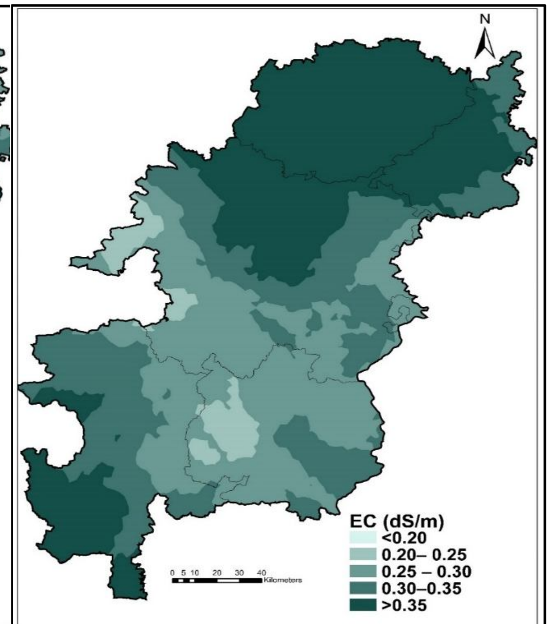
### *4.4 Soil fertility maps/spatial variability map of Gwalior division*

Spatial variation analysis results in the form of pH, EC, OC, CaCO3, N, P, K, S, Cu, Zn, Fe, Mn, and B maps are shown in Figure 1. 2 (a) to (m). Kriging maps of spatial soil nutrient variability can be used as the basis for site-specific fertilization to provide optimal nutrients for plant growth that can further optimize crop production.

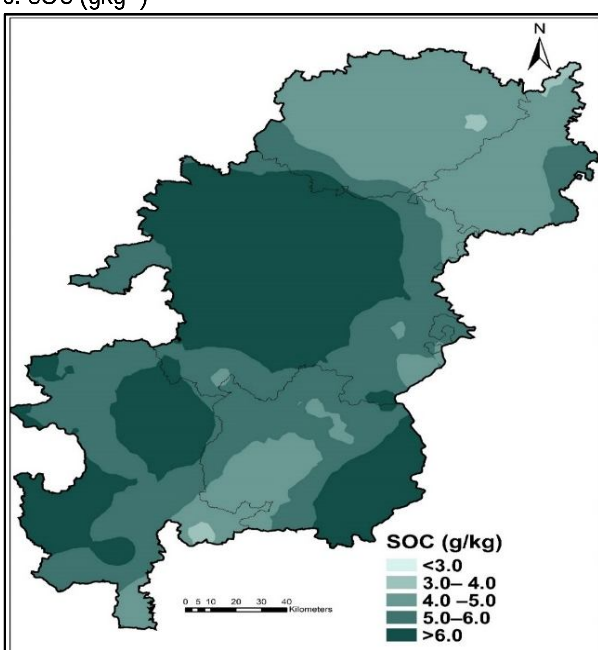
a. pH



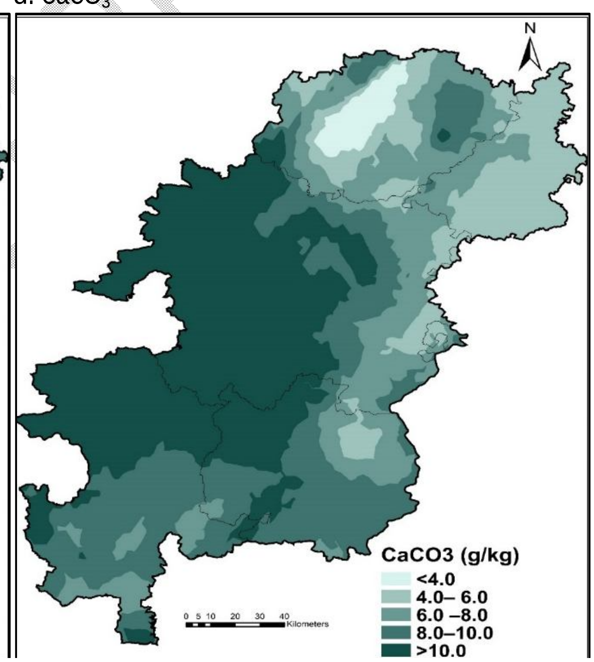

b. EC



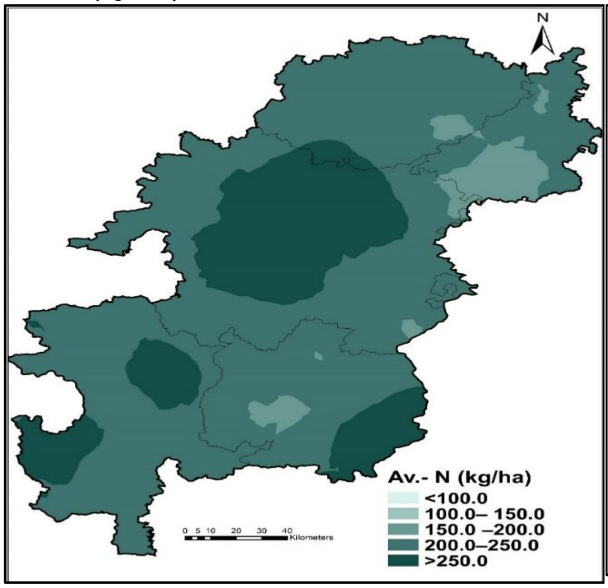

c. SOC (gkg$^{-1}$)



