GEOSTATISTICAL ASSESSMENT OF SOIL FERTILITY IN A SEMI-ARID REGION USING SPATIAL INTERPOLATION TECHNIQUES

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ABSTRACT

The foundation of agricultural sustainability and productivity is soil, a crucial but limited natural resource. This study uses geostatistical analysis and spatial interpolation techniques to evaluate soil fertility, which is defined by both nutrient availability and management. The study, which was carried out in Jari Village, in the Badokhar Khurd block of Banda district in the Bundelkhand region, used secondary data on important soil characteristics, such as pH, electrical conductivity, organic carbon, and N, P, and K concentrations. To assess spatial variability throughout the study area, 300 soil samples were gathered at uniform depths and subjected to analysis. Discrete data points were transformed into continuous surface maps appropriate for Geographic Information System (GIS)-based analysis using spatial interpolation techniques like IDW and OK. To optimize IDW parameters and identify the best semi-variogram model for OK, cross-validation techniques were used. The findings showed that OK was better at mapping the distribution of potassium, but IDW was better at predicting the majority of soil parameters. While soil salinity was minimal and in line with the region's moderately alkaline pH, there was notable variation in pH, OC, N, P, and K levels throughout the region. The effectiveness of geostatistical tools in enhancing soil fertility assessments and assisting precision agriculture in areas with limited resources is demonstrated by this study.

KEYWORDS: Inverse Distance Weighting (IDW), Ordinary Kriging (OK), Soil Parameter,

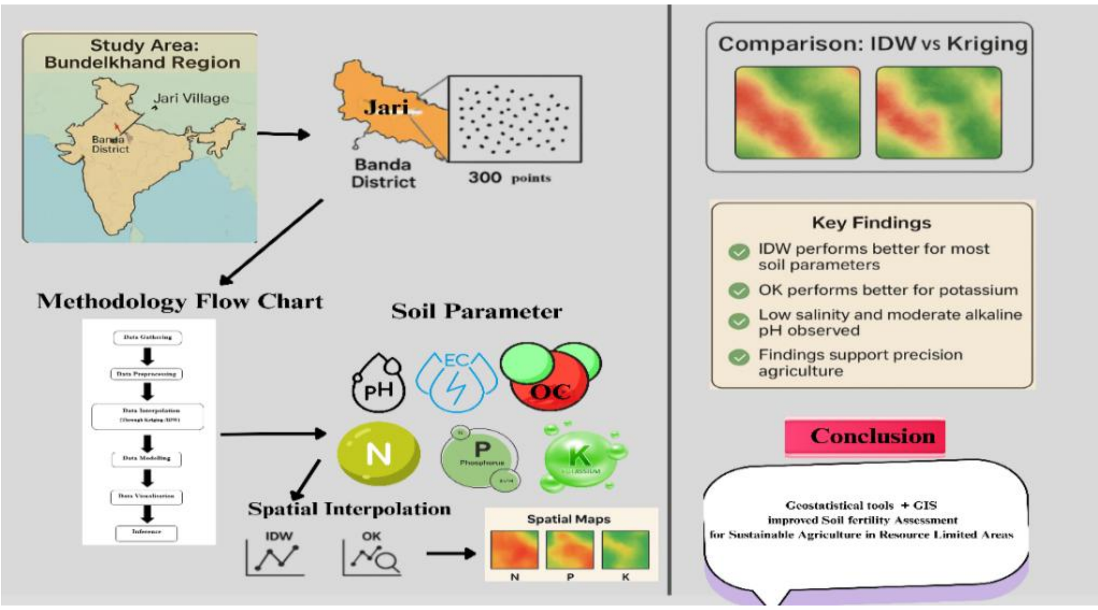


Fig. 1: Graphical Abstract

INTRODUCTION

Soil is an important and limited natural resource essential for agriculture (Gehlot et. al., 2019). Soil stands out as one of nature's most remarkable gifts to humanity. It is an important natural resource, performing essential functions that benefit both the environment and human well-being. Indigenous peoples hold the earth in deep admiration, referring to it as their 'mother' and cherishing the belief that they were created from its rich riches dirt itself. Currently, roughly 10% of the world's degraded soil is located in India, primarily due to intensive agricultural practices that lack sustainability, scientific backing, and reliability. Now more than ever, it is crucial for landholders, farmers, developers, and ordinary citizens to actively participate in conservation efforts. Protecting and maintaining soil quality has become a key priority, essential for securing productive and sustainable growth for future generations (Biradar et. al., 2020). Enhancing crop yields greatly relies on soil fertility, which encompasses both how effectively nutrients are managed and their availability. The soil's ability to supply nutrients is reflected in its overall fertility status. One of the simplest ways to decide on the best nutrient management approach is to evaluate soil fertility levels (Brady et.al., 2000).There are several techniques for evaluating soil fertility, among them all techniques soil testing is mostly used in the world (Havlin et.al., 2010). Soil testing evaluates the current fertility status of the soil and provides valuable insights into nutrient availability. This information is the essential basis for formulating fertilizer recommendations aimed at maximizing crop yields and maintaining soil fertility over an extended period (Bhayal et.al., 2022). Soil mapping is the process of estimating and revealing how topsoil qualities vary across different regions, so that is easy to understand and interpret by a wide range of users (Beckett 1976; Dent and Young 1982). One of the best ways to study how soil properties change across an area is through geo-statistics (Tekin et. al., 2011). Because managing these differences in soil fertility is so important for farming, it's key to use these techniques in precision agriculture (Srivastava et. al., 2015).

In GIS, we can use different methods to estimate values in places where we don't have data. For more advanced predictions that also tell us how confident we can be about the results, geostatistical interpolation methods are used. These are based on statistical principles. Geo-statistical methods have been effectively employed to assess the spatial variability of soil properties across diverse geographic and ecological settings. This approach is a valuable tool for improving soil health, precisely managing plant nutrients, preventing soil erosion, and analyzing how different land uses influence soil variability. Employing a grid sampling approach to collect data within the target area, followed by the application of one of the prevailing interpolation techniques to estimate variable values at unsampled locations, constitutes a standard methodology in map creation. These spatial interpolation methods use information from point measurements to provide reliable estimates of soil variables across spatial where measurements have not been taken (Webster and Oliver, 2001; Hengl, 2007). To enhance decision-making processes, spatial interpolation is a valuable technique that changes irregularly spaced discrete point data into a uniform, continuous surface suitable for analysis within a Geographic Information System (GIS).Managing vast amounts of data related to natural resources can be quite challenging, especially when dealing with information spread across different sources. Fortunately, GIS make it much easier to access, retrieve, and modify this kind of data. With GIS tools, you can efficiently handle both attribute data like soil properties and geographic data, which is essential when working with large datasets. For example, if you're trying to create a map that shows soil fertility across a region, collecting soil samples using GPS devices is important. This technology simplifies the process of pinpointing exact locations by providing precise latitude and longitude coordinates. In agriculture, tracking the nutritional health of soils in various fields over time is fundamental for knowledgeable decision-making and sustainable practices. Besides soil data, GIS also helps generate route maps for navigation, determine elevation levels, find the closest cities, and calculate movement speeds, which are all useful in planning and management (Mishra et. al., 2014).

Interpolation can be used to estimate the value of the unknown points between the known values. Inverse Distance Weighting (IDW) and Ordinary Kriging (OK) have been the most popular spatial interpolation techniques used in PA. IDW is a deterministic method using weighted average of data to be used for interpolation based on distance from neighbour to point to be interpolated. This is one of the easiest methods to be applied and has proved to generate good predictions for unsampled values. There is an assumption that the variables to be interpolated are stationary in OK, and the theory is that of the regionalized variable. A number of research projects have been carried out to predict soil attributes and map with the aid of Kriging. Kriging has many of the desirable properties of a good interpolator, having unbiased estimates, and is often used to overcome some of the limitations of the conventional interpolator. In addition to the statistical assumptions, kriging also needs a large number of samples to ensure the stability of the theoretical semivariance model fitted. Some authors have suggested that at least 100-140 sampled points should be used to perform a reliable semivariance modelling. Other authors suggest 31 or more pairs of points to be considered for a good estimation of the semivariance for a given distance h. In general, the better the semivariance model, the better is the quality of the kriging interpolation.

