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Data-Driven Geospatial Assessment of Soil Parameters for Precision Agriculture in Banda District Using Geostatistical Techniques

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ABSTRACT: Spatial heterogeneity in soil fertility is important and determination of soil fertility at the field and regional scale levels is vital for precision agriculture and sustainable nutrient management. The study aimed to assess the spatial variability and fertility status of the major soil chemical properties in Banda District of Uttar Pradesh with the help of Geostatistical techniques. One thousand samples of soil were taken at 0–20 cm depth in a systematic manner and analyzed. The soil pH, electrical conductivity (EC), organic carbon (OC), available nitrogen (N), phosphorus (P), and potassium (K) were measured in the usual laboratory manner. Soil properties were described and mapped using ordinary kriging (OK) and inverse distance weighting (IDW) methods. The mean values of pH, EC, OC, N, P and K were 7.555, 0.807 dS m^{-1}, 0.491%, 252.60, 16.18 and 315.80 kg ha^{-1}, respectively. The lowest variability (CV = 10.25%) was found in pH and the highest is found in EC (CV = 50.43%). The results of the semivariogram indicated that all the soil properties were highly spatial dependent. The spherical model was found most appropriate for pH and P and the exponential model for the rest of the soil properties; IDW showed better spatial predictions results for pH, EC, N and K while OK showed better results for OC and P. The soil fertility maps indicated that the soils were generally moderately alkaline, with low to moderate salinity, low to medium organic carbon, low to moderate nitrogen, medium to phosphorous and medium to high in potassium. The results indicate that GIS-based geostatistical approaches are useful in identifying nutrient deficient areas. The soil fertility maps generated can aid in site specific nutrient management, better utilization of fertilizer, enhance soil productivity and help in sustainable precision agriculture in Bundelkhand region.

INTRODUCTION

The soil is a precious natural resource which is essential for human beings and the environment in India as it is the base of agriculture, food security and rural livelihoods. It helps to supply plants with needed nutrients, water and physical support and contributes to the productivity of agricultural crops and livestock (Chandra et al., 2026). Soil also regulates and filters water, supports groundwater recharge, cycles nutrients, sequesters carbon and regulates climate. It nourishes a variety of soil organisms, promotes biodiversity and ecosystem stability. Soils that are not damaged are able to control erosion, lessen environmental pollution and keep land productive (Syed et al., 2026). Hence it is utmost important to ensure sustainable soil management and soil conservation for food security, environmental sustainability and long term wellbeing of India's population. Approximately 10% of the degraded soil of the world is present in India. This is a result of intensive agricultural that is not sustainable and is not scientifically supported and reliable. Now it is important that landholders, farmers, development community and everyday citizens engage in conservation in an active way. Soil quality protection and maintenance has been a priority and is crucial to ensure productive and sustainable growth for future generations (Singh et. al., 2022). Soil fertility is a major factor in improving yields and is related to the management of nutrients as well as nutrient availability. Soil fertility is an indicator of its nutrient supplying capacity. The most basic method is to determine the fertility level of the soil in order to formulate the best nutrient management program. There are several methods to determining soil fertility (Suman et al., 2024). In which, soil testing is mostly used in the world. Soil testing assesses the amount of fertility in the soil at the time of testing and gives a good indication of nutrient availability. This information is used in making fertilizer recommendations with the goal of achieving maximum crop production and soil productivity in the long term. Soil mapping involves the estimation and identification of topsoil quality in various areas, to be understood and interpreted by a broad audience. Geo-statistics is one of the best methods to learn soil properties change within an area. Because managing these differences in soil fertility is so important for farming, it's key to use these techniques in precision agriculture.

A common problem in soil science is to estimate the values of soil properties at unsampled locations based on measurements taken at sample points, which are often referred to as spatial interpolation. Spatial interpolation is a useful method for transforming discrete point data at irregular intervals into a continuous surface, suitable for analysis within a GIS, to aid in the decision-making process. Large volumes of data for natural resource management can be difficult to manage, particularly if the information is distributed among many sources. Fortunately, GIS allow this type of data to be easily accessed, retrieved, and modified. GIS tools are capable of managing both attribute (such as soil properties) and geographic data, both of which are necessary when dealing with a large number of data points. For instance, if you're creating a map of soil fertility in a certain area, it is significant to collect soil samples with GPS devices. This technology makes it easy to identify exact locations, giving 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. Inverse Distance Weighting (IDW) and Ordinary Kriging (OK) have been the most popular spatial interpolation techniques used in precision agriculture (Pereira et al., 2022).