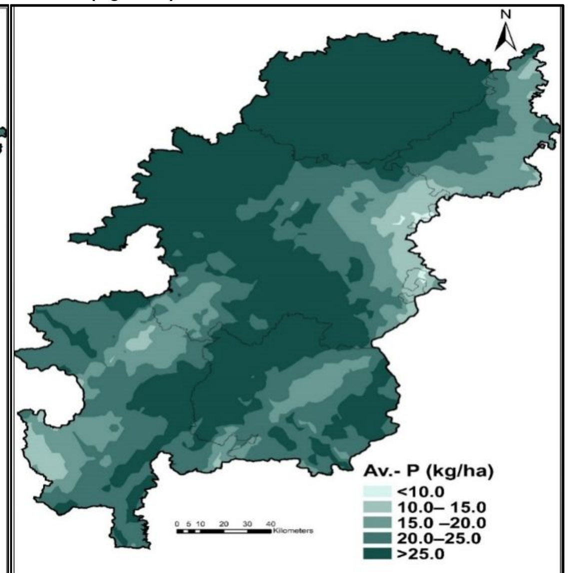

d. $CaCO_3$



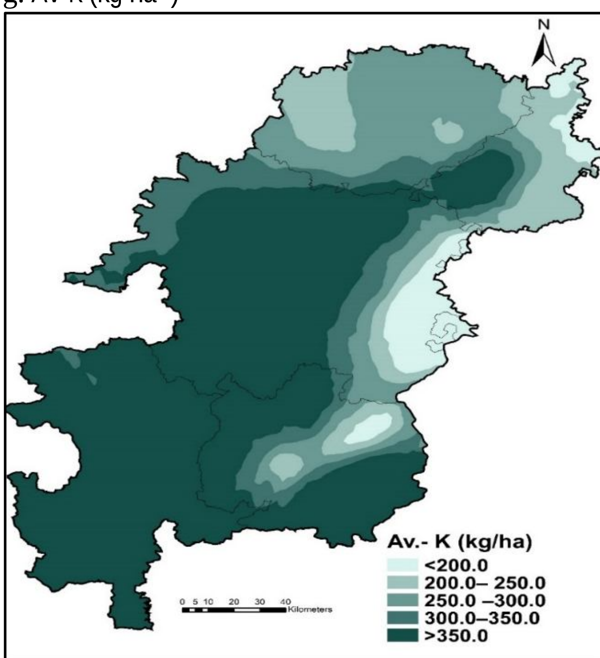
e. Av-N (kg ha$^{-1}$)



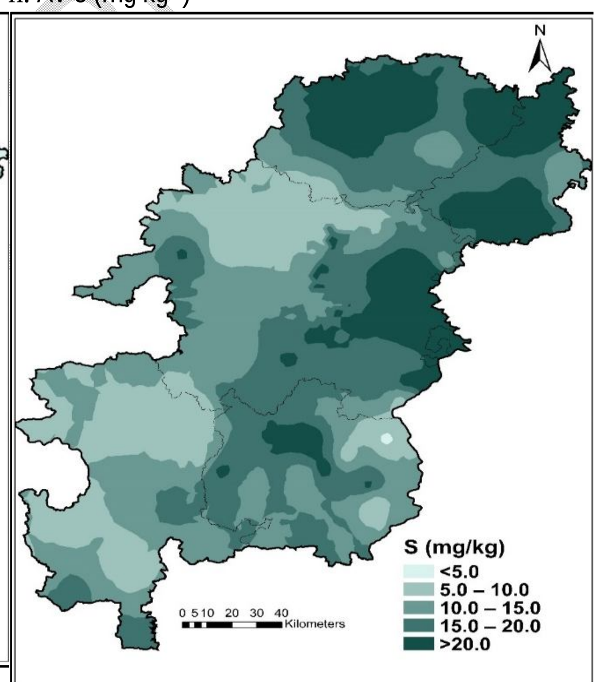

f. Av-P (kg ha$^{-1}$)




g. Av-K (kg ha$^{-1}$)




h. Av-S (mg kg$^{-1}$)



i. Cu (mg kg$^{-1}$) j. Fe (mg kg$^{-1}$)