One of the challenges with generating maps of soil attributes is the number of sampling points required to produce accurate maps of the soil physical and chemical attributes that can add significantly to the cost of mapping. One possible solution is to develop techniques with fewer sampling points that achieve accurate maps. In the recent years, Machine Learning (ML) algorithms have been identified as an effective technique for prediction and mapping of soil properties using inexpensive covariates that are sampled at high density such as the crop yield, vegetation index, apparent soil electrical conductivity etc. ML can be interpreted as the automatic process of learning from algorithms using a big data set.

Objective of the Study

In the present study, an attempt was made to get a reliable nutrient status of the soil of the Jari village taken under consideration and to curb both the direct and indirect loss of nutrients from the soil with the objective of taking prior measures for healthy soil, crop production and human health in the future. In summary, the primary goal of this research is to produce and test the fertility maps obtained by Ordinary Kriging (OK) and IDW, which will help to further precision agriculture and improve soil management. The evaluation of accuracy using R^2 and RMSE provides robust and reliable results, making this study valuable for agricultural decision making and optimization of resources.

Relevance of the Study

The findings of this study have implications for precision agriculture, as they use AI and geospatial technology to help better understand soil fertility and soil mapping which allowed farmers to optimize resource to make a greater contribution in productivity and minimize environmental impact. Comparative analysis of the different methods add value by explaining the best tools to use in different agricultural situations which helps to encourage the use of new and innovative farming methods based on data.

MATERIALS AND METHODS

Study Area

The Bundelkhand region of Uttar Pradesh is particularly known for its typical geographical and socio-economic aspects. It comprises seven district viz. Jhansi, Jalaun, Lalitpur, Hamirpur, Mahoba, Banda, and Chitrakoot. The monsoon has a major impact on crop production, making agriculture a very important aspect of the locals' livelihoods.Soil in this region varies, with some areas facing degradation due to erosion, nutrient depletion and poor management practices. Another frequent issue in the region is water scarcity, which has an impact on irrigation techniques. The study is focused on “Jari” Village lies in the Badokhar Khurd administrative block of Banda district, within the Bundelkhand area. Geographically, it is positioned between latitudes 25.51040 and longitudes 80.44930 and it covers a total area of about 2213.42 hectares. The elevation of the village ranges from mean sea level up to approximately 450 meters above it. Besides, Badokhar Khurd Block is located roughly 10 kilometers northeast of Banda city. The soils in Banda district comprise various types, including fine, black clayey soil known as (Mar), coarse-grained gray to grayish-brown soil referred to as (Paruwa); coarse, reddish-brown soil called (Rakar) and clay loam black soil known as (Kabar). The soil structure varies across the region; sandy soils tend to be loose, open, and drain easily, while loamy soils often become compact and impervious. Overall, the area is characterized by an undulating plain with limited water retention capacity. The status of organic carbon, phosphorus and micronutrients are also low in the soil of this district.

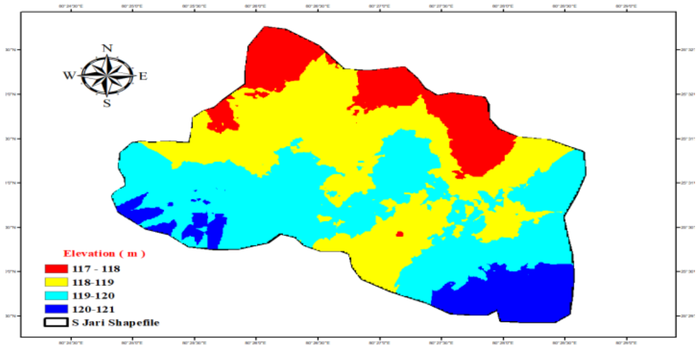


Fig.2: Study Area

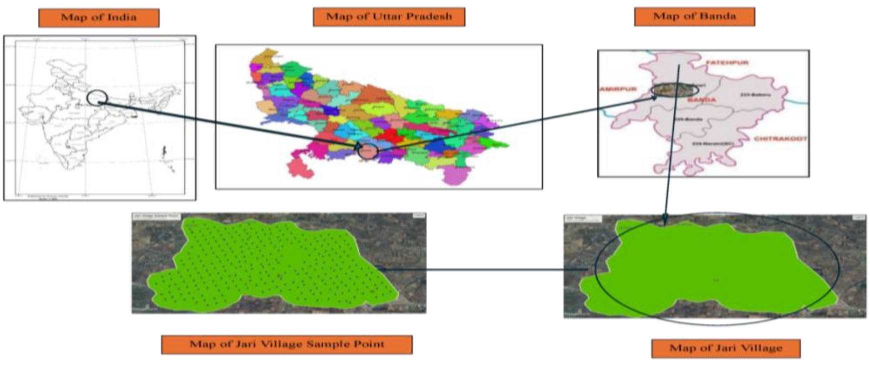


Fig.3: Map of Area

Data Collection

For this experimental study, 358 secondary data points were collected in zigzag manner from 0 to 20 cm depth. Out of which, 300 samples were used for the present study. Sampling coordinates in the study area were recorded by a GPS device. Stratified spatial sampling was used to select sampling points that covered the major soil and agro-ecological zones. The selected samples were labeled and properly kept in bags and sent to soil testing lab of Banda University of Agriculture and Technology, Banda, Uttar Pradesh. The soil samples were sieved with 2 mm sieve to get uniformity and to remove larger particles. The range and results of the soil characteristics are listed in Table 1. The treated soil was then placed in the polypropylene boxes. This systematic approach supports a consistent testing and analysis of the soil parameters, which can improve the soil health and agricultural capacity of the region.

Laboratory Analysis

Soil samples were taken from the study area and the pH of each sample was measured by preparing a 1:2.5 soil-water suspension and measuring using a pH meter with a glass electrode (Jackson, 1973). Soil water extract (1:2.5) was used to measure the electrical conductivity of the soil samples with Wheatstone Conductivity Bridge and expressed as dSm− 1 (Jackson, 1973). The Walkley and Black method (Jackson, 1973) was used to estimate the level of organic carbon in the soil; this involves oxidation of soil organic matter to estimate the carbon content. The available phosphorus content was determined by Olsen's method (Olsen, 1954) which extracts soil phosphorus by the use of a sodium bicarbonate solution.The available potassium content of soil was measured by Hanway and Heidel, (Hanway, 1952) method and the available nitrogen content of soil were determined by Subbiah and Asijamethod (Subbiah and Asija, 1954).

Descriptive Statistics

The soil properties were summarized using descriptive statistical analysis to describe the distribution and variation of the data. Microsoft Excel was used to calculate minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV), skewness and kurtosis for each soil parameter. The statistics gave a preliminary indication of the central tendency, dispersion and distributional features of soil data. The normality of soil variables was determined by skewness and Kolmogorov–Smirnov (K–S) test. Webster and Oliver (2001) provide a description of the skewness as a measure of the amount of deviation from a normal distribution. When there was significant positive or negative skewness of a soil variable, then it was deemed to be non-normally distributed. The variables that had major skewness were transformed using log function to meet the assumptions for geostatistical analysis. The log-transformation reduced skewness, helped to stabilize variance, reduced the impact of extreme values, and helped make the distribution closer to normal. After transformation, the normality of the transformed data was tested with K–S test. Variables that fulfilled the normality assumption were only used for subsequent semivariogram modeling and spatial interpolation analyses.

