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spatial variability of soil micronutrients in Raichur district of Karnataka

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Abstract
Geostatistical methods can be used to estimate spatial variability of soil characteristics and soil nutrients in farmer fields. The study aims to know the spatial variability of four micronutrients (Zn, Fe, Cu & Mn) in farmer fields of Raichur district and to determine the nutrient status at unsampled locations by creating surface maps of soil nutrients for the entire study area. The spatial variability of these soil nutrients was assessed using three semivariogram models: exponential, Gaussian, and stable, and relevant surface maps for the entire district were created using ordinary kriging to determine the nutrient status at unsampled locations. The results showed that the Exponential model provided the greatest fit in all trace elements, with a decreased nugget effect and a wide range. The prediction accuracy of krigged maps was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and goodness of prediction (G), and the exponential model was determined to be the best fit to data. The outcomes of this work will assist farmers and agricultural planners in predicting micronutrient concentrations in soils using geostatistical models.

Keywords: Semivariogram, micronutrient, geo-statistical, spatial variability, estimation

1. Introduction
In intensive agriculture, a lack of soil micronutrients has a negative impact on crop output. Recent Indian studies report extensive deficiency of micronutrients in farms due to regular withdrawal of these nutrients through crop uptake (Shukla *et al*., 2015) [25]. Further, an increased use of chemical fertilizers and high yielding crop varieties alongwith increased cropping intensity in last three decades, deficiency of micronutrients has become a major constraint to production and productivity of rice, wheat and pulses (Behera S.K. *et al.* 2009) [2]. It has been well established that micronutrients in the soil plays a major role in agriculture; still Indian farmers are not paying much attention in their applications. Majority of the Indian farmers do not have the facility of soil testing for their agriculture fields but the knowledge of status of soil in relation to micronutrients content is needed to maintain soil health, plant health as well as human health.

Geostatistical tools are useful to estimate spatial variability of soil properties and soil nutrients at field, catchment as well as regional scales (Tesfahunegn *et al*., 2011) [27]. Geostatistical estimation helps in predicting values at unsampled locations by taking into account the spatial correlation between sampled points. There is not much information on the regional variability of micronutrients in the study area. As a result, the current study was conducted in Raichur district of Karnataka, India for spatial estimation of four soil micronutrients *viz*., Zinc (Zn), Iron (Fe), Copper (Cu), and Manganese (Mn) in absence of any soil testing facility to cater the needs of framers (Kumar *et al*., 2011) [14].

2. Materials and Methods
2.1. Study area and data collection
The study was carried out in Raichur district of Karnataka, India. It is situated in the eastern part of Karnataka and lies between 15^0 09'N and 75^0 46' E. The climate is semi arid and arid. The district has Laterite, Medium Black, Deep Black and Red Loamy soils. The present study covers an area of 8,442 sq kms.

The average rainfall of the district is 681 mm.

The data on 532 geo-referenced soil nutrients of farmer's fields were collected asa part of the Soil Health Card scheme of Government of India. The collected soil sample data contains latitude & longitude of the sample location along with micronutrient status *viz*., Zinc (Zn), Copper (Cu), Iron (Fe), & Manganese (Mn) in the soil. The location map of study area and sample data points is shown in Figure-1.

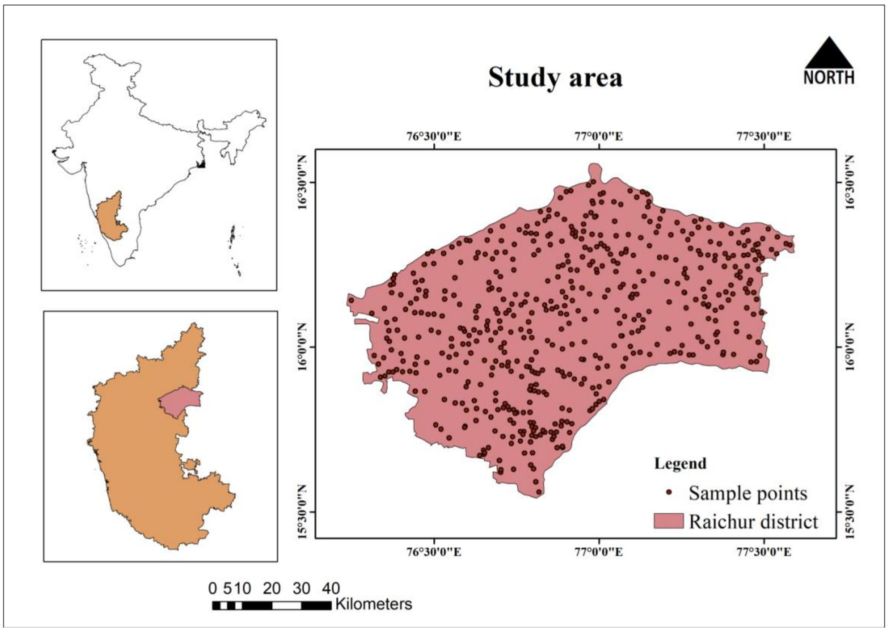


Fig 1: Location map of study are and sample points

2.2 Spatial interpolation method

To estimate the status of micronutrient content at unsampled locations Ordinary Kriging interpolation method was used. Kriging method assumes that the distance or direction between sample points reflects a spatial correlation which can be used to explain variation in the surface. Kriging goes through two step process *viz*., creation of variograms and prediction of unknown values. Before application of ordinary kriging interpolation, semivariogram analyses were carried to determines the interpolation function (Goovaerts, 1998) [8]. Semivariogram depicts the spatial autocorrelation of the measured sample points. In this study, three Semivariogram models *viz*., Linear, Exponential and Guassian were evaluated to select the best fit with the data. The 532 geo-referenced soil sample data were analyzed using ArcGIS 10.4 package to define the semivariograms. The general equation of ordinary kriging is given below (1)