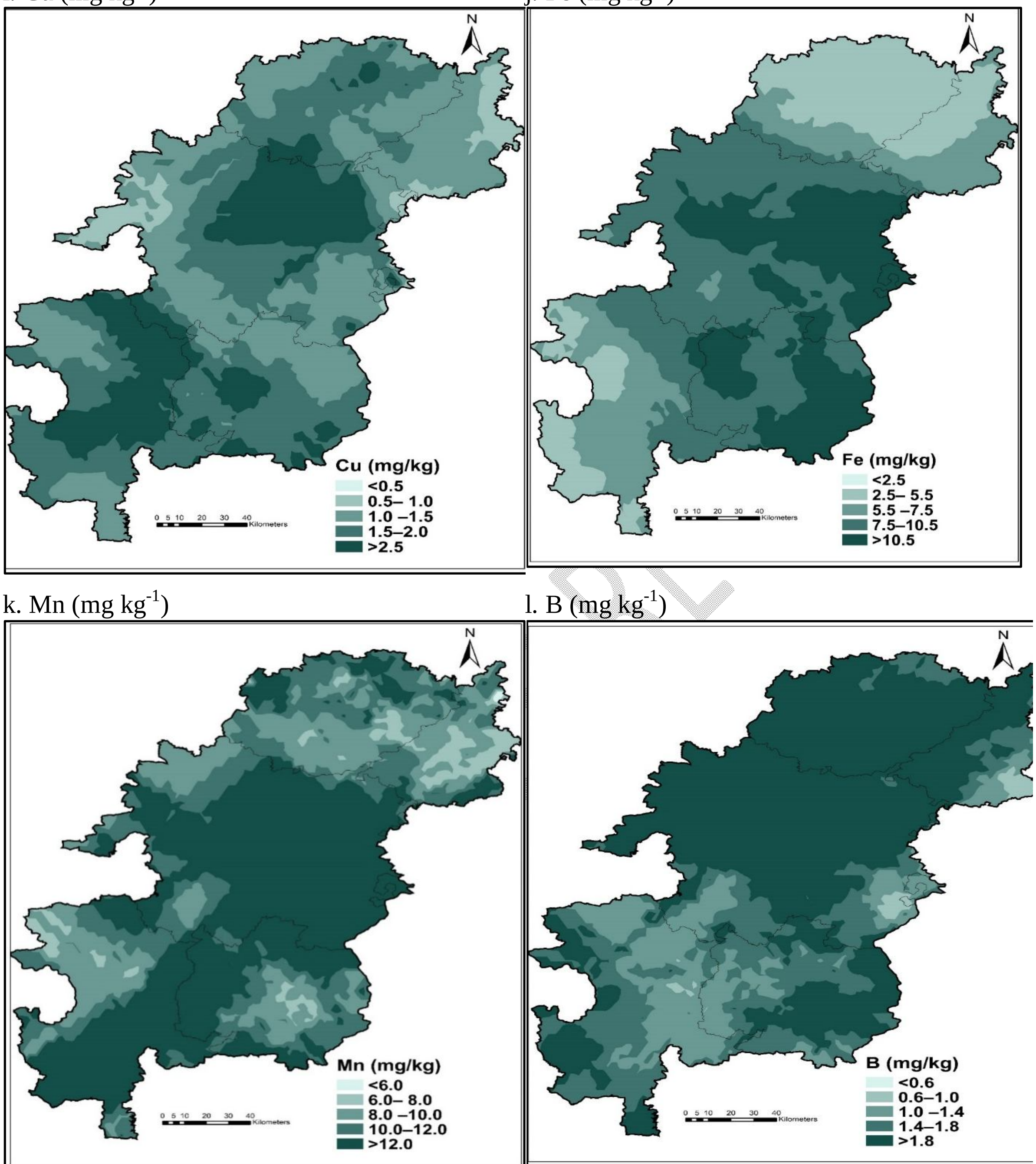



**Fig. 2. Distribution maps of soil properties in the soil generated by ordinary kriging.**

## *Correlation coefficient*

Current studies show that organic carbon has a major impact on soil N, P, K and S. Available P affects DTPA-Zn, DTPA-Fe, DTPA-Cu and DTPA-Mn. Organic carbon and available N and K affected DTPA-Zn only, while available S affected DTPA-Zn and DTPA-Cu. pH and EC showed negative values for DTPA-Zn, DTPA-Fe and DTPA-Mn. CaCO3 did not affect micronutrient availability. All micronutrients have been shown to be significantly and positively correlated with each other. Non-significant relation was due to narrow range of data (table -3).