Spatial Interpolation Techniques

Ordinary Kriging (OK)

One of the most widely used kriging techniques is OK. It predicts the value (yo), which essentially involves summing the known measurements (the observed values) to provide an estimate for the unmeasured location yo. OK offers an elegant and straightforward approach, well described by Isaaks and Srivastava (Isaak and Srivastava, 1989; Cressie,1993), and many other researchers. The location and degree of variations between known data points are considered. We combined these factors in a weighted linear manner to produce the most reliable possible estimates (Gotway et. al., 1996).

$$\widehat{W}(y_0) = \sum_{i=1}^{N} \lambda_i W(y_i) \qquad \ldots (1)$$

Where $\widehat{W}(y_0)$ represents the predicted value at an unrecorded location y_0, while $W(y_i)$ refers to the measured value at position y_i. The coefficient λi indicates the weighting assigned from the measured pointyito the prediction point y0, and N denotes the entire number of neighbouring points taken under the search area (Hengl, 2009). To accurately model the spatial continuity of the data, it is essential to develop a fitted model based on the data distribution. Such a model helps capture the spatial relationships between pairs of points, ensuring more reliable spatial predictions. In this study, the Interpolation toolset calculated the OK method under the Spatial Analyst toolbox integrated with ArcMap 10.8.1 software. The amount of statistical association is a function of distance measured by the semi-variogram, employed to assist the ordinary kriging process (Reza et.al.,2016). The following formula is a means to compute the semi-variogram (Liu et. al., 2011).

$$\gamma(\mathrm{H}) = \frac{1}{2n(H)} \sum_{i=1}^{n(h)} [\,\mathrm{U}(\mathrm{y_i}) - \mathrm{U}(\mathrm{y_i} + \mathrm{H})]^2 \qquad \ldots (2)$$

$\gamma(\mathrm{H})$ Represents semi-variance at a specific interval of distance H; n(H) denotes the number of sampling pairs in that range of distances. The terms $\mathrm{U}(\mathrm{y_i} + \mathrm{H})$ and $\mathrm{U}(\mathrm{y_i})$ represents sample values which are taken at two locations $(\mathrm{y_i} + H)$ and $(\mathrm{y_i})$. Semi-variogram models based on Exponential, Gaussian, Spherical, Linear, and Circular functions give the best fitted for the soil properties.

Table 2: Expressions for different semi-variogram models

Semi variogram models	Expressions
Linear Model:	$\delta(\mathrm{H}) = \mathrm{C_0} + \left(\frac{\mathrm{c}}{\mathrm{b}}\right)\mathrm{H}$

Exponential Model:	$\delta(H) = C_0 + C\left[1 - \exp\left\{-\frac{h}{b}\right\}\right]$ for $H > 0$
Gaussian Model:	$\delta(H) = C_0 + C\left[1 - \exp\left\{-\frac{H^2}{b^2}\right\}\right]$ for $H > 0$
Spherical Model:	$\delta(H) = C_0 + C\left[\frac{3h}{2b} - \frac{1}{2}\left\{\frac{H^3}{b^3}\right\}\right]$ for $0 < H \leq b$ C_0+C for $H > b$
Circular Model:	$\delta(H) = C_0 + \left[\frac{2c}{\pi}\frac{H}{b}\sqrt{1 - \left(\frac{H^2}{b^2}\right)} + \arcsin\left(\frac{H}{b}\right)\right]$ for $0 < H \leq b$ C_0+C for $H > b$

Where H refers as lag distance, C_0+C represents sill value, C_0 is the nugget effect, C is the structural or partial sill, b is the range

When implementing the semi-variogram models, it is essential to determine key parameters like the nugget value, partial sill, and range to ensure accurate analysis and the application The variation at zero distance is the nugget., and the stable is used to describe the spatial structure of the data, specifically, how similarity between data points changes with distance. The sill, or variance, refers that how far you can go from a data point before it stops affecting its neighbors. It's like the distance over which points are related to each other. When choosing the right semi-variogram models for our data, we kept adjusting these settings until we found the one with the smallest nugget effect and the best fitted model (Yaserebi et. al., 2003).To evaluate the geographical dependency of soil parameters, the nugget variance was employed. This reliance was determined by dividing the nugget by the total sill ($C_0/(C_0+C)$) by the nugget's ratio. Strong spatial dependency (H) was defined as having a ratio of less than or equal to 0.25, moderate geographic dependence (M) as having a ratio between 0.25 and 0.75, and weak spatial dependence (W) as having a ratio greater than 0.75. The spatial continuity and variations of soil properties are better understood mainly to this classification. (Cambardella and Karlen ,1999).

Inverse Distance Weighting

The Inverse Distance Weighting method is widely favoured by professionals working with Geographic Information Systems (GIS). It offers reliable estimates of spatial variables (Wong, 2016) and is appreciated for its straightforward approach, making it accessible to users with varying levels of experience. The nearness of two points tends to make them more similar than the distance between them. Using the IDW approach, one can estimate the value at an unknown place. The IDW uses the average of known nearest locations. (Zeiler, 2010). Have a greater effect on the expected value than those that are farther away. The specific data points included in the calculation are determined by a defined and customizable search neighbourhood, which delineates the region around the point of interest within which the data points are considered relevant for the estimation process. Usually, weights and a power of distance are inversely related. (Burrough, 1986; Watson, 1992). The formula of IDW interpolator is (Burrough and McDonnell, 1999).

$$\frac{\sum_{i=1}^{n} w(X_i) {d_{ij}}^{-t}}{\sum_{i=1}^{n} {d_{ij}}^{-t^2}} \quad \ldots (3)$$

Where X_0 the point where the value is being estimated and the known data points used in the estimation are denoted Xi are the data points. The distance dij, which represents the separation between each data point and the estimation location, has an impact on the weights (t) allocated to each data point. The IDW interpolation method has the drawback of treating every sample point within the search radius similarly and without making any difference between them.

The interpolation process is carried out using the Geostatistical Analyst extension available within the Arc Map 10.8.1 software (ESRI, 2001).The cross-validation statistical method is used to evaluate these predictive models' reliability. (Voltz and Webster, 1990).The process of cross-validation involves removing each data point one at a time, estimating the value from the remaining observations, and then comparing the expected result with the measured value. (Mueller et al , 2004).Determining the best semi-variogram model is the main purpose of the cross-validation procedure. among the proposed models for ordinary kriging, and to determine the optimal parameters for inverse distance weighting (IDW) from those tested (Tomczak,1998). This method was used to identify which model delivers the most reliable predictions. This approach involved assessing the predictive accuracy by comparing the estimated error rates associated with each model, providing a comprehensive evaluation of their performance.

Performance criteria for comparison between interpolation methods

Root mean square error (RMSE)

We calculated the prediction errors using the equations, including the root mean square error (RMSE).The RMSE helps us see how well a model can predict real data and gives an idea of the typical size of the errors. Lower RMSE numbers mean the predictions are more accurate and the errors are smaller. The RMSE and R-squared (R2) computed from the measured and interpolated data at each sample location are used to compare various interpolation techniques.

$$\mathbf{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left\{w(x_i) - \widehat{w(x_i)}\right\}^2} \qquad \ldots (4)$$

Where n represents the number of observations, $w(x_i)$ denotes the observed value at location or instance and $\widehat{w(x_i)}$ indicates the predicted value at the same location.

