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Estimation of micronutrients in soil using geo-statistical approach

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Abstract
Deficiency of micronutrients in the soil during the last three decades have been increased because of increased use of chemical fertilizers and high yielding crop varieties along with increased cropping intensity. Farmers must have the knowledge of micronutrients content in their soil to maintain soil health. In this study, an attempt has been made to estimate the soil micro nutrient status using geo-statistical approach for lingsugur block of Raichur district (Karnataka) using 100 soil samples data along with GPS coordinates. The Kriging interpolation method (Krige, 1951) was used for preparing the micronutrients (Zn, Cu, Mn & Fe) maps to show spatial distribution of micronutrients in entire block. The method can be used to estimate the content of micronutrients in unsamples areas of the block.

Keywords: Semivariogram, micronutrient, geo-statistical, nugget, sill, kriging

1. Introduction

Soil is a major component of the Earth's ecosystem. It is a highly heterogeneous mixture of minerals, organic matter, gases, liquids and micro-organisms that together support life of plants and soil micro-organisms. Soil is a three-state system of solids, liquids, and gases. It consists of a solid phase of minerals and organic matter (The soil matrix), as well as a porous phase that holds gases (the soil atmosphere) and water (the soil solution). A typical soil is about 50% solids (45% mineral and 5% organic matter), and 50% voids (Or pores) of which half is occupied by water and half by gas.

Soil is a product of several factors: the influence of climate, relief (elevation, orientation, and slope of terrain), organisms, and the soil's parent materials (original minerals) interacting over time (Gilluly James *et al* 1975) [23].

Soil acts as an engineering medium, a habitat for soil organisms, a recycling system for nutrients and organic wastes, a regulator of water quality, a modifier of atmospheric composition, and a medium for plant growth (Dominati *et al* 2010) [3]. Soil has a wide range of variability in its nutrients composition which plays a major role in determining the sustainable productivity of an agro-ecosystem. The sustainable productivity of a soil mainly depends upon its ability to supply essential nutrients to the growing plants. The deficiencies of these nutrients had become one of the major constraints in sustaining crop production in the present exploitive agriculture in our country.

Plants require 17 nutrients which are essential for its growth. The nutrients nitrogen (N), phosphorous (P) and potassium (K) are called primary nutrients whereas sulphur (S), calcium (Ca) and Magnesium (Mg) are known as secondary nutrients. Out of 17 nutrients, eight are required in small quantities and hence called micronutrients such as iron (Fe), boron (B), zinc (Zn), manganese (Mn), copper (Cu), molybdenum, (Mo), nickel (Ni) and chlorine (Cl). They are also called 'trace elements'. Trace elements mean elements present at low concentrations (mg kg-1 or less) in agro ecosystems (He, Z. L *et al* 2005) [5]. In addition to these 14 nutrients, plants require carbon, hydrogen, and oxygen, which are extracted from air and water to make up the bulk of plant weight.

Deficiency of micronutrients in the soil during the last three decades have been increased because of increased use of chemical fertilizers and high yielding crop varieties alongwith increased cropping intensity (Behera S.K. *et al* 2009) [1]. This has become a major constraint to production and productivity of rice, wheat and pulses. 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.

In absence of any soil testing facility, attempts may be made to forecast and estimate soil micronutrients contents to cater the needs of Indian agriculture (Kumar *et al*., 2011) [10].
Considering all the above facts, a study was conducted to predict the status of micro nutrients (Zn, Cu, Fe & Mn) in soils of Lingsugur block of Raichur district (Karnataka). Prediction models are used to provide an aid to decision-making and it can be used for recommending judicious applications of micronutrients for sustainable soil management.

2. Research Methodology

Secondary data on soil nutrient status mentioned in Soil Health card issued to farmers of Lingsugur block of Raichur District (Karnataka) during the second cycle (2017-18) of Soil Health Card scheme were collected. A total of 100 soil samples data from the Lingsugur block were collected for 11 soil parameters *viz*., PH, Electronic Conductivity (EC), Organic carbon (OC), Nitrogen (N), Phosphorous (P), Potassium (K), Sulphur (S), Zinc (Zn), Copper (Cu), Iron (Fe), & Manganese (Mn) along with GIS coordinates (latitudes & longitudes). However, in this study, spatial estimation is done for four micronutrients elements (Zn, Fe, Cu & Mn).
The present study covers an area of 1967 sq kms, covering 181 villages.with an annual rainfall of 608 mm. The net sown area of Linsgsugur taluk is 1,33,781 ha with net irrigated area of 36,732 ha (Source: District at Glance 2009-10, Govt of Karnataka)
Geo-statistics is based on spatial correlation between observations or samples and this correlation can be expressed with mathematical model which called variogram. The experimental semivariograms were calculated for the analysis of the spatial variability of micronutrients by using the following equation

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

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).

Kriging Interpolation

Kriging interpolation is one of the method in geo-statistical spatial interpolation. It is a powerful tool for determining spatial variability and estimation (Shukla *et al.*, 2015) [17]. The prediction weights in Kriging interpolation (Krige, 1951) [9] are based on spatial dependence between observations modelled by the variogram. Given spatial data Z(s_i) that follows an intrinsically stationary process, *i.e.* having constant unknown mean μ, known spatial covariance function C = (h) for spatial lags h= s_i - s_j and can be written as Z (s_i) = μ + ε(s_i), we typically want to predict values of major micronutrients at unobserved locations, s_o ϵ D. Kriging method gives statistical weight to each observation so their linear structure's has been unbiased and has minimum estimation variance. This estimator has high application due to minimizing of error variance with unbiased estimation. In the case of an intrinsically stationary process with constant unknown mean, the Ordinary Kriging (OK) method is used.

$$\hat{z}(s_0) = \sum_{i=1}^{n} \lambda_i . z(s_i)$$

Now for finding best linear unbiased predictor (BLUP) variance of interpolation error will be minimized. Thus mean square error of variance of an ordinary kriging was calculated using equation:

$$\sigma_{ok}^2 = \sigma^2 - \sum_{i=1}^{N} w_i(cov[Z(s_i), Z(S_o)] - \lambda$$

Where σ_{ok}^2 is variance of Ordinary Kriging, 'w' is vector of weights and λ is lag range multiplier.