Kriging is a geo-statistical method which takes into account the spatial structure and spatial dependence of the observations, typically expressed in terms of a semi-variogram. It offers statistically best predictions given specific models assumptions and can even compute the uncertainty of the predictions (Coelho et al., 2018; Moharana et al., 2020). IDW is a deterministic interpolation method that assumes that the observations that are near an unsampled point have more influence on that point than those further away; weights are normally weighted by distance and tend to be inversely proportional to it. IDW is much easier to implement, and does not involve the modelling of spatial autocorrelation, whereas Kriging involves the explicit modelling of spatial structure (Wong, 2017). Thus, IDW and Kriging methods can be compared with cross validation statistics like RMSE, MAE and R-Square and the best method to map the spatial variability of soil fertility attributes can be determined.

In recent days, several machine learning (ML) algorithms and models are used for effectively addressing the classification and prediction problems. The problems of the agricultural domain are also solved to a great extent with the introduction of ML techniques. The classification and regression algorithms can be used to efficiently predict agricultural yield. Estimation, yield mapping, supply and demand matching and overall crop management can be performed with the help of these models. Livestock prediction, water management, soil management, crop failure detection, and various other agricultural and farming applications are greatly benefitted by the machine learning algorithms.

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In the present study, an attempt was made to get a reliable nutrient status of the soil of the Banda district 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. This study seeks to investigate the applicability and utility of the ML approaches at the field-scale pertinent to precision agriculture.

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 of Uttar Pradesh. Banda is one of them. Banda district lies between latitudes 24° 53' and 25° 55' North and longitudes 80° 07' and 81° 34' East. The district has a semi-arid climate, monsoon rainfall with irregularity, scarcity of water resources and varied soil characteristics that affect the agricultural productivity. The main soil groups are Kabar (Deep Black Clayey soil), Mar (Fine Black Soil), Paruwa (Coarse Textured grey to greyish-brown soil) and Rakar (Reddish-brown soil). Soil texture, soil fertility, organic carbon, available phosphorus and micronutrient status vary significantly with space. Limited water holding capacity, soil l erosion, nutrient depletion and inadequate soil management are important constraints to sustainable crop production. The map of study area is shown in Fig.-1.

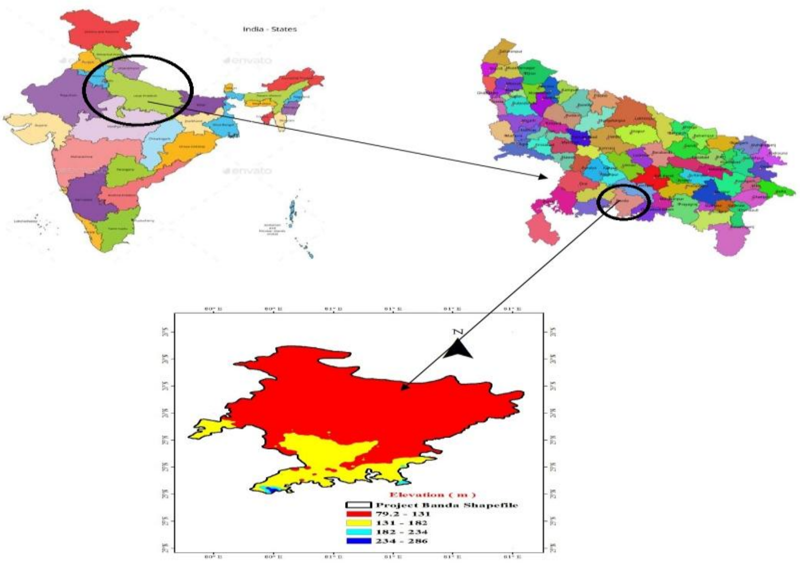

Fig.1: Study Area

DATA COLLECTION

In this experimental study, 1052 data points were collected by proper grid manner from 0 to 20 cm depth. Out of which, 1000 samples were used for the present study. Sampling coordinates in the study area were recorded by a GPS device. Stratified spatial sampling approach was employed to choose the sampling points that represented the major soil and agro-ecological zones. The selected samples were labelled and kept in proper sample bags and were forwarded to soil testing lab, Banda university of Agriculture and Technology, Banda (Uttar Pradesh). The soil samples were sieved with 2 mm sieve to obtain uniformity and to have larger particles removed from the samples. The treated soil was then placed in the polypropylene boxes. The systematic approach helps to provide a consistent analysis and testing of soil parameters that can lead to enhanced soil health and agricultural productivity in the region.