Coefficient of Determination (R2)

The R-squared value is a statistical measure that tells us how well the data points align with the regression line fitted to them. Generally, a higher R-squared suggests a better fit, reflecting a closer relationship between the model and the observed data.

$$\mathbf{R^2 = 1} - \frac{\textit{Residual sum of Square}}{\textit{Total sum of square}} \qquad \ldots (5)$$

Moran's I (Index)

The Moran's I is a measure of the spatial autocorrelation of an environmental variable. The range of its value is from − 1 (perfect negative spatial autocorrelation) to + 1 (perfect positive spatial autocorrelation); the value 0 means that there is no autocorrelation (Guo et al., 2015). Moran's I was computed as (Legendre & Fortin, 1989):

$$I = \frac{n}{W}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad \ldots (6)$$

If the p-value is very small ($p<0.05$) and the z-value is very large or very small ($1.96< z <-1.96$) then the spatial pattern is unlikely to be a random form of distribution, according to ESRI. Positive values for Moran's I mean that the values around a point tend to be alike, meaning that there is likely to be spatial dependency. A negative Moran's I index value represents inverse spatial dependence of the neighbouring values. When the value of Moran's I is zero, there is no spatial pattern.

Results

Descriptive Statistics for soil chemical properties

The dataset underwent analysis using descriptive statistics and geostatistics, while the statistical data were tested for normality through the Kolmogorov-Smirnov (K-S) test with a p-value (> 0.05). The dataset needed to be normalized before geostatistical analysis because of outliers and significant skew (Table 1). Except for pH, P, and K, therefore, the variance was stabilized using the logarithmic transformation (Goovaerts , 1999). For EC, OC, and N, the logarithmic modification reduced skew and kurtosis, and the resulting data passed the normality test. Table 3 shows the result of soil parameters along with the Kolmogorov-Smirnov (K-S) test (p-value > 0.05) normality test. Normality test execution took place in the R software.

Table 3:Descriptive statistics of the soil parameters in the research region.

Descriptive Statistics	pH	EC (ds/m)	OC (%)	N (Kg ha-1)	P (Kg ha-1)	K (Kg ha-1)
Mean	8.01	0.25	0.39	232.3	15.45	259.8
SD	0.57	0.06	0.15	55.7	5.26	59.5
CV (%)	7	26	38	23	33	22
Min	6.87	0.05	0.12	145.2	5.54	115.6
Max	9.35	0.41	0.67	348.5	26.9	421.6
Skewness (0)	0.2284	0.2061	0.2967	0.1640	0.2240	0.2302
Kurtosis (O)	-0.588	-0.2389	-1.0683	-1.0106	-0.8478	-0.3450
p-value (O)	0.063	0.0001	0.0188	0.0090	0.1537	0.055
D-value (O)	0.075	0.1267	0.088	0.094	0.065	0.077
Skewness (T)	-	-0.053	-0.3110	-0.1727	-	-
Kurtosis (T)	-	-0.675	-0.725	-1.074	-	-
p-value (T)	-	0.079	0.1031	0.0540	-	-
D-value (T)	-	0.073	0.0703	0.0775	-	-

T= log transformation

Min stands for minimum, Max for maximum, skew for skewness, SD for standard deviation, and CV for Coefficient of variation. Skewness and kurtosis(O) and kurtosis(O). Skewness(T) and Kurtosis(T) are derived from log transformation data.

The soil parameter descriptive statistics were shown in Table 3. The following were the mean soil property values: pH at 8.017, electrical conductivity is 0.24 dS/m, Organic carbon (OC) is 0.40 %, Nitrogen at 232.3 kg ha-1, phosphorus (P_2O_5) at 15.45 kg ha-1, Potassium(K) at 259.8 kg ha-1, The SD ranged from 0.06 for EC, 0.15

for Organic carbon, 55.7 for Nitrogen (N), 5.26 for Phosphorus (P_2O_5), 59.5 for Potassium (K) demonstrating the dataset's notable variability. The pH values ranged from 6.87 to 9.35, and the EC ranged from 0.05 to 0.41 dS/m. The coefficient of variation divides the data into three categories, including most variable (CV>35%), moderate variable (15%-35%) and least variable (CV<15%). Potassium (K) concentration shown a wide spectrum, ranging from 115.62 to 421.65 kg ha-1 (CV = 22%). Although slightly (CV = 23%), and (CV = 26%), the concentrations of nitrogen and electrical conductivity also fluctuated. with values ranging between 145.2 and348.5 kg ha, 0.05 and 0.41 (ds/m) for EC. With a standard deviation of 0.15, the OC content varied between 0.12 and 0.67%. Most of the soil characteristics showed positive skewness, with kurtosis values ranging from -1.0106 to -0.2389 and minimum and maximum values between 0.1640 and 0.2967.

Geo-statistics for soil chemical properties

The present study used ArcMap version 10.8.1 was used to create the spatial maps to examine the spatial structures of the various parameters of the soil.The spatial pattern analysis consisted of ordinary kriging and IDW interpolation methods.

In Ordinary Kriging, the semi-variogram analysis showed that the various properties of soil were best modelled by different models and hence there were different spatial distribution patterns among the soils (Table 4). For each soil parameter, the semi-variogram was computed. The model with the lowest RMSE and the highest R2 value was selected as the best fit to these experimental variograms, out of several models, including the exponential, linear, circular, spherical, and Gaussian models, as shown in Table 3.The Gaussian model was the best model for soil pH and available phosphorus (P) while the linear model was best for available electrical conductivity (EC) and the exponential model was best for organic carbon (OC), available nitrogen (N), and available potassium (K). The chosen modelswere adequate in representing the spatial variation of soil properties and were used to accurately predict these soil properties spatially.All soil parameters showed high spatial dependence in terms of the nugget-to-sill ratio. A nugget-to-sill ratio of less than 25% means that the spatial variability of these soil properties is largely driven by internal soil properties rather than chance, soil-forming processes, parent material, topography and land management over the years which are the main reason of the spatial variability of soils. The performance of the spatial interpolation models in predicting and reliability were assessed using the Leave-One-Out Cross-Validation (LOOCV) algorithm. One observation is temporarily omitted from data set, and the model is calibrated with the rest of the observations. For the excluded observation, prediction is made using the fitted model and the prediction error is computed. This is repeated for each observation within the data set with each observation only used once for validation. The validation statistics such as mean square error (MSE), root mean square error (RMSE), coefficient of determination (R^2), and Nash–Sutcliffe efficiency (NSE) were used to evaluate the accuracy of the model and determine the best semivariogram model for spatial prediction.

The availability of nitrogen and phosphorus showed a zero nugget, showing very good spatial continuity and very little unexplained variation at short distances.Model validation statistics showed that the models predict well. Coefficient of determination (R2) ranged from 0.962 to 0.995 showing that more than 96 percent of the variability in the soil properties was explained by the models. Available nitrogen showed the highest prediction accuracy (R^2 = 0.995), followed by phosphorus (R^2 = 0.987), organic carbon (R^2 = 0.976), pH (R^2 = 0.972), EC (R^2 = 0.967), and potassium (R^2 = 0.962). The mean square error (MSE) and root mean square error (RMSE) values also showed that the predictions were reliable. N and P showed the highest spatial structure and good model fitting with the lowest prediction errors among all parameters.

Nitrogen and phosphorus had Nash–Sutcliffe efficiency values (N/S) near about zero while the others were relatively low, showing minor deviation between the observed and predicted values. Overall, the resulting high R^2 and low prediction errors and strong spatial dependence indicated that the selected semi-variogram models were appropriate for describing the spatial variability of soil properties and can be used for site-specific nutrient management and precision agriculture planning. The spatial prediction approach proved to be very robust in generating reliable soil fertility maps with the particularly good results for available N and P.