For the model fitting to the experimental semivariograms, software package ArcGis 10.4 was used for geostatistical analysis. The semivariogram is the plot of the semivariance against the distance (lag). The shapes of these variograms indicate whether the variables are spatially autocorrelated or not. Nugget (C_0), sill (C_0+C) and range of spatial dependence are the descriptive parameters of semivariograms. The nugget variance (C_0) expresses the variability due to unseen patterns (sampling errors and scales shorter than minimum inter-sample distance). The difference of sill variance and the nugget variance is the structural variance (C). This term accounts for the part of the total variance that can be modelled by the spatial structure. Selection of models was made principally on visual fit, regression coefficient (R^2) and residual sum of square (SSR), which provided an indication of how well the model fits the semivariograms data. The degree of spatial dependence (GD) was calculated using equation

$$GD= (C_0 /C+C_0)*100 \qquad (4)$$

Nugget/sill ratio (called also nugget effect) is regarded as criteria for classifying spatially structured variation for a regionalized variable as well as gives goodness of prediction. The ratio is equal or lower than 25%, variable was considered to be strongly dependent; ratio between 25-75%, then moderately dependent and ratio >75%, weakly dependent. Usually, a strong spatial dependence of soil properties can be attributed to intrinsic factors and a weak spatial dependence can be attributed to extrinsic factors (Shukla *et al.*, 2015) [17]. An ordinary Kriging was used for constructing of soil distribution maps to provide enough estimated data.

3. Results & Discussion

The present study attempts to estimate the status of micronutrients at unsampled locations by using Kriging interpolation method. Management of micronutrient behavior requires an understanding of how soil micronutrients vary across the land. Integrated nutrient management is important for sustainable agricultural production and protecting environment quality and has been widely investigated around the world.
Table-1 describes the semivariogram models and parameters of spatial distribution of soil soil micronutrients (Cu, Fe, Mn & Zn). The C_0 in Table 1 is nugget value or spatial variability arising from the random components. C_0 of Mn was least compared to other micronutrients. In other words, a small nugget effect and close to zero indicates a spatial continuity

between the neighbouring points. Nugget/sill ratio (called also nugget effect) is used to classify spatially structured variation for a regionalized variable as well as gives goodness of prediction. The nugget effect for Fe & Mn were 24.40 & 19.76 respectively which is less than 25% indicates, there is strong spatial dependence. Similarly, the nugget effect for Cu & Zn were 32.85 & 48.44 respectively which is more than 25% indicates, there is a moderate spatial dependence. Therefore, Spatial dependence level of variables was found moderate and strong.

The geostatistical range (called the largest spatial correlation distance) reflected the autocorrelation range of variables and was related to the interaction between various processes of soil properties, which are affected at both observing and sampling scale. The soil micronutrients have spatial autocorrelation within the range; otherwise it does not exist. Similar findings were observed by Wang *et al*. (2008) [21].

The range values of Cu, Fe, Mn & Zn were also small as 0.2344, 0.231, 0.2489 & 0.2375 m, respectively (Table1). The smaller range suggests smaller sampling intervals. Figure 2, Figure 5, Figure 8 & Figure 11 are the semivariogram models for Cu, Fe, Mn & Zn respectively. On the basis of these semivariograms prediction weights were taken for Kriging interpolation method and spatial distribution maps were generated and shown in Figure 3, Figure 6, Figure 9 & Figure 12 for Cu, Fe, Mn & Zn respectively. With the help of these spatial distribution map amount of major micronutrients namely at different unsampled locations of Lingsugur block of Raichur district were estimated.

Figure 1, Figure 4, Figure 7 & Figure 10 shows both predicted and observed values and a line of best fit for Cu, FE, Mn & Zn respectively. Root mean square error or root mean square deviation is one of the most commonly used measures for evaluating the quality of predictions. It shows how far predictions fall from measured true values using Euclidean distance. In other words, Root Mean Square Error (RMSE) tells about how best is prediction model? Lesser the RMSE value indicates best model. The RMSE values shown in table-1 for Cu, Fe, Mn & Zn are 1.4359, 1.3095, 0.8965 & 1.3612 respectively. The RMSE value in Mn is least compared to other micronutrients, indicates best fit model compared to other micronutrients. The results of this study may be used to make recommendations of micronutrients in unsampled areas of Lingsugur Block of Raichur district for maintaining good soil health.

Table 1: Seminvariogram models and parameters of spatial distribution of soil micronutrients

Soil micronutrients	Copper (Cu)	Iron (Fe)	Manganese (Mn)	Zinc (Zn)
Nugget (C_o)	0.3897	0.2990	0.0434	0.5609
Sill (C_o+C)	1.1862	1.2253	0.2196	1.1578
Spatial Dependence Ratio (N/S)	32.85	24.40	19.76	48.44
Range (m)	0.2344	0.2310	0.2489	0.2375
Spatial dependence level	Moderate	Strong	Strong	Moderate
RMS	1.4359	1.3095	0.8965	1.3612