**Table 3. Correlation coefficient in fertility parameters of division**

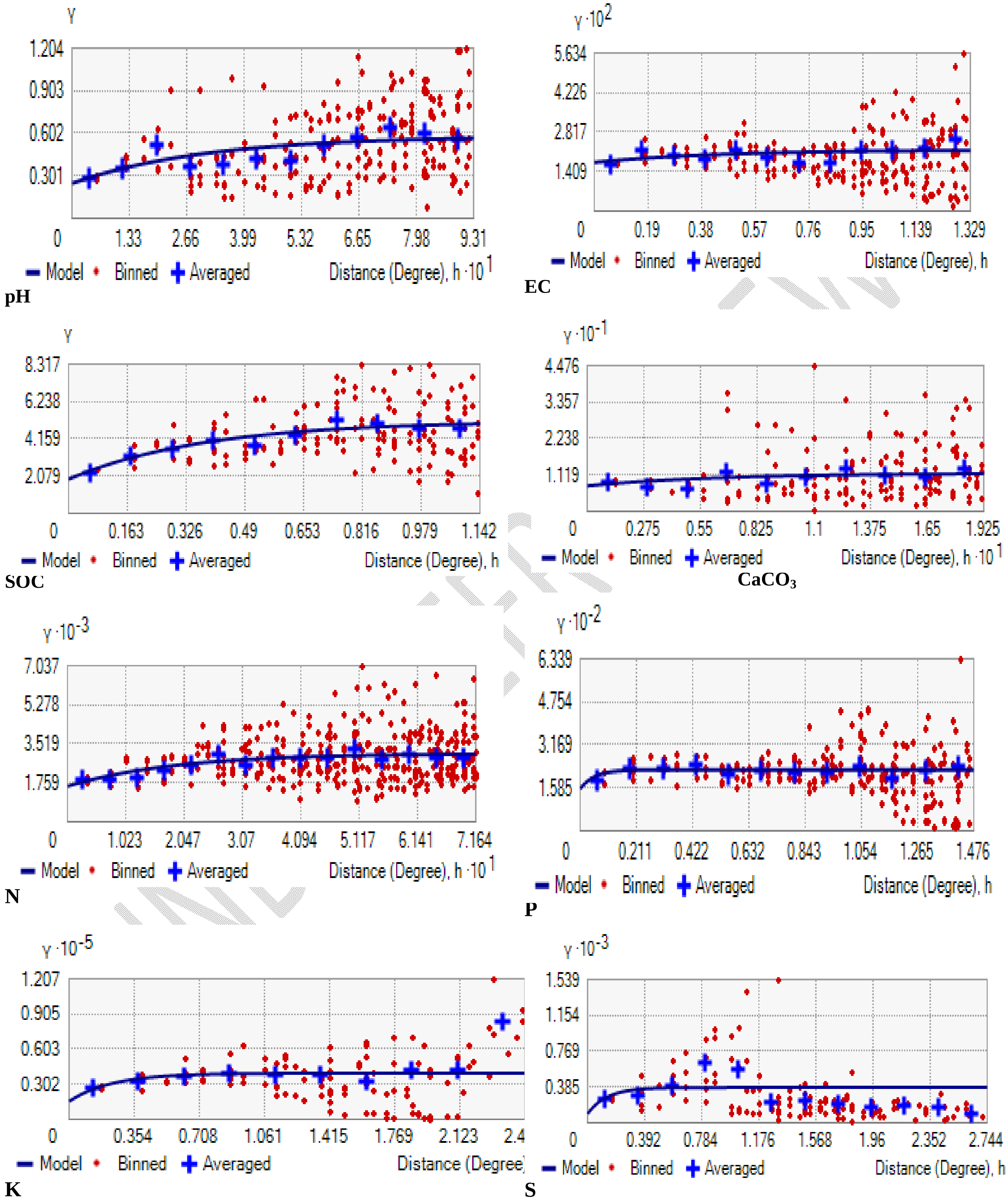
| Parameters | pH | EC | OC | CaCO3 | N | P | K | S | Cu | Zn | Fe | Mn | B |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **pH** | 1.000 | | | | | | | | | | | | |
| **EC** | **0.270**** | 1.000 | | | | | | | | | | | |
| **OC** | -0.055 | -0.028 | 1.000 | | | | | | | | | | |
| **CaCO3** | **0.211**** | **-0.160*** | 0.104 | 1.000 | | | | | | | | | |
| **N** | 0.076 | **0.171*** | **0.832**** | 0.085 | 1.000 | | | | | | | | |
| **P** | **0.242**** | 0.068 | -0.059 | 0.151 | 0.006 | 1.000 | | | | | | | |
| **K** | **0.242**** | 0.131 | **0.464**** | **0.211**** | **0.388**** | 0.070 | 1.000 | | | | | | |
| **S** | 0.005 | 0.052 | -0.082 | -0.132 | -0.053 | -0.060 | -0.153 | 1.000 | | | | | |
| **Cu** | -0.021 | -0.101 | 0.131 | -0.070 | **0.195*** | **-0.193*** | 0.101 | **0.169*** | 1.000 | | | | |
| **Zn** | -0.099 | 0.098 | **0.263**** | 0.013 | **0.207**** | **-0.197*** | 0.119 | -0.026 | **0.215**** | 1.000 | | | |
| **Fe** | **-0.479**** | **-0.252**** | **0.261**** | **-0.164*** | **0.199*** | **-0.170*** | -0.016 | 0.053 | **0.374**** | **0.219**** | 1.000 | | |
| **Mn** | **-0.247**** | 0.024 | 0.032 | -0.090 | 0.020 | **-0.161*** | 0.006 | 0.096 | 0.148 | **0.266**** | **0.238**** | 1.000 | |
| **B** | 0.004 | 0.053 | 0.104 | 0.124 | 0.126 | 0.040 | 0.074 | **0.256**** | 0.027 | 0.039 | 0.005 | -0.106 | 1.000 |