Table 4:Semi-variogram Parameters of Ordinary Kriging

Parameter	Model	Nugget (C0)	Partial sill (C)	Sill (C0+C)	MSE	RMSE	R2	N/S	Spatial Dependence
pH	Gaussian	0.0006	0.0247	0.0254	0.00064	0.0254	0.972	0.024	Strong
EC	Linear	0.00003	0.0005	0.00053	0.00001	0.004	0.967	0.062	Strong
OC	Exp.	0.00051	0.0029	0.0031	0.00007	0.0083	0.976	0.048	Strong
N	Exp.	0.00004	556.03	556.03	2.4884	1.5774	0.995	0.000	Strong
P	Gaussian	0.00001	2.0643	2.0643	0.4191	0.2047	0.987	0.000	Strong
K	Exp.	23.819	388.35	412.169	12.7336	3.5689	0.962	0.057	Strong

Using the IDW technique, several soil parameters in the study region were interpolated. Three common statistical measures were used to evaluate the interpolation's effectiveness and accuracy: the R2, MSE, and RMSE. With a very low RMSE of 0.0192 and an R2 of 0.996 for soil pH, the IDW model demonstrated a high degree of agreement between observed and predicted values. Similarly, with an R2 of 0.9966 and an RMSE of 0.0026, EC showed excellent accuracy. Additionally, with an R2 value of 0.997 and an RMSE of 0.0054, the OC parameter was accurately predicted. With a high R2, the model continuously demonstrated good performance for both nitrogen (N) and phosphorus (P).

Table 5: Experimental cross-validation of theoretical model parameters for soil properties

Parameter	Model	RMSE	MSE	R2
pH	IDW	0.0192	0.00037	0.9961
EC	IDW	0.0026	0.00007	0.9965
OC	IDW	0.0054	0.00003	0.9967
N	IDW	1.8431	3.39720	0.9970
P	IDW	0.1690	0.02850	0.9965
K	IDW	2.0043	4.01750	0.7097

In both Inverse Distance Weighting (IDW) and Ordinary Kriging (OK) soil chemical characteristics, the pattern analysis showed a positive spatial autocorrelation with very significant values for all selected soil properties (Table 6). Moran's I values were between 0.9525 and 0.9955, suggesting that neighbouring sampling points had very similar soil chemical properties and not randomly distributed. The z-scores associated with the observed spatial clustering were very high (around 196.83 to 202.15) and the p-values were very low (< 0.001), making it highly unlikely that the observed spatial clustering is due to chance.

Of the soil attributes measured, the highest Moran's I value (0.9955) was obtained for organic carbon (OC), followed by available nitrogen (N) (0.9948) and electrical conductivity (EC) (0.9939), which is indicative of very strong spatial continuity. In the same way, Moran's I values for soil pH were 0.9897 (IDW) and 0.9914 (OK), respectively, indicating soil acidity or alkalinity was spatially clustered throughout the study area. The other parameters of the spatial model, available potassium (K), also showed strong positive spatial dependence in both the IDW and OK models with Moran's I values of 0.9635 and 0.9903, respectively; the IDW model showed less spatial dependence than the kriging model for available potassium. The available phosphorus (P), Moran's I values were 0.9891 (IDW) and 0.9525 (OK) indicating strong positive spatial dependence and a relatively higher degree of local variation than the other soil properties.

According to the comparison of the interpolation methods, the Moran's I's for most soil parameters were higher under Ordinary Kriging, which shows that Ordinary Kriging has the ability to capture the spatial autocorrelation by modeling the semivariogram. This indicates that OK was able to model the spatial structure of soil properties better than the IDW method, which is the deterministic method. The higher spatial dependency used in kriging suggests it has the ability to represent the spatial variability of soil chemical properties more smoothly and realistically.

Spatial dependence was significant for all soil parameters, suggesting that soil fertility characteristics are determined by a common set of soil-forming factors such as parent material, topography, land use, crop management practices and nutrient application history. The soil chemical properties are the same in the areas close to it, so site-specific soil fertility management and precision agriculture interventions can be effectively implemented by delineating the management zones based on the soil chemical properties. The overall relatively high Moran's I values confirmed the existence of spatial aggregation and provide the basis for the use of geo-statistical techniques for soil fertility mapping, specifically Ordinary Kriging, for making sustainable nutrient management decisions.

Table 6: Pattern analysis significance test results for selected soil chemical characteristics

Soil Parameter		Moran index	Variance	z- score	p- value	Spatial dependency
pH	IDW	0.9897	0.000024	200.9692	0.0000	Strong positive
	OK	0.9914	0.000024	201.3124	0.0000	Strong positive
EC	IDW	0.9898	0.000024	201.0081	0.0000	Strong positive
	OK	0.9939	0.000024	201.8171	0.0000	Strong positive
OC	IDW	0.9913	0.000024	201.2904	0.0000	Strong positive
	OK	0.9955	0.000024	202.1492	0.0000	Strong positive
N	IDW	0.9915	0.000024	201.3376	0.0000	Strong positive
	OK	0.9948	0.000024	202.0053	0.0000	Strong positive
P	IDW	0.9891	0.000024	200.8608	0.0000	Strong positive

	OK	0.9525	0.000024	193.4180	0.0000	Strong positive
K	IDW	0.9635	0.000024	196.8304	0.0000	Strong positive
	OK	0.9903	0.000024	201.0930	0.0000	Strong positive

Model Comparison

Table 7 displays the R2 derived from the cross-validation of every spatial interpolation method that was examined. The technique with the highest R2 value was selected. The best technique to estimate soil pH, EC, OC, N, and P is IDW interpolation, while Ordinary Kriging (OK) is best fitted for K. Multiple researchers' findings demonstrate that kriging delivers superior results than inverse distance weighting (IDW) as a stochastic geo-statistical solution. (Laslettet. al.,1987; Leenaers et. al.,1990; Hosseini et. al.,1994; Kravchenko and Bullock,1999; Panagopoulos et.al.,1990; Chaubey et al., 2022).However, other researchers discovered that this wasn't the case (Weber and Englund,1992; Wollenhaupt et.al.,1994; Gotwayet.al.,1996).As a result, it is still unclear which approach is best for a given set of circumstances. The main characteristics of the commonly used approaches have been compared (Li and Heap, 2011). Regretfully, there is currently no compromise on the most reliable techniques, and it is unclear from published research which interpolation technique is best for mapping soil parameters (Shi et. al., 2009)

Table 7: RMSE and R2 summary based on cross-validation of all tested models

Soil parameter	**Cross-validation results**		
	Interpolation method	**RMSE**	**R^2**
pH	OK	0.0254	0.972
	IDW	0.0192	0.9961
EC	OK	0.0041	0.967
	IDW	0.0026	0.9965
OC	OK	0.0083	0.976
	IDW	0.0054	0.9967
N	OK	1.5774	0.995
	IDW	1.8431	0.997
P	OK	0.2047	0.987
	IDW	0.169	0.996
K	OK	3.5689	0.962
	IDW	2.0043	0.709

Area of the Land using Geo-statistical Techniques

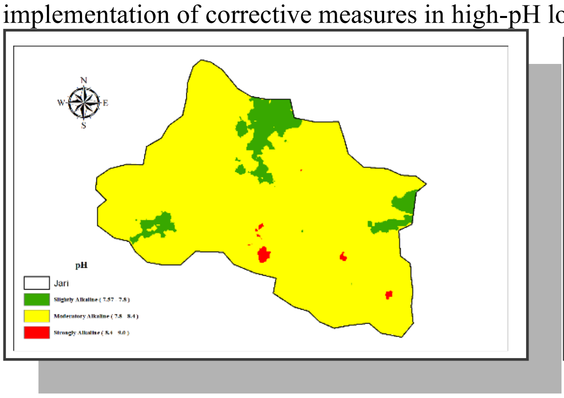
Table 8: Area of the Land using Geo-statistical Techniques