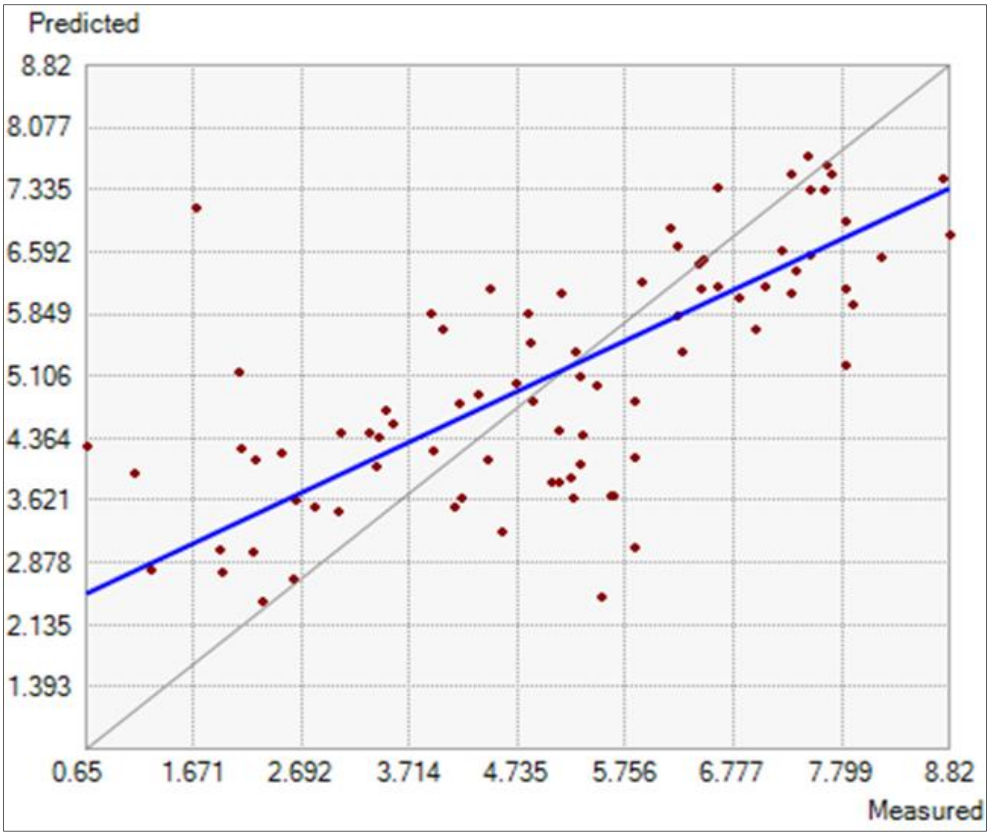
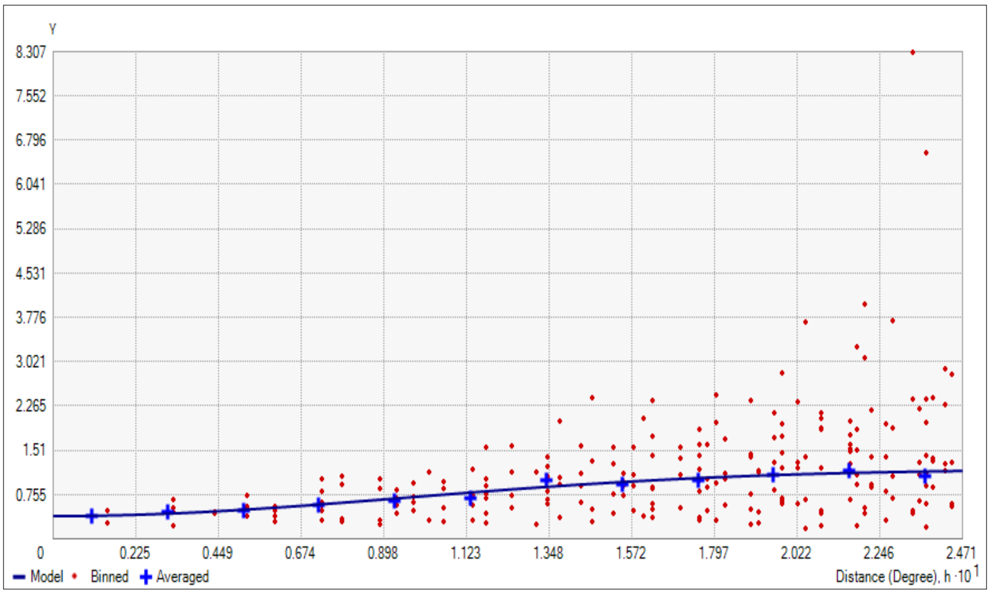