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

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

## *Spatial variability analysis*

The semi-variogram was computed, and the most suitable model for capturing the spatial organisation of the various soil attributes was selected. Table 4 displays the findings of the semivariogram study. Except for AP, AK, Fe, and Mn, for which the circular, pentaspherical, and exponential Gaussian models are more suited, the spherical model is the most acceptable theoretical model for most soil parameters. The majority of soil characteristics were found to be consistent with the spherical model, as reported by several authors (Jiang et al., 2012; Liu et al., 2008; Lopez-Granados et al., 2002). Soil qualities are shown to be spatially autocorrelated, with structural variables including proximity to streams or rivers, parent material, mangrove ecosystem features, and water table depth, and human-induced factors include agricultural management methods, soil, and fertiliser. The geographic associations between soil attributes were established by the applications and the dominant farming techniques in the research region (Goovaerts, 1998). The knob-to-sill ratio was adjusted for the studied soil characteristics (Table 3). The nugget and slab's interaction exemplifies how soil qualities vary from one location to the next (Cambardella et al., 1994). The criteria used in this research are quite similar to those described by Cambardella et al (1994). A low ratio (below b25%) indicates that the variable is very geographically dependent. If the ratio is between 25% and 75%, the variable has moderate dependency; otherwise, it has weak spatial dependence. Strong spatial dependency was seen for soil EC, AP, Fe, and Cu in this research; this was ascribed to the synergistic impact of proximity to the sea and the mangrove environment. Due to the many rivers, streams, and natural alluvial materials in this area, substantial hydrological processes occur. Some soil parameters showed moderate spatial dependency, which may be related to fertilisation and soil management activities. Jiang et al. (2012) and Amirinejad et al. (2011) found comparable findings. Moreover, AN, AP, AK, and Mn have high concentrations that may be linked to biological processes including naturally occurring disturbances in mangrove ecosystems, hydrological variances, nutrient cycling, and small-scale biotic and abiotic interactions, which are particularly visible in the research region. Figure 2 shows soil property distribution maps. In the scrub forest and surrounding surroundings, most soil nutrients and SOC were high, while in other sections of the research area where most of them were planted, they were low. Even though these agricultural soils were deficient in nutrients or used less inorganic fertilizers and unprotected multi-species field management, leaf litter and enhanced biological activity improved mangrove nutrient content. The map gives quantitative information on nutrient content that may be utilized to execute site-specific nutrient management suggestions and multi-rate fertilizer application methods to achieve maximum rice production and yield, boosting farmer incomes by minimizing input costs.


γ
1.204
0.903
0.602
0.301
0
1.33
2.66
3.99
5.32
6.65
7.98
9.31
Model
Binned
Averaged
Distance (Degree), h ·10^1
pH
γ ·10^2
5.634
4.226
2.817
1.409
0
0.19
0.38
0.57
0.76
0.95
1.139
1.329
Model
Binned
Averaged
Distance (Degree), h
EC
γ
8.317
6.238
4.159
2.079
0
0.163
0.326
0.49
0.653
0.816
0.979
1.142
Model
Binned
Averaged
Distance (Degree), h
SOC
γ ·10^-1
4.476
3.357
2.238
1.119
0
0.275
0.55
0.825
1.1
1.375
1.65
1.925
Model
Binned
Averaged
Distance (Degree), h ·10^1
CaCO3
γ ·10^-3
7.037
5.278
3.519
1.759
0
1.023
2.047
3.07
4.094
5.117
6.141
7.164
Model
Binned
Averaged
Distance (Degree), h ·10^1
N
γ ·10^-2
6.339
4.754
3.169
1.585
0
0.211
0.422
0.632
0.843
1.054
1.265
1.476
Model
Binned
Averaged
Distance (Degree), h
P
γ ·10^-5
1.207
0.905
0.603
0.302
0
0.354
0.708
1.061
1.415
1.769
2.123
2.4
Model
Binned
Averaged
Distance (Degree
K
γ ·10^-3
1.539
1.154
0.769
0.385
0
0.392
0.784
1.176
1.568
1.96
2.352
2.744
Model
Binned
Averaged
Distance (Degree), h
S