Soil parameter	**Unit**	**Rating**	**Class**	**OK**		**IDW**	
				Area(ha)	**% of total Area**	**Area(ha)**	**% of total Area**
pH		6.5-7.3	Neutral	0	0%	23.108	1.04%
		7.3-7.8	Slightly Alkaline	172.180	7.79%	511.129	23.11%
		7.8-8.4	Moderatory Alkaline	2025.973	91.61%	1421.850	64.29%
		8.4-9.0	Strongly Alkaline	13.470	0.61%	242.461	10.96%
		>9.0	Very Strongly Alkaline	0	0%	13.076	0.59%
EC		≤ 2.0	Non-Saline	2211.62276	100.00%	2211.623	100%
OC	%	≤ 0.5	Low	2157.912	97.57%	1789.092	80.89%
		0.5-	Medium	53.711	2.43%	419.657	18.98%

		0.75					
		≥ 0.75	High	0	0%	2.874	0.13%
N	Kg ha-1	≤ 280	Low	2181.076	98.62%	2031.834	91.87%
		280-560	Medium	30.547	1.38%	179.788	8.13%
P	Kg ha-1	≤ 10	Low	13.970	0.63%	60.812	2.75%
		10-25	Medium	2196.518	99.27%	2147.485	97.10%
		≥25	High	0.958	0.04%	3.325	0.15%
K	Kg ha-1	≤120	Low	0	0%	0.169	0.01%
		120-280	Medium	1915.226	86.60%	1671.807	75.59%
		>280	High	296.397	13.40%	539.647	24.40%

pH

The pH of the soil varied from 6.87 to 9.35 with the average pH being 8.01, which highlights that soils in the study area were predominantly moderately alkaline. The coefficient of variation (CV) was 7%, which was low indicating little spatial variation. The results of cross validation indicated that the IDW interpolation method had a higher coefficient of determination ($R^2 = 0.9961$), and a lower RMSE (0.0192) than Ordinary Kriging (OK) ($R^2 = 0.972$, RMSE = 0.0254). There was strong positive spatial autocorrelation evidenced by Moran's I values of 0.9897 (IDW) and 0.9914 (OK). Maps of the spatial distribution in Fig 4 and 5 indicated that the majority of the study area was moderately alkaline with a small percentage of neutral and strongly alkaline areas. Based on these results, pH control may be necessary in high pH areas for nutrient availability. Soils in the majority area (91.61%) maintain moderate alkalinity between 7.8 to 8.4 pH levels by OK method and 64.29% area by IDW. The slightly alkaline category (7.3 to 7.8) comprises 7.79% by OK and 23.11% by IDW method while strongly alkaline (8.4 to 9.0) represents 0.61% by OK and 10.96% by IDW of the study area and very strongly alkaline (>9.0) area was found 0% by OK and 0.59% by IDW. Neutral area was only 1.04% by IDW. The implementation of corrective measures in high-pH locations becomes essential to enhance nutrient absorption.



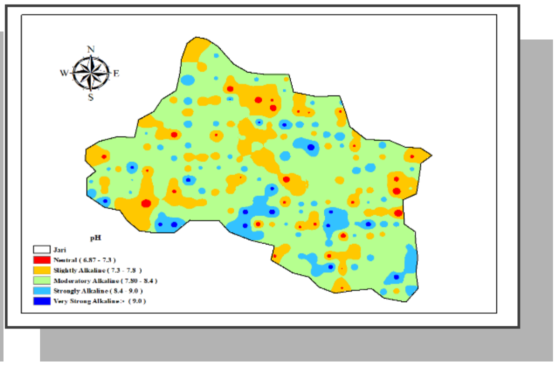
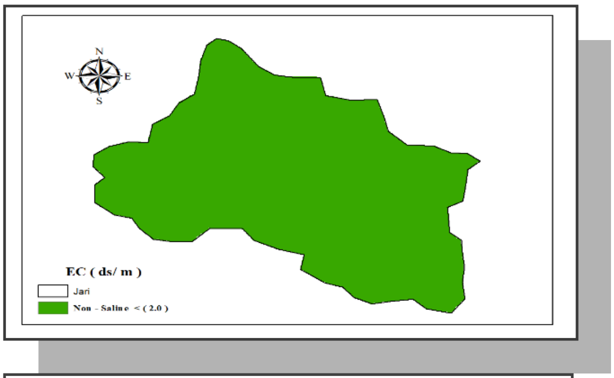


Fig. 4: pH (OK) **Fig. 5: pH (IDW)**

Electrical Conductivity (EC)

The soil of the study area was non-saline with electrical conductivity ranging from 0.05 to 0.41 dS m^{-1} with a mean of 0.25 dS m^{-1}. Moderate variability was found with the CV of 26%. The IDW model provided better prediction accuracy ($R^2 = 0.9965$, RMSE = 0.0026) than OK ($R^2 = 0.967$, RMSE = 0.0040). Moran's I values (between 0.9898 and 0.9939) indicated that the spatial dependence of the data was good. Spatial distribution map revealed that all the study area was non-saline, thus salinity is not a restriction for crop production. The results of electrical conductivity measurements showed that the entire study area (100% or 2213.42 units) falls within the non-saline range (≤ 2.0 ds/m) by both methods. All surveyed soil areas lack salinity problems, which means they are suitable for various agricultural crops because salt stress does not pose a risk. Across the entire study area, no segments exhibit saline conditions within the ranges of very slightly saline (2.0 to 4.0 ds/m), slightly saline (4.0 to 8.0 dS/m), moderately saline (8.0 to 16 ds/m), and strongly saline (≥ 16 to dS/m). The result of the interpolation map created for the EC is shown in Fig. 6 and 7.



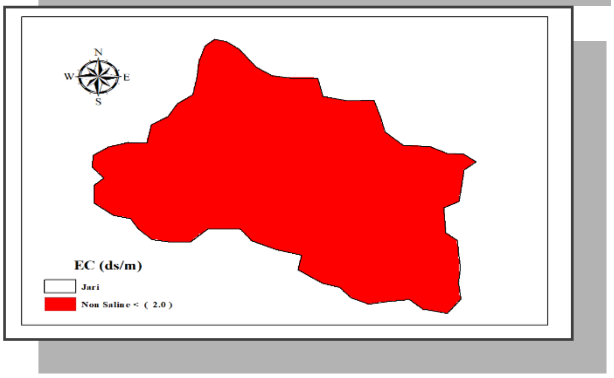
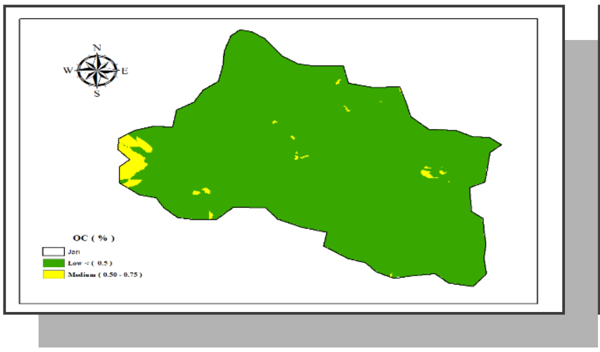


Fig. 6: EC (OK) **Fig. 7: EC (IDW)**

Organic carbon (OC)

The mean value of the organic carbon content ranged from 0.12 to 0.67%, and the overall average was 0.39%, which is generally low. The CV was 38% which was very high in the study area. IDW produced more accurate predictions (R^2 = 0.9967, RMSE = 0.0054) than OK (R^2 = 0.976, RMSE = 0.0083). The Moran's I values (0.9913–0.9955) were very strong, suggesting high spatial dependence. The majority of the study area belonged to low organic carbon class indicating need for application of farmyard manure, compost, crop residues and green manure to enhance soil fertility. This study reveals a significant variation in soil organic carbon (OC) levels, with 97.57% of the area exhibiting low OC (≤ 0.5%) by OK method while it was found 80.89% by IDW, indicating poor soil health likely caused by intensive farming and low organic input. Such soils are typically characterized by poor structure, reduced water-holding capacity and limited nutrient availability. Medium OC levels (0.5–0.75%) cover 2.43% area by OK and 18.98% area by IDW, suggesting moderate fertility under better management or natural conditions. Only 0.13% of the area has high OC (≥ 0.75%) only by IDW, reflecting optimal soil health and sustainable land use. This distribution highlights the need for soil restoration practices like organic amendments and conservation tillage to enhance soil fertility and support climate change mitigation through carbon sequestration. The result of the interpolation map created for the OC is shown in Fig. 8 and 9.