$$\hat{Z}(S_0) = \sum_{i=1}^{N} \lambda_i \, Z(S_i) \tag{1}$$

where, **Z(s$_i$)** = the measured value at the ith location, **λ_i** = an unknown weight for the measured value at the ith location, **s$_0$** = the prediction location, **N** = the number of measured values (Eldrandaly, 2011) [6]

The semivariograms were calculated for the analysis of the spatial variability of micronutrients by using the following equation (2)

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

where y(h) is a experimental semivarince, N(h) is the number of pairs of measured values, Z (X_i) and Z (X_i+h) are the values of regionalized variable at location X_i and X_{i+h} respectively separated by a vector (h) (Dey *et al*. 2017) [4]

In this study, three semivariogram functions *viz*., Exponential, Gaussian & stable were evaluated to select the best fit with the data and the equations of these semivariograms functions were given below (Batistella *et al*. 2014) [1]

A. Exponential Semivariogram model

$$\gamma(h) = c_o + C_1 \left\{1 - \exp\left(\frac{-h}{a}\right)\right\} \tag{3}$$

B. Gaussian Semivariogram model

$$\gamma(h) = c_o + C_1 \left\{1 - \exp\left(-\frac{h^2}{a^2}\right)\right\} \tag{4}$$

C. Stable Semivariogram

$$\gamma(h) = c_o + C_1 \left\{1 - \exp\left(-3\left(\frac{h}{a}\right)^{\theta}\right)\right\} \tag{5}$$

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), 0<θ<2

The spatial dependence ratio (or 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 spatial dependence ratio (also called as nugget effect) 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).

2.3. Prediction accuracy of spatial interpolation maps

The accuracy of the soil maps were evaluated through a cross-validation by using three evaluation indices (Dey *et al*., 2017) [4] were used in this study *viz*., mean absolute error (MAE), root mean square error (RMSE), and goodness of prediction (G). The MAE, MSE, and RMSE measure the accuracy of prediction, whereas (G) measures the effectiveness of prediction. The mathematical equations for the above measures are given below

$$MAE = \frac{\sum_{i=1}^{n} |Z(x_i,y_i) - Z^*(x_i,y_i)|}{n} \quad (6)$$

$$MSE = \frac{\sum_{i=1}^{n} [Z(x_i,y_i) - Z^*(x_i,y_i)]^2}{n} \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} [Z(x_i,y_i) - Z^*(x_i,y_i)]^2}{n}} \quad (8)$$

$$G = \left[1 - \frac{\sum_{i=1}^{n} [Z(x_i,y_i) - Z^*(x_i,y_i)]^2}{\sum_{i=1}^{n} [Z(x_i,y_i) - \bar{Z}]^2}\right] X\ 100 \quad (9)$$

Where, n is the number of observations, ***z* (*x*$_i$, *y*$_i$)** is the observed soil parameter, ***z*(x*$_i$, *y*$_i$)** is the estimated soil parameter, **(*x*$_i$, *y*$_i$)** are sampling coordinates and $\bar{Z}$ is the mean of observed values.

RMSE provides a measure of the error size, but is sensitive to outliers as it places a lot of weight on large errors. MSE suffers the same drawbacks as RMSE. Whereas MAE is less sensitive to extreme values and indicates the extent to which the estimate can be in error. In this study the comparison of performance between interpolations was achieved by using MAE and RMSE, whereas (G) measures the effectiveness of prediction.

3. Results & Discussion

The descriptive statistics *viz*., minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV), skewness and kurtosis values for each analyzed soil property (11 soil parameters) were computed and depicted in table 1. It clearly indicates that there is more variability in soil micronutrients over space in the study area. The variability observed in the nutrient concentrations was largely due to variation in soil parent material, rainfall and soil management (Li *et al*., 2008). The frequency distribution of soil samples in difference concentration for Zinc (A), Iron (B), Copper (C) & Manganese (D) are shown in Figure-2.