LABORATORY ANALYSIS

The laboratory procedures of the soil parameters are given in Table-1

Table-1: laboratory procedures

Soil Parameters	Methods	Procedures	Reference
pH	pH meter (1:2.5 soil:water suspension)	Measures hydrogen ion activity in soil solution using a glass electrode	Jackson(1973)
EC	Conductivity meter (1:2.5 soil:water extract or saturated paste extract)	Measures the ability of dissolved salts to conduct electrical current	Rechards(1954)
OC	Walkley and Black Wet Oxidation Method	Organic carbon is oxidized by potassium dichromate and sulphuric acid; residual dichromate is titrated	Walkley& Black (1934)
N	Alkaline $KMnO_4$ Method	Oxidizable nitrogen is released as ammonia, distilled, and titrated	Subbiah and Asija, (1956)
P	Olsen's Method (alkaline soils) / Bray-I Method (acidic soils)	Phosphorus is extracted and determined calorimetrically	Olsen (1954)
K	Neutral Normal Ammonium Acetate Extraction followed by Flame Photometry	exchangeable potassium is extracted and measured using a flame photometer	Hanway (1952)

DESCRIPTIVE STATISTICS

The soil properties were summarized using descriptive statistical analysis to describe the distribution and variation of the data. R 4.3.1 software was used to find out basic statistics 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 Q-Q plot. Webster and Oliver (2001) provide a description of the skewness as a measure of the amount of deviation from a normal distribution. If there was any significant positive or negative skewness in 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 geo-statistical analysis. The log-transformation reduced skewness, helped to stabilize variance, reduced the impact of extreme values, and helped make the distribution closer to normal. In soil fertility studies, Q–Q plots can be used to analyze the normality of soil properties prior to soil analysis as well as statistical and geostatistical analysis. If the plot is considered to be a normal Q–Q plot, the sample quantiles are plotted against the expected theoretical quantiles of the normal distribution. If the observations are seen to be approximately following a straight diagonal line, then the data are approximately normally distributed. Variables that fulfilled the normality assumption were only used for subsequent semivariogram modelling and spatial interpolation analyses.

GEOSTATISTICAL INTERPOLATION TECHNIQUES

Ordinary Kriging (OK)

One of the important Geostatistical interpolation techniques is ordinary Kriging (OK). It takes into account the spatial dependence between observations by using a semivariogram, which is not the case for deterministic interpolation methods like Inverse Distance Weighting (IDW). The semivariogram is used to define the weights of neighbors, as a measure of how similarity of observations diminishes as distance increases. In Kriging, the estimated value at an unsampled location is taken as a weighted linear combination of the known observations, with the weights chosen to give an "unbiased" estimate that has a "minimum" estimation variance (Gotway et. al., 1996; Chandra et al., 2026). Kriging has been extensively used in agricultural and soil science research, especially for mapping spatial variability of soil properties like pH, electrical conductivity, organic carbon, available nitrogen, phosphorus, potassium, sulphur and micronutrients. The accuracy of Kriging is related to sampling density, spatial dependence, selection of an appropriate semivariogram model and cross validation of predictions. Therefore, the Kriging can be a good tool to develop continuous spatial distribution maps and to detect soil fertility and other environmental properties differences. Kriging weights can be evaluated as

$$\widehat{W}(a_0) = \sum_{i=1}^{N} \lambda_i W(a_i)$$

$$\sum_{i=1}^{N} \lambda_i = 1$$

By minimizing the variance of the interpolation error, the best linear unbiased predictor (BLUP) will now be found. Therefore, the mean square error of the variance of an OK can be calculated as:

$$\sigma_k^2 = \sigma^2 - \sum_{i=1}^{N} v_i[\mathrm{cov}\,\{W(a_i)\, W(a_0)\}] - \lambda$$

A semivariogram measures the data variability and spatial correlation among the data points over space. By fitting observed values to a semivariogram model and checking it with a jackknife validation method, we can determine the hidden spatial patterns within the dataset. The semi-variogram can be computed by the given formula (Chandra et. al., 2026).

$$\gamma(S) = \frac{1}{2n(S)} \sum_{i=1}^{n(s)} [\, U(a_i) - U(a + S)]^2$$

Some very common semivariogram models are shown in Table-2.