Fig 1: Observed and predicted values of Copper (Cu) in soils of Lingsugur Block



a

Fig 2: Semivariogram model of Copper (Cu) content in soils of Lingsugur block

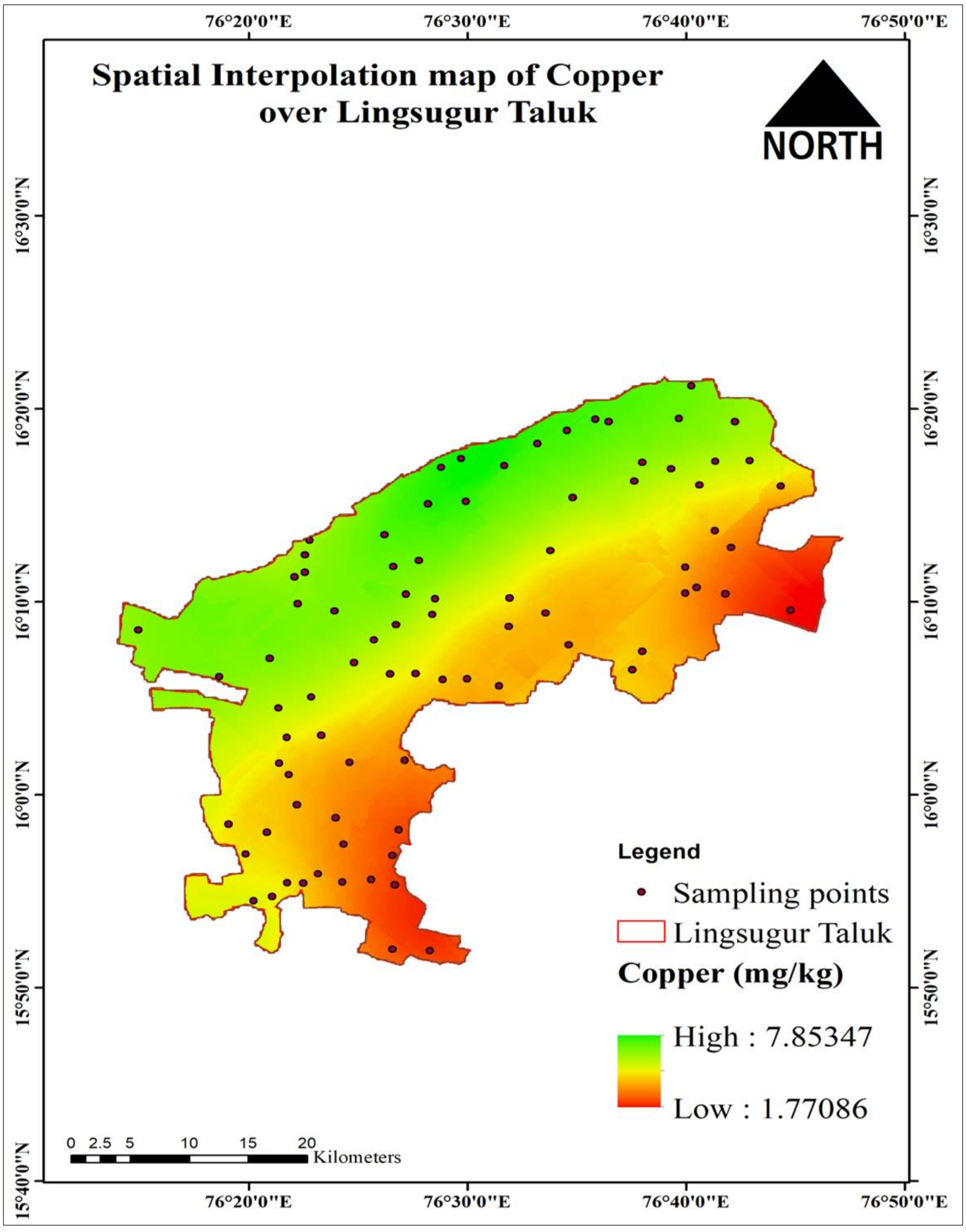


Fig 3: Spatial Interpolation of Copper (Cu) over Lingsugur Taluk

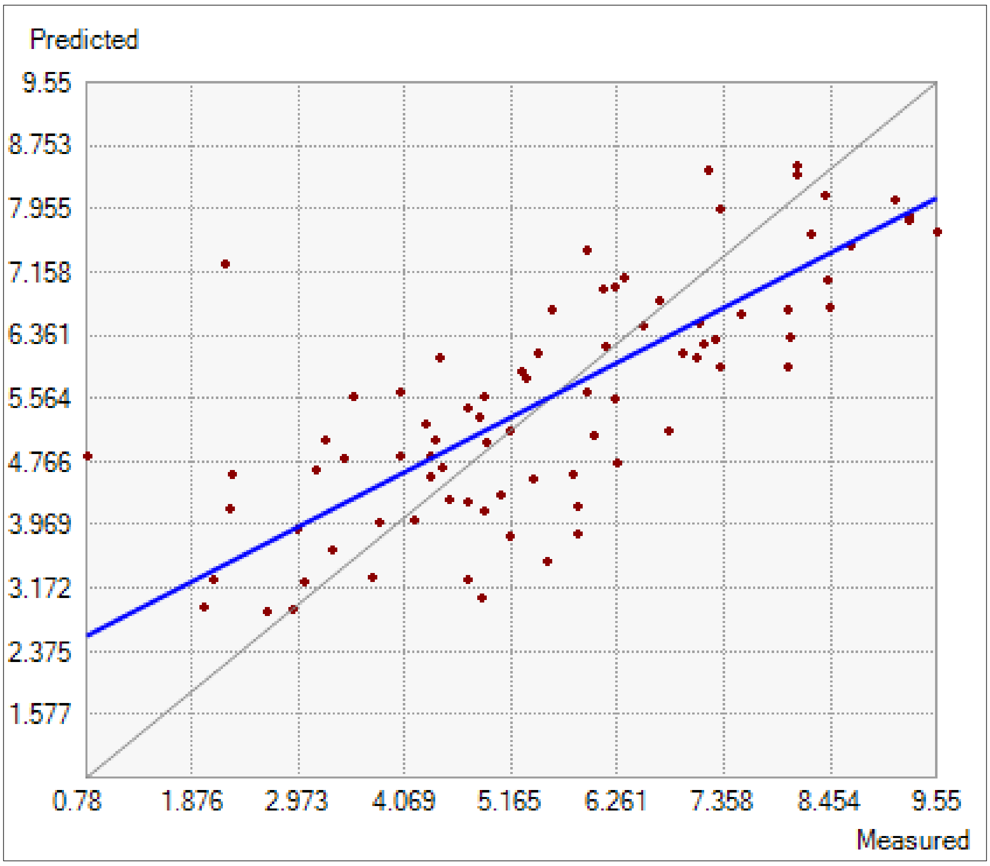


Fig 4: Observed and predicted values of Iron (Fe) in soils of Lingsugur Block