Table 1: Statistical summary of micronutrients in soils of Raichur District

Micronutrient	Minimum	Maximum	Mean	SD	CV%	Skewness	Kurtosis
Zn (mg/kg)	0.69	9.47	2.94	1.71	58.16	1.22	1.14
Fe (mg/kg)	0.59	10.13	5.59	2.35	42.04	-0.19	-0.94
Cu (mg/kg)	0.49	10.93	4.42	2.30	52.04	0.36	-0.68
Mn (mg/kg)	0.86	10.45	5.68	2.51	44.19	-0.01	-1.10

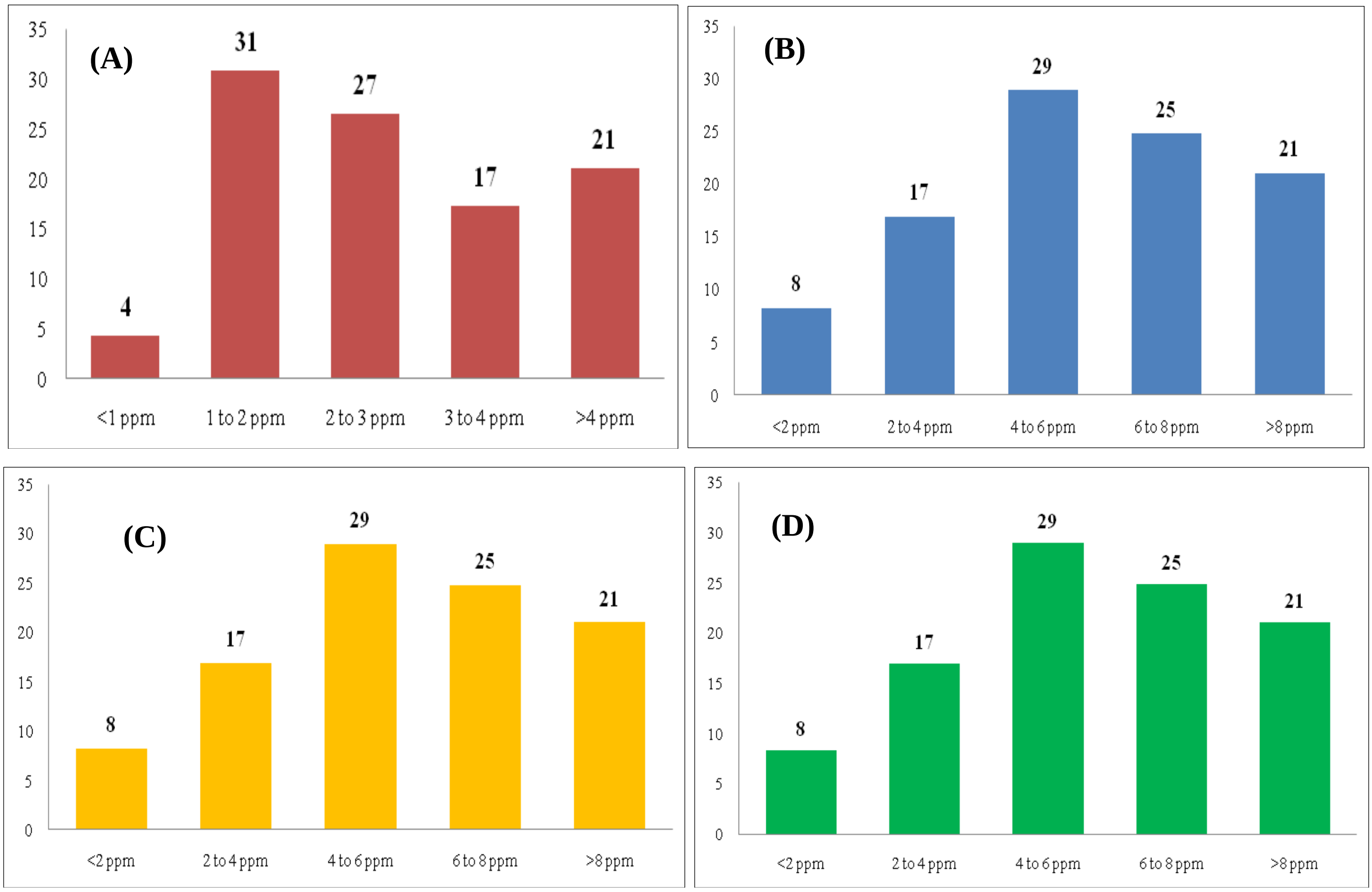


Fig 2: Frequency distribution showing percent soil samples in difference concentration for Zinc (A), Iron (B), Copper (C) & Manganese (D).

In this study, Ordinary kriging is applied to the chosen dataset for all the three Semivariogram models *viz*., Exponential, Gaussian and stable for each micronutrient (Zn, Fe, Cu & Mn) and the results are shown in table 2. The graph of these semivariogram models for each micronutrient (Zn, Fe, Cu & Mn) are shown in Figure-3.