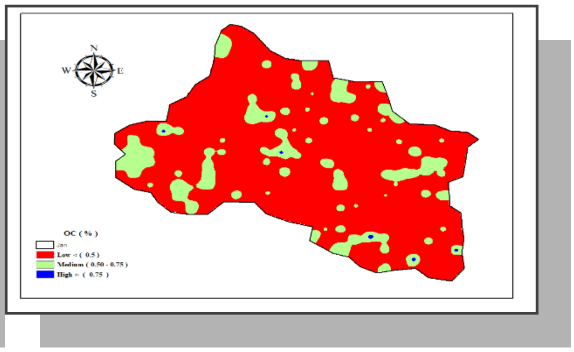


Fig. 8:OC (OK) **Fig. 9: OC (IDW)**

Nitrogen (N)

Available nitrogen (kg ha-1)in the study area ranged from 145.2 to 348.5 kg ha-1 with an average of 232.3 kg ha-1, showing that most of the soils were nitrogen deficient. There was moderate variability with a CV of 23%. The R2 of the IDW model was slightly higher (0.997) than OK (0.995), while the RMSE for OK was lower (1.5774) than IDW (1.8431). Moran's values were shown to have good positive spatial autocorrelation ranging from 0.9915 to 0.9948. The spatial distribution map indicated that most of the area was in low nitrogen category, highlighting the importance of balanced nitrogen fertilisation and more application of organic amendments. Results showed that nitrogen deficiency affects majority of the study area since most land falls below the 280 kg/ha threshold for available nitrogen (98.62% area by OK and 91.87% area by IDW). Soils under the classification of medium nitrogen availability (280–560 kg/ha) cover a limited area of total land (1.38% area by OK and 8.13% area by IDW) despite this category's size ranging between the low and high nitrogen levels. The study shows that the examination area requires targeted soil fertilizer approaches which must include the spread of nitrogenous fertilizers and application of green manures along with legume rotations and organic materials. Sustainable farming practices and enhanced soil fertility require protective measures to restore N content in the soil. The result of the interpolation map created for the nitrogen is shown in Fig. 10 and 11.

Fig. 10: N (OK)

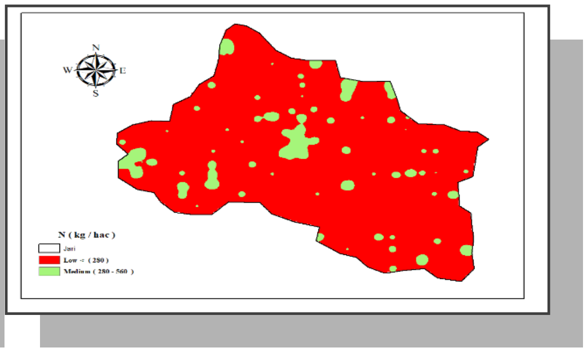


Fig. 11: N (IDW)

Phosphorus (P)

The available phosphorus content was found to be in the range of 5.54 to 26.90 kg ha-1 with an average of 15.45 kg ha-1, indicating medium available phosphorus content of most of the soils. The CV is 33% which indicated low to moderate variability. The IDW interpolation method outperformed OK, with a higher R^2 (0.9965) and lower RMSE (0.169) than OK (R^2 = 0.987, RMSE = 0.2047). The Moran's I values (0.9891 and 0.9525 respectively for IDW and OK) supported strong spatial dependence. The phosphorus distribution map revealed that overall the study area was suitable for growing rice as its majority of the area had adequate level of phosphorus, but some low phosphorus areas were found which need site specific phosphorus management.

Distribution of available P in the soil shows promising results as most land (99.27% area by OK and 97.10% area by IDW) falls under the medium category (10–25 kg/ha). Phosphorus availability levels across the study area exist at moderate levels, ensuring adequate conditions for plant growth, root development, flowering function, and energy transfer in crops. The study area comprises only 0.63% area by OK and 2.75% area by IDW under low phosphorus land (<10 kg/ha). The total area containing high phosphorus levels (≥ 25 kg/ha) represents just 0.04% by OK and 0.15% by IDW. Hence here, a targeted intervention is needed in low-phosphorus zones to boost nutrient levels, while careful management is required in high-phosphorus areas to avoid environmental risks. Balanced phosphorus fertilization based on soil testing is recommended to sustain long-term soil fertility and crop yields. The result of the interpolation map created for the phosphorus is shown in Fig. 12 and 13.

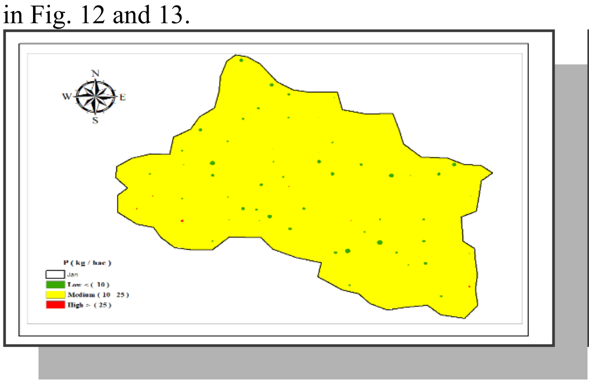


Fig. 12: P (OK)

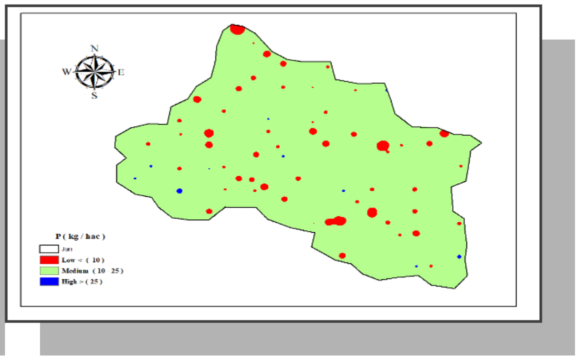


Fig. 13: P (IDW)

Potassium (K)

The available potassium level ranged from 115.6 to 421.6 kg ha−1 with an average of 259.8 kg ha−1, which is considered medium to high. The CV was 22% which is considered moderate variability. The other soil properties showed better performance with IDW than with Ordinary Kriging (OK) in terms of R^2, RMSE and MAPE. IDW gave better RMSE than OK while OK gave higher R^2 than IDW in the case of potassium interpolation. The Moran's is values for IDW and OK were 0.9635 and 0.9903 respectively, suggesting strong positive spatial dependence. Spatial distribution map indicated that there were sufficient levels of K throughout the study area, except for a small area under low K, indicating that fertilization with potassium should be mainly done in the low potassium areas.

The investigation site does not show any potassium deficiency because all areas have sufficient potassium levels. Medium potassium levels spanning from 120 to 280 kg/ha account for 86.60% by OK and 75.59% by

IDW of the land area and show that most crops have sufficient nutrient supply. The soil potassium content exceeds 280 kg/ha in the high potassium category representing 13.40% of the region by OK and 24.40% by IDW. Recommendations for effective nutrient management must be maintained to protect soil health even though potassium levels remain sufficient in the entire region. This indicates a strong potassium base in the soil, contributing to robust plant growth and resilience. Continued monitoring and balanced fertilization practices are recommended to maintain this favourable status and prevent nutrient imbalances. The result of the interpolation map created for the potassium is shown in Fig. 14 and 15.