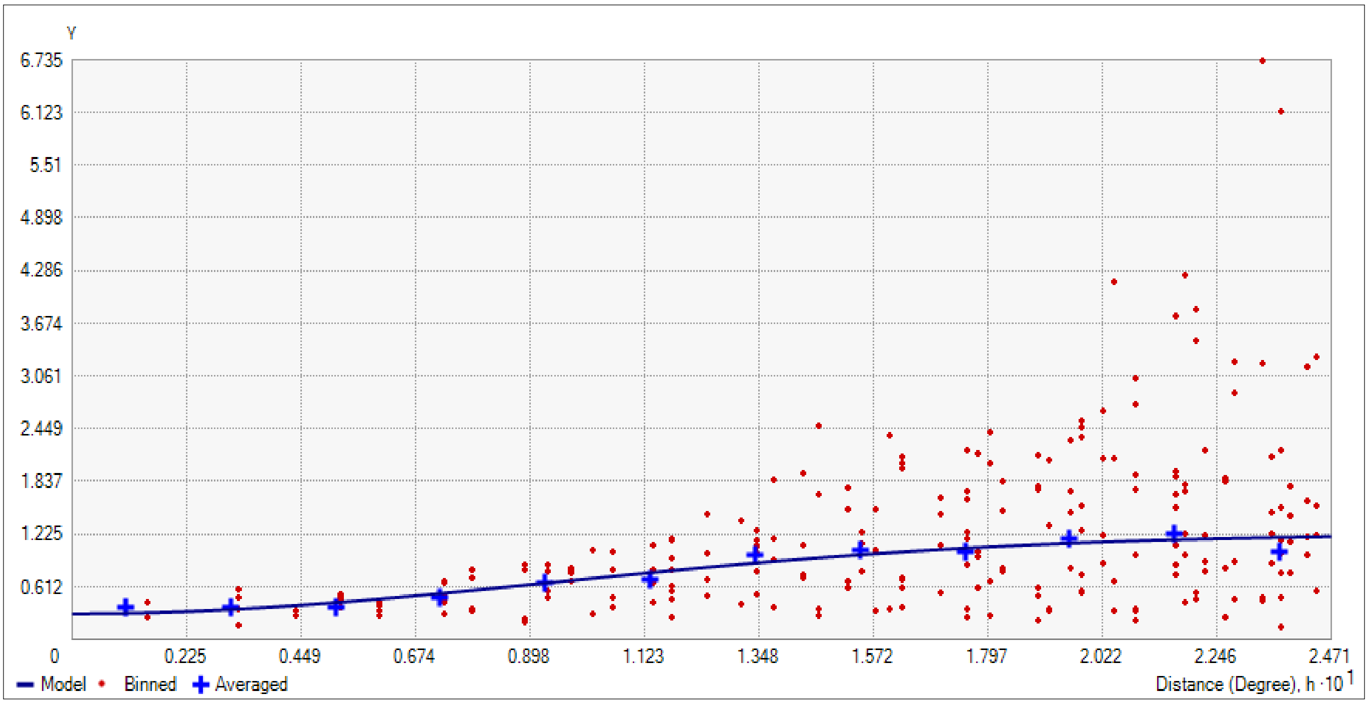


Fig 5: Semivariogram model of Iron (Fe) content in soils of Lingsugur block

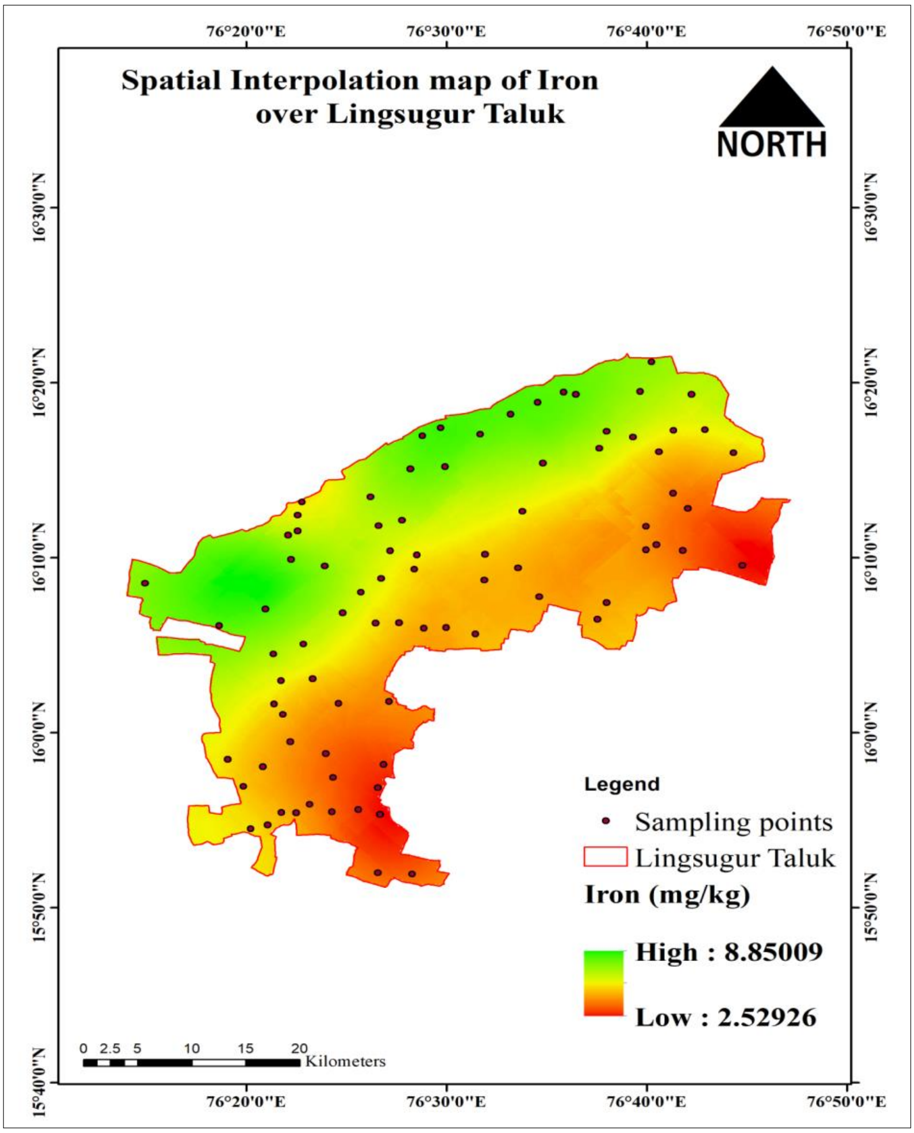


Fig 6: Spatial Interpolation of Feron (Fe) over Lingsugur Taluk

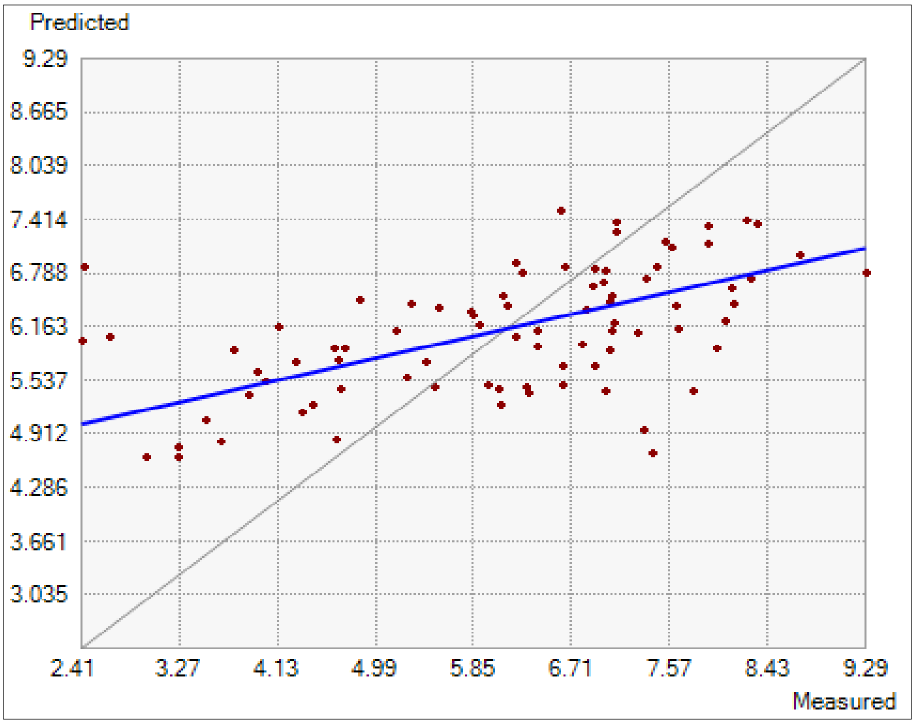


Fig 7: Observed and predicted values of Manganese (Mn) in soils of Lingsugur Block