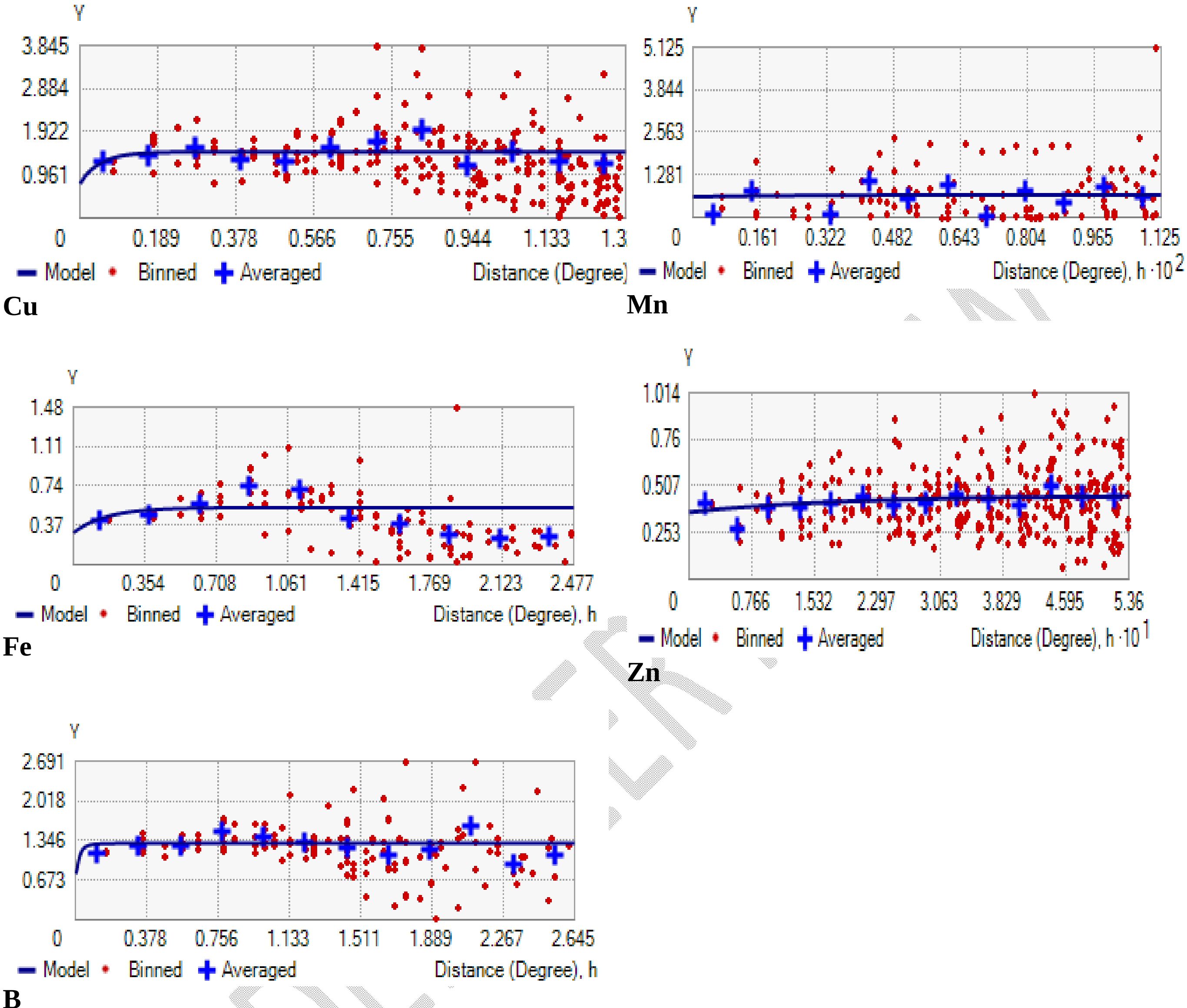



Fig. 3. Experimental semi-variograms and their fitted models fora. pH, b. EC, c. SOC, d. $CaCO_3$, e.Av-N, f. Av-P, g. Av-K, h. Av-S, i. Zn, j. Cu, k. Mn, l. Fe, m. B