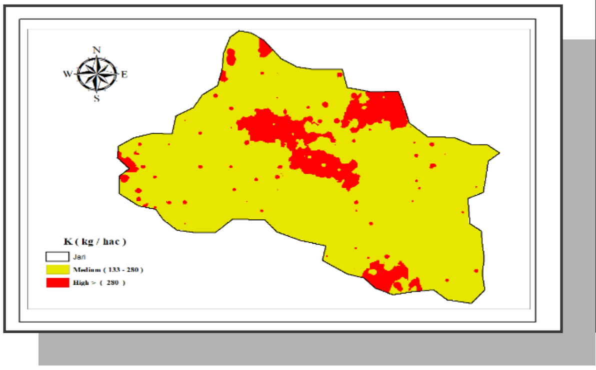


Fig. 14: K (OK)

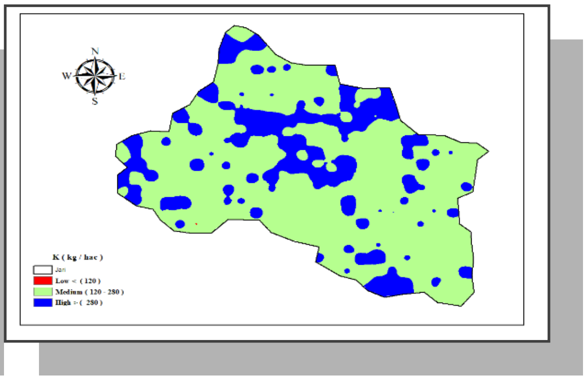


Fig. 15: K (IDW)

Discussion

The present study revealed that there was a great spatial variability in the soil fertility characteristics of the study area, which indicates the need for soil management at the site level for sustainable agricultural production. The descriptive statistics showed that the soils were mostly moderately alkaline, non-saline, low in organic carbon content, low in organic nitrogen content, medium in phosphorus content and medium to high in potassium content. Such soil fertility differences have also been documented in the semi-arid regions of Bundelkhand and other regions of India where nutrient leaching is caused due to low rainfall, continuous cultivation and low organic matter input in the soil resulting in spatial variations (Vasu et al., 2017; Chaubey et al., 2022).

Inherent soil-forming processes (parent material and climate) generally control soil reaction as reflected by the relatively low coefficient of variation for soil pH, while the variability observed for organic carbon, soil phosphorus and soil nitrogen is associated with agricultural management processes (cropping history, distribution of organic matter, fertilizer application). Several essential nutrients might be limited in moderately alkaline soils, and this could impact the productivity of crops. The same has been observed by Gehlot et al. (2019), Suman et al. (2024) and Emadi et al. (2009).

The low organic carbon values measured throughout the study area suggest low soil quality and the biological activity of the soils. Organic carbon is a key factor in soil structure, water holding capacity, nutrient availability and microbial activity. The low organic carbon status in the study area is probably linked to heavy cultivation, inadequate incorporation of crop residues and low application of organic manures. The same result was reported by Cambardella and Elliott (1994) and Vasu et al. (2017) who pointed out that frequent cultivation without proper organic amendments results into rapid depletion of SOM.

The prevalence of nitrogen deficiency was noted in a significant part of the study area and this is to be expected as available nitrogen is also related to the soil organic matter content. The low nitrogen status may be caused due to high mineralization rates under semi arid climatic conditions, removal of crops and low nitrogen inputs Vasu et al. (2017). This is corroborative of the earlier study which suggests N is the most limiting nutrient in rainfed agricultural system of Bundelkhand. Thus, there is a need to promote integrated nutrient management (balanced application of nitrogen, use of green manure, incorporation of crop residues, and use of legumes cropping systems) to enhance soil fertility and productivity (Raghuvanshi et al., 2026; Sherchan and Gurung,1995 and Chaubey et al., 2021).

Medium phosphorus availability and sufficient Potassium levels were seen in most of the soils. This relatively high potassium content could be due to the parent materials which are rich in potassium and minerals containing potassium that are found in the region. Phosphorus was usually adequate but some areas were phosphorus deficient and required balanced fertilization of phosphorus as suggested by soil phosphorus testing. Sustainable crop yield without nutrient losses to the environment depends on maintaining optimum levels of phosphorus and potassium.

The geostatistical analysis showed that there was good spatial dependence for all soil properties, with the nugget to sill ratios being low and Moran's I values were high. This indicates that the intrinsic factors, including parent material, topography, and pedogenic processes, in addition to long-term land management practices, primarily control spatial variability of soil fertility. The high spatial auto-correlation confirms the appropriateness of soil fertility mapping and delineating site-specific management zones using geostatistical methods.

This comparison of interpolation methods showed that Inverse Distance Weighting (IDW) was the most accurate interpolation method for soil pH, EC, OC, N and P, while Ordinary Kriging (OK) was the most successful interpolation method for soil K. Smooth spatial variation and a relatively dense sampling network

within the study area are possible reasons for the high performance of IDW in most soil properties. Potassium, on the other hand, showed greater spatial continuity, which was better captured by semivariogram modelling and consequently, Ordinary Kriging produced better prediction results. The same conclusion is reached by Gotway et al. (1996), Kravchenko and Bullock (1999), Li and Heap (2011) who found that there is no single interpolation technique that works best for all soil properties and that the choice of model should be based on the spatial characteristics of the individual soil property.
Overall the soil fertility maps generated in this study can be used to direct precision agriculture and will help identify nutrient deficient regions which can then be managed accordingly. Use of the spatial maps for site-specific nutrient management will optimize fertilizer use efficiency, lower production costs, increase crop productivity and reduce environmental degradation. Geostatistics and GIS are henceforth a sound instrument for decision making in sustainable soil fertility management for agricultural areas in semi-arid regions.

CONCLUSIONS

India's economy greatly depends on agriculture, which is facing difficulties like nutrient shortages, water scarcity, and climate change. Improved fertilizer and soil management can be effective in minimizing these problems. Recent research supports government initiatives to increase soil health and the production of crops. The selection of crop, pH of the soil, and the village-level fertility indicators of OC and P all affect the soil quality. Classifying soil nutrients like nitrogen, phosphorus, potassium, and EC helps optimize analysis, saving time and chemicals. The measurement range exceeds what's needed for good fertilizer recommendations. Thus, their levels (low, medium, and high) are predicted using a large collection of different classes. Soil parameters spatial assessment in the study region delivers fundamental information about soil productivity to interpret agricultural production rates. Inverse Distance Weighting (IDW) interpolation was more beneficial for all soil parameters except K, but Ordinary Kriging (OK) produced superior results for K. Essential indicators comprising pH, OC, N, P, and K were significantly different per soil analysis results. Soil salinity throughout the study area remained non-existent due to moderate alkaline pH values, although it affected nutrient absorption, the crops maintained good quality. Soil fertility management requires urgent, focused attention in regions with low organic carbon and nitrogen content since these areas can be improved with the application of organic materials and green manure, and nitrogen fertilizers. The soil health depends on strategic fertilization practices because most parts of the area exhibit suitable phosphorus and potassium levels. The study indicates sustainable management approaches should match soil requirements to create agricultural success and preserve environmental health. Addressing important agricultural issues in India, especially in areas with limited resources regions like Bundelkhand, can greatly benefit from this research. The study provides a solid foundation for precision soil fertility management, which is essential for sustainable agriculture, by fusing geo-statistical methods with GIS technology.

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