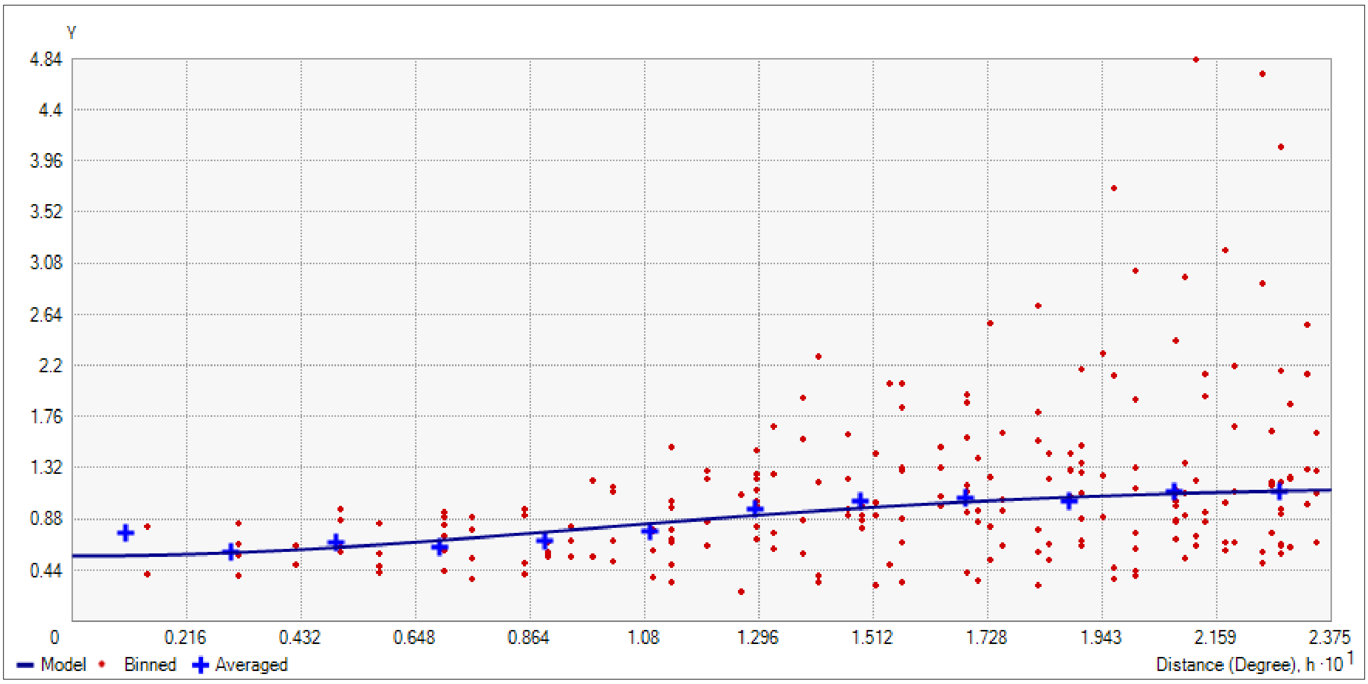


Fig 8: Semivariogram model of Manganese (Mn) content in soils of Lingsugur block

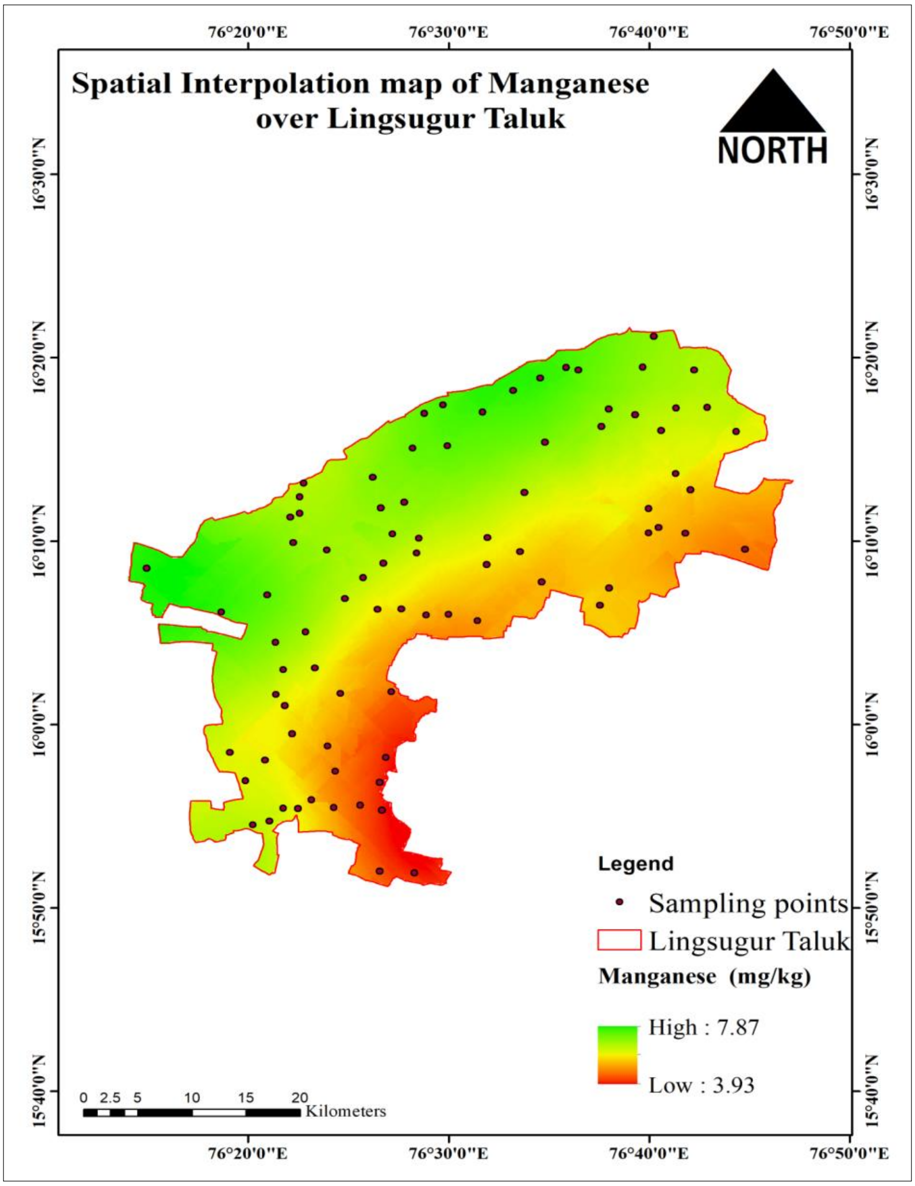


Fig 9: Spatial Interpolation of Manganese (Mg) over Lingsugur Taluk