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

| Para-Meters | Trans formation | Model | $C_0$ | C + $C_0$ | Range(km) | $C_0/C+C_0*100$ | Spatial dependence |
|---|---|---|---|---|---|---|---|
| **pH** | Non | Exponential | 0.25 | 0.58 | 0.93 | 42.63 | Moderate |
| **EC** | Non | Exponential | 0.02 | 0.02 | 1.66 | 66.69 | Moderate |
| **SOC** | Non | Exponential | 1.92 | 5.17 | 1.14 | 37.15 | Moderate |
| **$CaCO_3$** | Non | Exponential | 7.92 | 11.81 | 0.19 | 67.05 | Moderate |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **N** | Non | Exponential | 1606.84 | 3082.11 | 0.56 | 52.13 | Moderate |
| **P** | Non | Exponential | 155.90 | 225.84 | 0.16 | 69.03 | Moderate |
| **K** | Non | Exponential | 15601.95 | 39711.67 | 0.69 | 39.29 | Moderate |
| **S** | Non | Exponential | 99.82 | 380.45 | 0.39 | 26.24 | Moderate |
| **Cu** | Non | Exponential | 0.77 | 1.48 | 0.15 | 52.11 | Moderate |
| **Mn** | Log | Exponential | 0.62 | 0.69 | 0.01 | 89.97 | High |
| **Fe** | Log | Exponential | 0.36 | 0.46 | 0.54 | 79.81 | High |
| **Zn** | Log | Exponential | 0.30 | 0.54 | 0.49 | 55.91 | Moderate |
| **B** | Non | Rational Quadratic | 0.79 | 1.30 | 0.09 | 60.42 | Moderate |

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

For the five micronutrients with low MSE values, the best fit model is exponential (Table 4). The highest nugget (representative microvariability) for Zn, Mn, which accounts for the fact that the selected sampling area does not capture the spatial dependence well. For Mn, Fe, Zn, B, and Cu, the nugget to sill ratio values were 0.62, 0.36, 0.30, 0.79, and 0.77, respectively, indicating substantial regional dependency. This is attributable to soil pH, EC, SOC, mineralogy, and management considerations including fertilisation. Samples fewer than the interval are geographically associated, whereas samples bigger than the interval are spatially uncorrelated. Wide ranges imply measured soil property values affected by natural and anthropogenic ranges . These soils may have varied Zn, Cu, Mn, Fe, and B values owing to raw materials, climate, and land management. This research revealed values of 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 (Behera et al., 2012). The term "ecosystem" refers to a group of people who work in the construction industry. The semivariogram ranges Zn, Cu, Mn, Fe, and B recommend soil sampling in comparable locations. The sample interval should be less than half the semi-variogram interval (Kerry and Oliver, 2004). So, future research intending to define the spatial dependency of Zn, Cu, MnFe, and B in comparable locations should sample soils at shorter distances than this study.

***Principal component analysis***

The 10 soils characteristics that were taken into consideration for this research all have a strong link with one another. To aggregate and summarise the variability across the 10 variables, a principal component analysis (PCA) was carried out. The principal components that yielded eigenvalues more than 1 and a cumulative contribution rate greater than 60% were kept. Table 5 displays the various maps for the three different PCs. The eigenvalues for these three PCs are

N1, showing that one PC explains more variation than one characteristic (Sharma, 1996). pH, EC, AK, and AP dominated principal component 1 (PC 1), which explained 34.61 percent of the overall variation (Table 4). The second main component, often known as PC 2, is responsible for explaining an extra 13.33% of the overall variance, whereas the SOC is the most important component. Copper was the third principal component (PC 3), which was responsible for explaining an extra 12.33% of the overall variation. In conclusion, the principal component analysis takes the 10 variables and combines them into three main components. These principal components account for the majority of the overall geographic variability in these attributes.

**Table-5 Principal Component analysis of the division**

| Principal Components | PC1 | PC2 | PC3 | PC4 | PC5 |
|---|---|---|---|---|---|
| **Total** | 2.541 | 2.190 | 1.354 | 1.244 | 1.019 |
| **% of Variance** | 19.544 | 16.844 | 10.413 | 9.568 | 7.839 |
| **Cumulative %** | 19.544 | 36.387 | 46.801 | 56.369 | 64.208 |
| **pH** | -0.229 | 0.685 | 0.265 | -0.094 | 0.282 |
| **EC** | -0.027 | 0.348 | 0.605 | -0.510 | -0.175 |
| **OC** | 0.817 | 0.339 | -0.143 | 0.053 | -0.257 |
| **$CaCO_3$** | 0.021 | 0.449 | -0.339 | 0.340 | 0.581 |
| **N** | 0.765 | 0.419 | 0.029 | -0.001 | -0.287 |
| **P** | -0.261 | 0.442 | -0.092 | 0.157 | -0.148 |
| **K** | 0.465 | 0.562 | -0.063 | -0.091 | 0.139 |
| **S** | -0.005 | -0.223 | 0.696 | 0.410 | 0.025 |
| **Cu** | 0.478 | -0.252 | 0.216 | 0.152 | 0.325 |
| **Zn** | 0.529 | -0.116 | 0.148 | -0.289 | 0.378 |
| **Fe** | 0.574 | -0.528 | -0.158 | 0.177 | -0.140 |
| **Mn** | 0.308 | -0.406 | 0.130 | -0.343 | 0.334 |
| **B** | 0.135 | 0.164 | 0.416 | 0.632 | -0.035 |