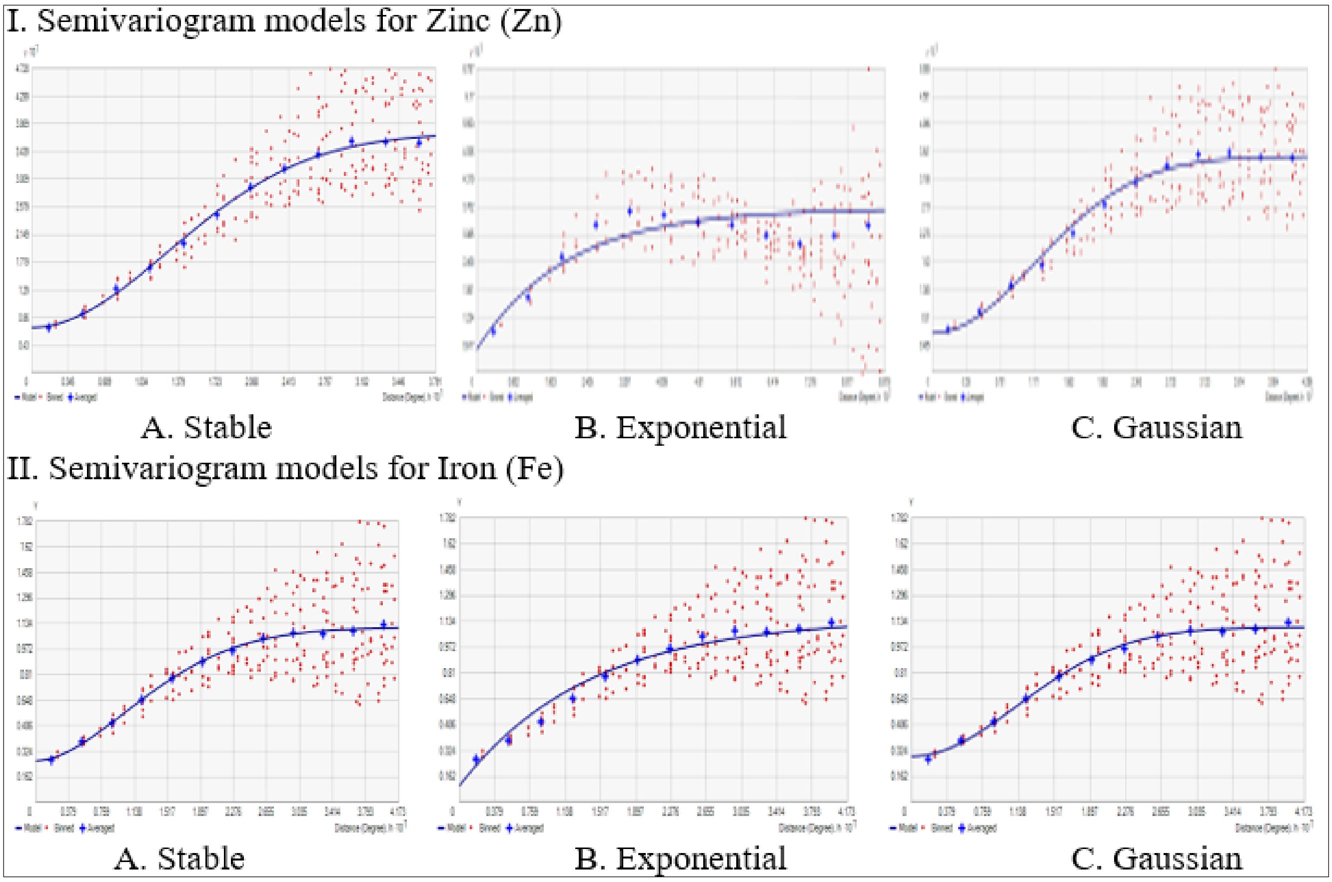
Table 2: Semivariogram models for Soil micronutrients

Micronutrient	Model parameters	Stable	Exponential	Gaussian
Zinc	Spatial Dependence Ratio (N/S)	70.05	14.30	18.26
	Spatial dependence level	Weak	Strong	Strong
	Range (km)	35.45	56.26	31.78
Iron	Spatial Dependence Ratio (N/S)	23.82	9.01	26.22
	Spatial dependence level	Strong	Strong	Moderate
	Range (km)	32.77	46.31	30.70
Copper	Spatial Dependence Ratio (N/S)	25.36	16.34	27.44
	Spatial dependence level	Moderate	Strong	Moderate
	Range (km)	34.01	38.96	31.77
Manganese	Spatial Dependence Ratio (N/S)	25.35	10.01	24.97
	Spatial dependence level	Moderate	Strong	Strong
	Range (km)	22.71	50.49	32.65

Semivariogram depicts the spatial autocorrelation of the measured sample points. The distance where the model first flattens is known as the range. Sample locations separated by distances closer than the range are spatially auto correlated, whereas locations farther apart than the range are not. The value at which the semivariogram model attains the range (the value on the y-axis) is called the sill. The value at which line touch y-axis is called nugget. Variance explained by spatial autocorrelation – partial sill.

Low value of RMSE, N/S ratio and high range indicates higher precision of soil micronutrient estimation by the semivariogram model. The range information in the semivariogram serves as a reference in future soil sampling strategies. The sample interval should be less than half the range of the semivariogram (Kerry and Oliver, 2004) [10]. The findings (Table-2) of three semivariogram models, Stable, Exponential, and Gaussian, show that the Exponential model had the best fit in all trace elements, with a lower nugget effect and higher range values than Stable and Gaussian. Surface maps for all trace elements (Zn, Fe, Cu, and Mn) were generated for the entire district from these models using kriging interpolation, which could be used as a guide for precise and site-specific micronutrient management as well as to know the status of nutrient status at unsampled locations in the study region.

The prediction accuracy of the interpolation technique was assessed using three evaluation indices: mean absolute error (MAE), root mean square error (RMSE), and quality of prediction (G). The study discovered that the prediction accuracy outcomes of the semivariogram models under consideration for soil nutrient quantification (Table-3).