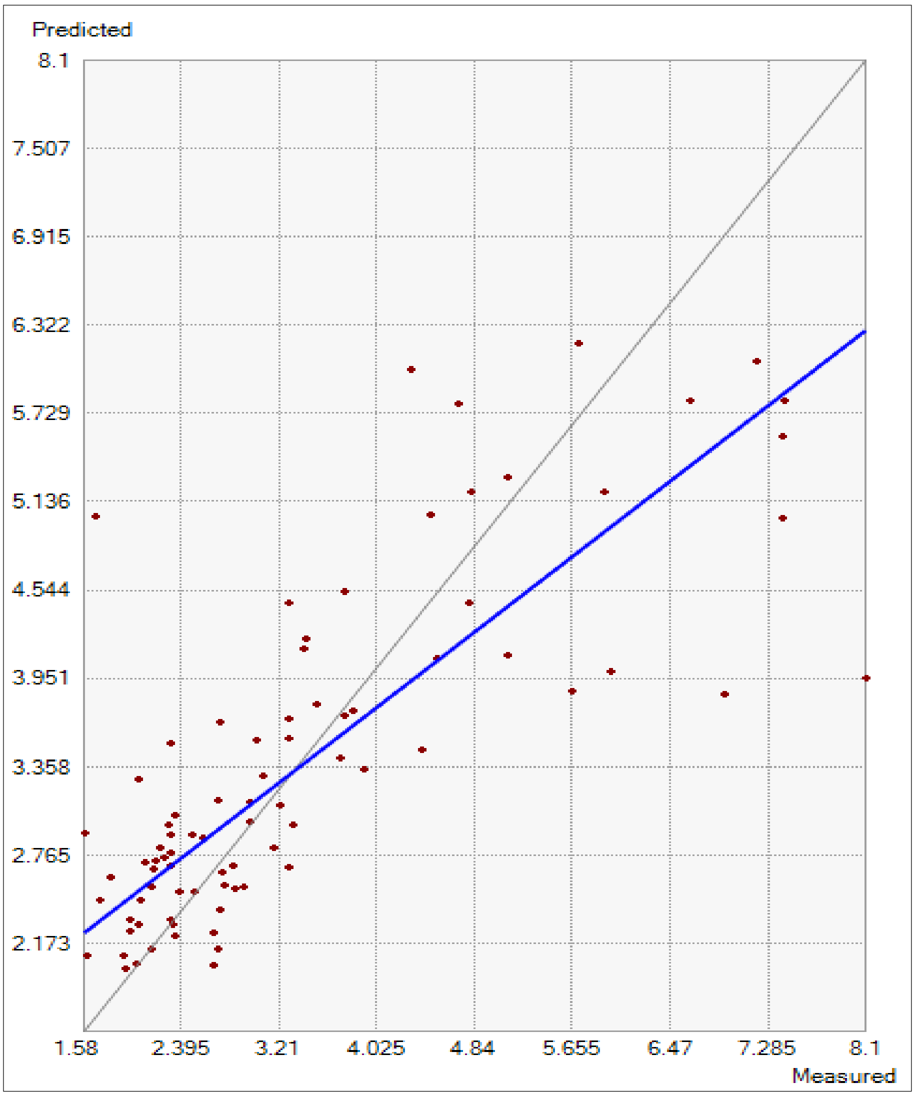


Fig 10: Observed and predicted values of Zinc (Zn) in soils of Lingsugur Block

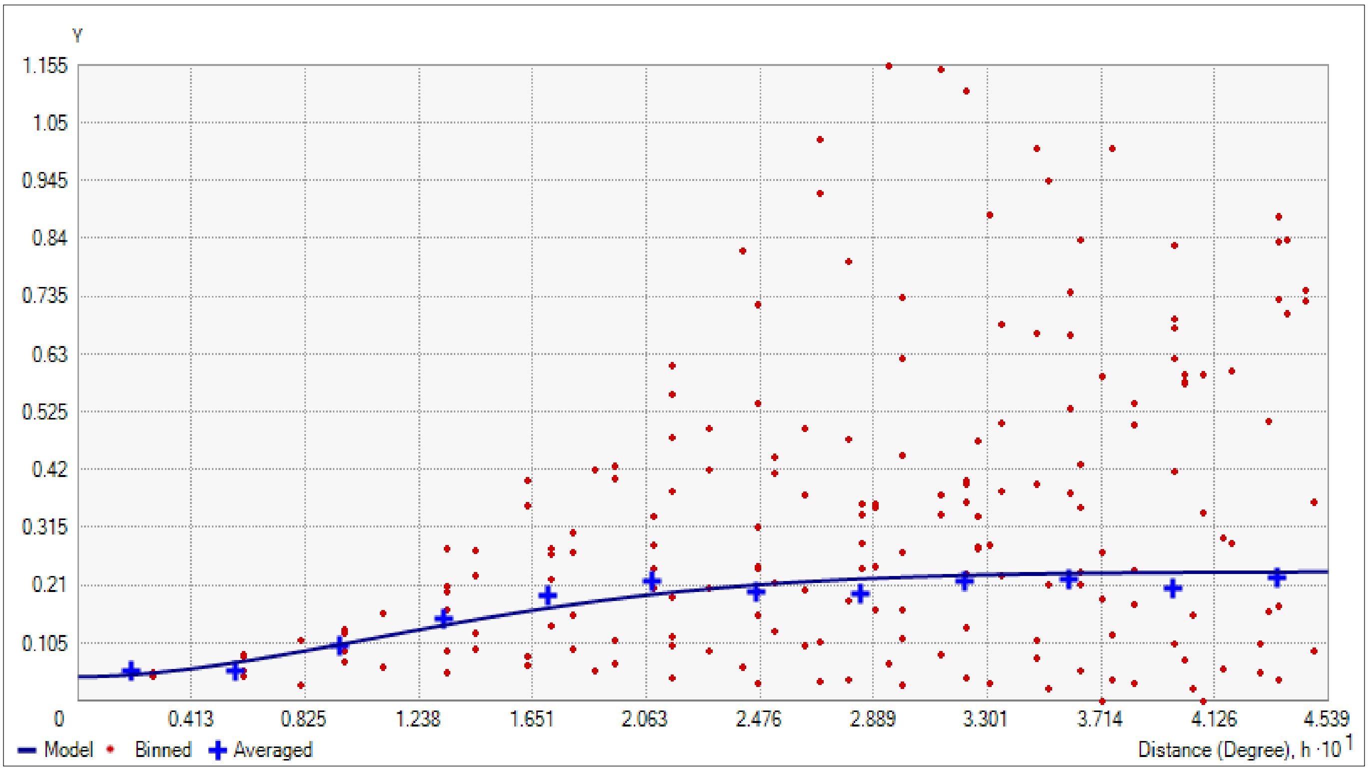