### 3.4. Clustering analysis for delineating management zones

The principal component (PC) scores for the first three PCs were imported into FuzME management zone analysis software to classify the three PCs into MZs, where a c-method fuzzy clustering algorithm was performed. The IPT and NCE values are plotted against the number of classes in Figure 3. The optimal number of clusters is determined when each index represents at least the smallest membership share (CCT) or largest organizational size (NCE) as a result of the clustering process. Clustering the two computers produces the best sum of the three cluster classes. The resulting MZ map is shown in Figure 3. Analysis of variance was performed to evaluate whether using a combination of PCA and fuzzy clustering algorithms to determine MZ could effectively characterize the spatial variability of soil properties. The heterogeneity of soil chemical properties among different MZs is evident from the analysis (Table 3). Regarding pH, EC, Fe, Zn and Mn there were significant and significant differences (Pb 0.05) between the three MZs. For AK, AP and AN, significant differences were recorded between MZ 1 and MZ 3. The created MZ can be an important and user-friendly rice field management information base for location specific nutrient management in the study area that farmers only use their traditional knowledge in growing rice. For example, MZ 3 has the lowest AP level, so increasing the application rate of phosphorus fertilizer will increase rice productivity. However, given the small-scale and temporal variability, soil-based static MZ may not be sufficient to apply variable fertilization, especially for nitrogen (Ye et al., 2006). Combining MZ delineation with real-time remote sensing data during the harvest season may be a better method for site-specific N management (Song et al., 2007). Further studies are needed to determine the MZs based on the temporal variation or stability of soil properties and also to evaluate the growing conditions of plants in the field by evaluating the cultivation pattern and calendar of the study area.

**3.5. Three management zones developed based on soil fertility**

Figure 3 shows a management zone map showing the three fertility management zones. To evaluate the effectiveness of using a combination of PCA and fuzzy clustering algorithms to characterize the spatial variation of soil nutrient properties to define MZ, a t-test was performed. This analysis shows that the three MZs created are very different from each other, as other researchers have also noted (Davatgar et al., 2012; Xin-Zhang et al., 2009). Analysis of variance showed statistically significant differences between the three MZs for each property (Table 4). The reason for the low AN content in zone 1 can be attributed to continuous rice cultivation without the addition of chemical fertilizers. Areas exposed to seawater absorption through small banks during high tides can fertilize the soil with potassium, so potassium deficiency is less common in the study area. Because rice straw is used as animal feed and fuel and also to build shelter huts, little or no straw is incorporated into the soil, resulting in a low organic carbon content in zones 2 and 3.Zone 1 can be seen as an area that is less affected by soil salinity because seawater intrusion is less than zones 2 and 3 which are surrounded by estuaries and mangroves and are affected by sea salt during high tides. DTPA extractable Fe in all study areas was found to be above the critical upper limit required for rice cultivation. Similarly, the soil content of Zn, Mn and Cu was sufficient to support rice cultivation in the three zones, although the variability of these micronutrients was high across the three zones. Time and related yields must be classified to delineate the different soil management zones. Therefore, future research can rely on spatial data sources such as yield data, crop condition or satellite-derived NDVI data, soil properties and soil characteristics over several years.

## 4. Conclusion

In this study, spatial variations of selected soil properties indicating soil fertility were quantified using geo-statistical tools and aggregated into three management zones through principal component analysis and c-method fuzzy clustering algorithms. The soil fertility indicators measured in this case study indicate that low nitrogen availability appears to be the main constraint for sustainable rice production. Therefore, nitrogen management in this area is very important to increase rice production. Differentiation into three management zones can be very useful for farmers to apply site-specific nutrient management, which meets the criteria of a simple, functional, easy to understand and economically viable management zone. The average soil nutrient value in each zone can be used as a reference for variable rate fertilization. Complex field assessments and fertilizer recommendations may not be justified in terms of time, benefits or economy. Thus, cluster analysis will reduce within-zone variability, providing the opportunity to identify on-site management zones and perhaps apply site-specific management to maximize agricultural production across the area. Knowledge of these management zones can reduce the amount of soil analysis needed to create application maps for a particular aquaculture operation.

Soils in Gwalior Division were found to be neutral to alkaline reaction, safe in electrical conductivity, low to moderate organic carbon, non-calcareous in nature, the amount of N deficiency in the soil sample was 66.36% and the amount of excess Cu, Ba, Mn and B in the soil samples are 92.73, 100 and 69.09%, respectively.



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**Highlights**-

I. Study of spatial variability in the soil fertility using geo-statistical approach of the division.
II. Differentiation into management zones may be very useful for farmers to adopt site-specific nutrient management, which satisfies the criteria of management zones to be simple, functional, easy to understand and economically feasible.
III. Complex field assessments and fertilizer recommendations may not be justifiable in terms of time, benefit or economics.
IV. Fertility maps are indicate of site specific nutrient status and is justified site specific nutrient management.