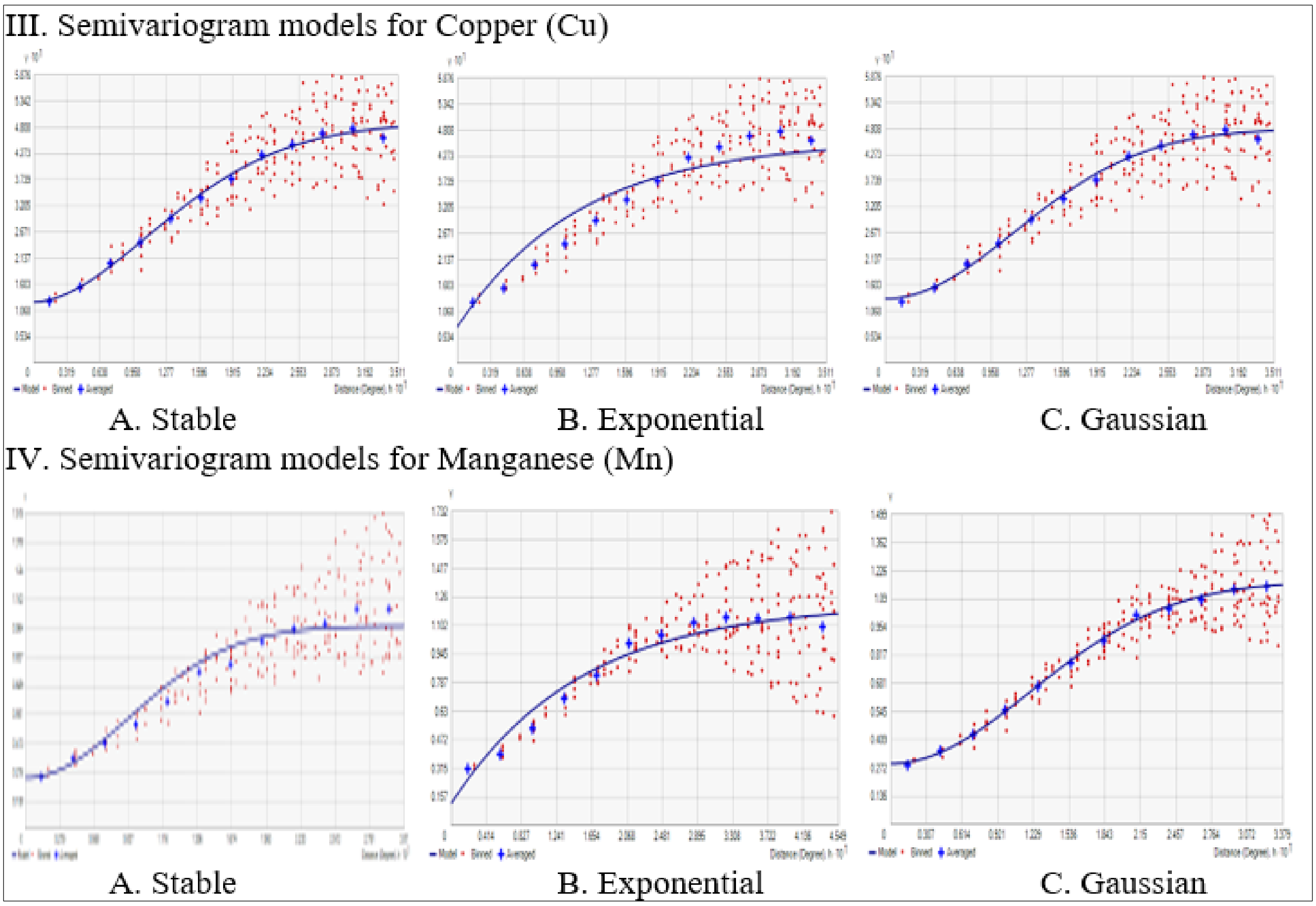


Fig 3: Semivariogram models for Zinc (I), Iron (II), Copper (III) and Manganese (IV)