Fig 11: Semivariogram model of Zinc (Zn) content in soils of Lingsugur block

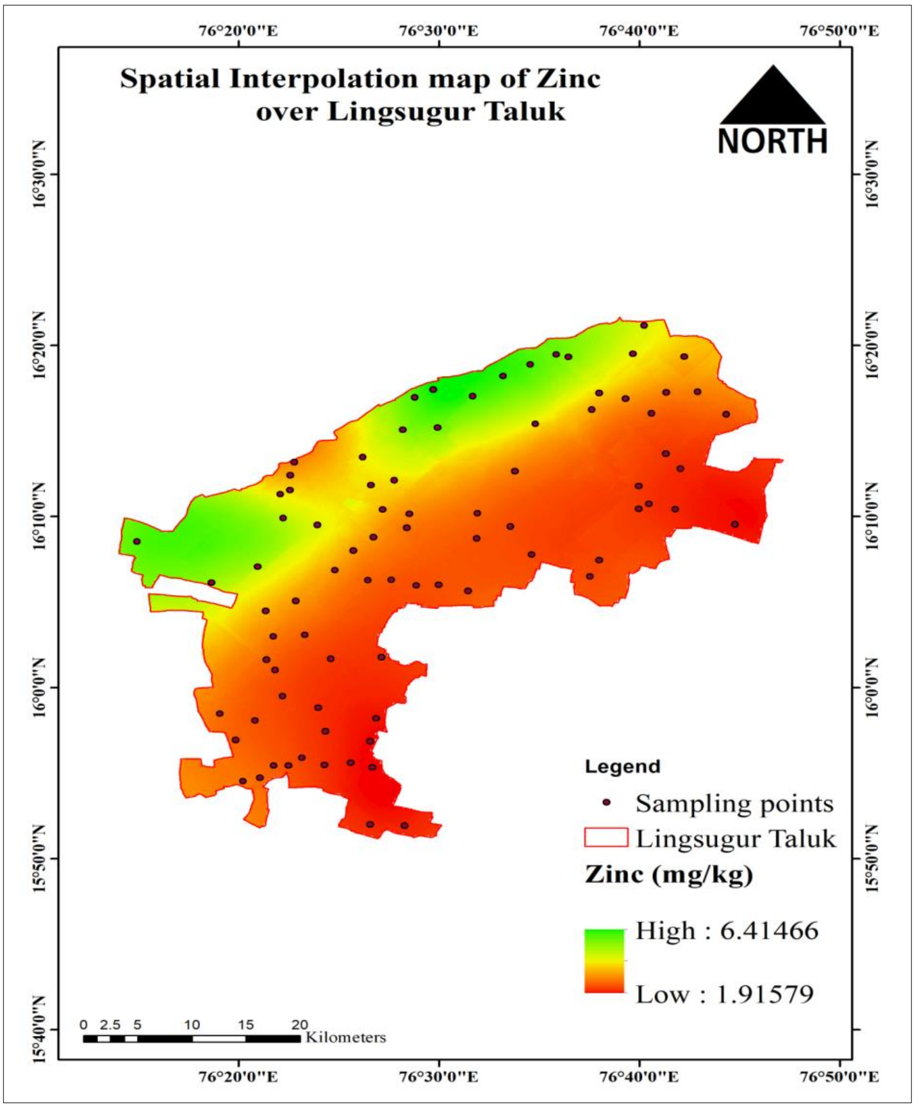


Fig 12: Spatial Interpolation of Zinc (Zn) over Lingsugur Taluk

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