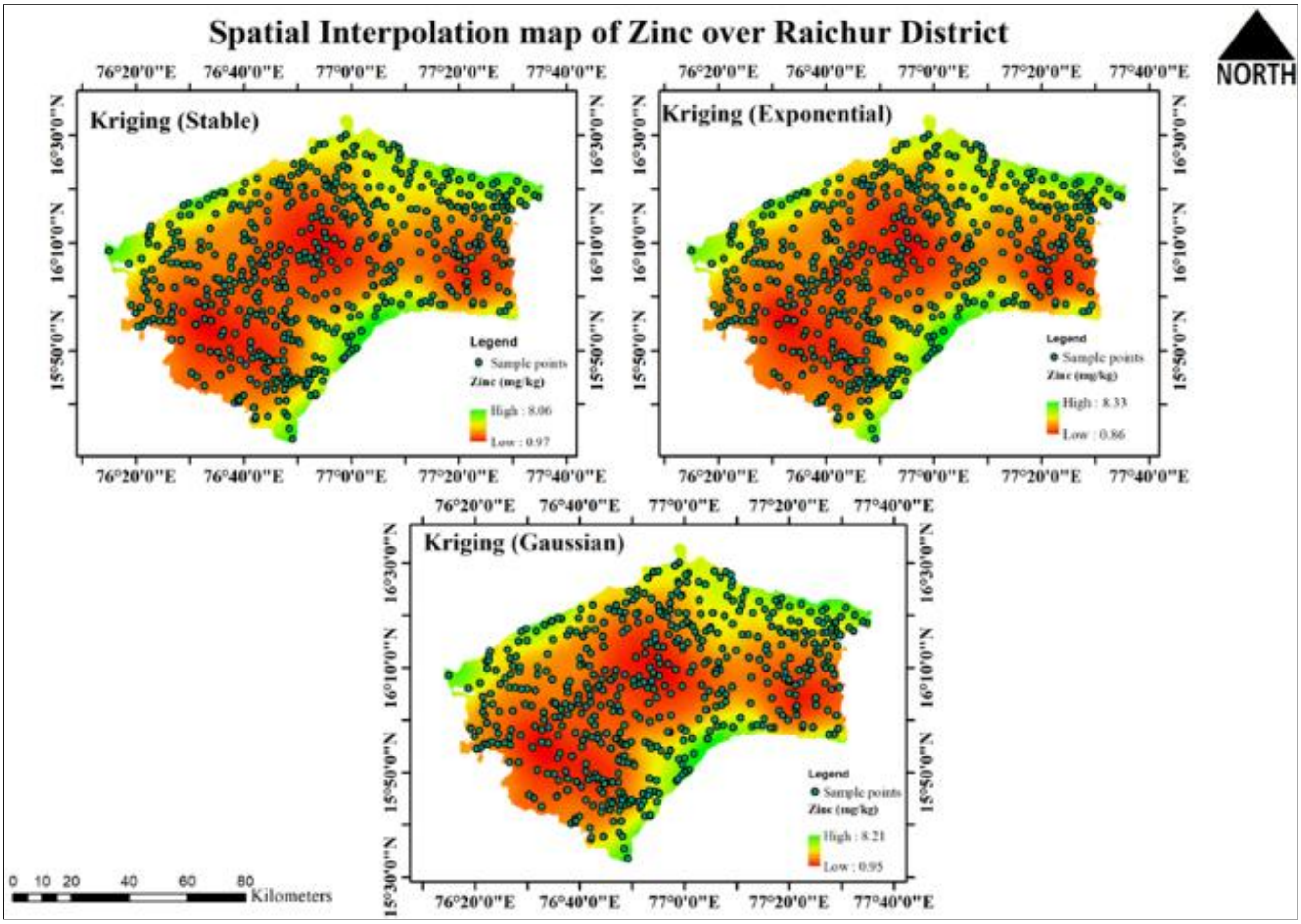


Fig 4: Spatial Interpolation map of Zinc over Raichur District

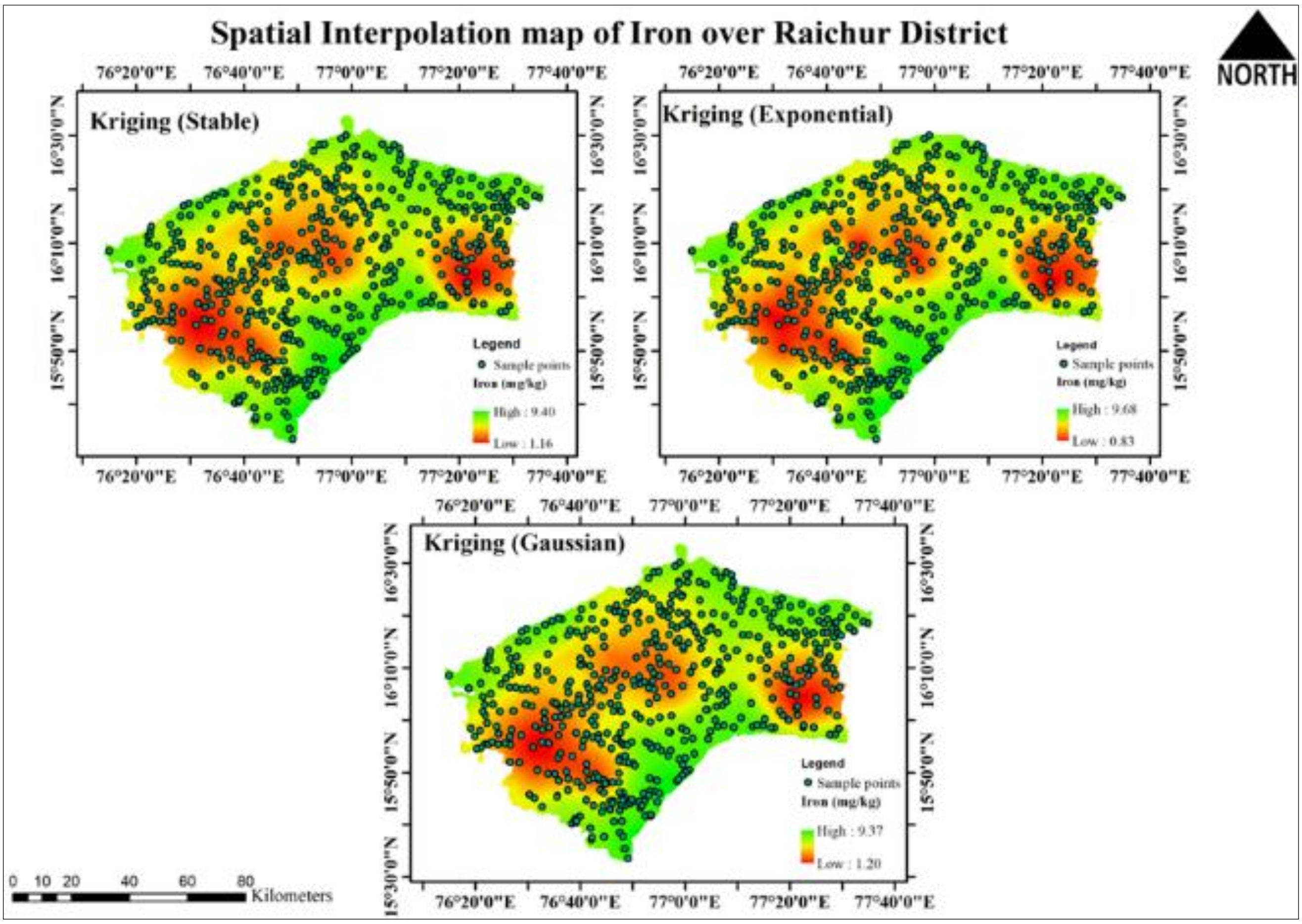


Fig 5: Spatial Interpolation map of Iron over Raichur District

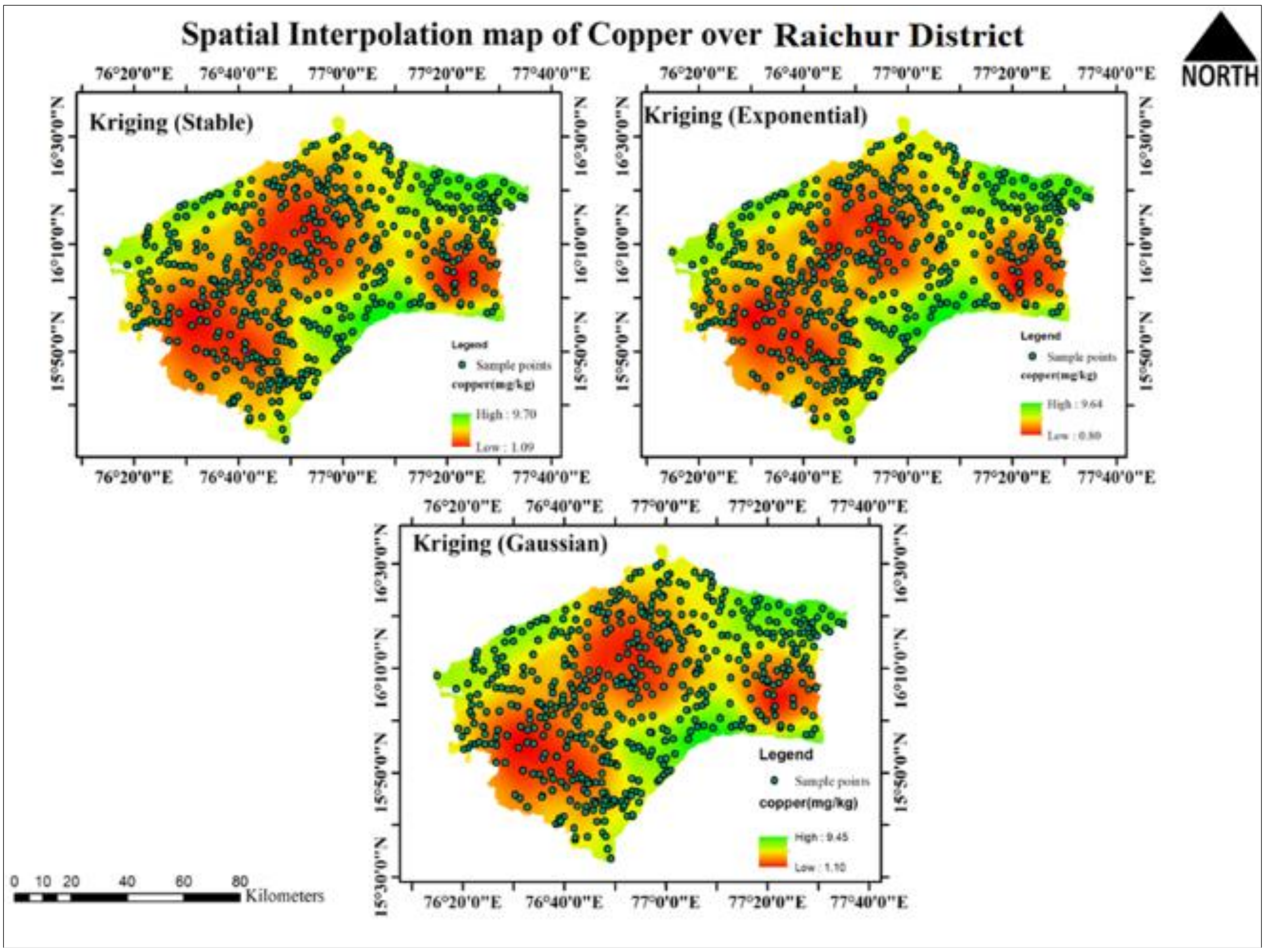


Fig 6: Spatial Interpolation map of Copper over Raichur District

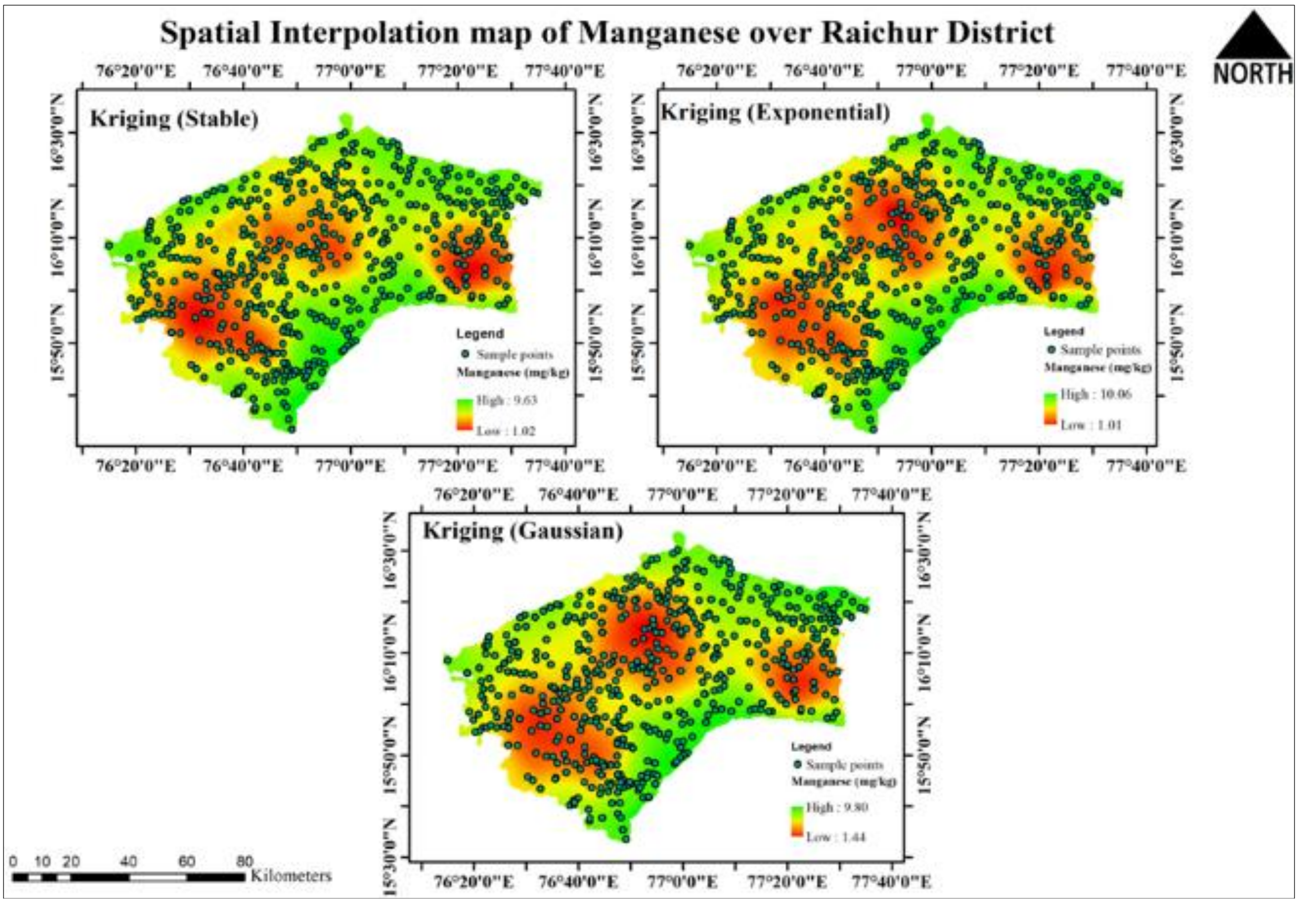


Fig 7: Spatial Interpolation map of Manganese over Raichur District

4. Conclusion

Geostatistical approaches can be used to assess the spatial variability of soil properties and nutrients at the field, catchment, and regional scales. The investigation intends to identify the spatial variability of four micronutrients (Zn, Fe, Cu, and Mn) in farmer fields and the nutrient status at unsampled places by constructing surface maps of soil nutrients for the entire study area. To determine the micronutrient status, three semivariogram models were used: exponential, Gaussian, and stable, and appropriate surface maps were produced for the entire district using ordinary kriging. The results revealed that the Exponential model provided the best fit in all trace elements, with a lower nugget effect and a wide range. The semivariogram's range information will be used as a reference in future soil sampling procedures. The sample interval should be less than half the semivariogram's range. This research will help farmers and agricultural planners to predict micronutrient concentrations in soils using geostatistical models.

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