Table 2: Expressions for different semi-variogram models

Semi variogram models	Expressions
Linear Model:	$\Upsilon(S) = C_0 + \left(\frac{c}{b}\right) S$
Exponential Model:	$\Upsilon(S) = C_0 + C\left[1 - \exp\left\{-\frac{s}{b}\right\}\right] for S > 0$
Gaussian Model:	$\Upsilon(S) = C_0 + C\left[1 - \exp\left\{-\frac{S^2}{b^2}\right\}\right] for S > 0$
Spherical Model:	$\Upsilon(S) = C_0 + C\left[\frac{3s}{2b} - \frac{1}{2}\left\{\frac{S^3}{b^3}\right\}\right]$ $for\ 0 < S \leq b$ C_0+C for$S > b$
Circular Model:	$\Upsilon(S) = C_0 + \left[\frac{2c}{\pi}\frac{S}{b}\sqrt{1 - \left(\frac{S^2}{b^2}\right)} + arcsin\left(\frac{S}{b}\right)\right]$ for 0 < S ≤ b C_0+C for$S > b$

Where S 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. The nugget value, partial sill, and range are very important parameters to ensure accurate analysis. The nugget value describes the spatial structure of the data by pointing out the change in similarity of data point with distance. It is nothing but the variation at zero distance. Sill or variance is like the distance over which points are related to each other. Now the problem is to choose right semivariogram model for our data, we continued to change these parameters until the smallest nugget effect was obtained and the best fitted model was found. (Yaserebi et. al., 2003). To evaluate the geographical dependency of soil parameters, we use

$$M = \frac{C_0}{C_0 + C}$$

Strong spatial dependency was considered as having M less than or equal to 0.25, moderate geographic dependence as having the value of M between 0.25 and 0.75 and weak spatial dependence as having M greater than 0.75. To this classification the continuity and variation in soil properties is better understood. (Cambardella and Karlen, 1999).

Inverse Distance Weighting (IDW)

The Inverse Distance Weighting method is a commonly known and popular method used in geographic information system (GIS). It provides accurate values of space variables and has an advantage of simplicity that makes it suitable to use for people with different experience level. The method assumes that observations nearest to the prediction site have the most impact on the prediction than observations further away. The estimated value is a weighted average of the local observations, with weights inversely proportional to the distance between the sample location and the locations for which it is a sample (Zeiler, 2010). IDW is also a popular option in soil fertility mapping, rainfall estimation, crop yield assessment and environmental studies due to its simplicity, efficiency in computation and ease of implementation in GIS software. For IDW we use the following formula

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

where Xi is the known data points used in estimation The distance dij reflects the separation between the point and the estimation location, w is 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 Geo-statistical Analyst extension available within the Arc Map 10.8.1 software (ESRI, 2001). The reliability of the predictive models was evaluated by cross validation technique (Voltz and Webster, 1990). With the help of this technique we can get the best semi-variogram model. 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

Root mean square error (RMSE)

The root mean square error (RMSE) is used to 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 can be computed as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left\{w(x_i) - \hat{w}(x_i)\right\}^2}$$

Where n = total samples, $w(x_i)$ = observed value, $\hat{w}(x_i)$ = predicted value

Coefficient of Determination (R^2)

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.

$$R^2 = 1 - \frac{\textit{Residual sum of Square}}{\textit{Total sum of square}}$$

RESULTS

The dataset underwent analysis using descriptive statistics and geo-statistics, while the statistical data were tested for normality through Q-Q plot. The results of the descriptive statistics (Table 3) showed a great variation of soil fertility parameters. The soil pH level was found to range from 6.20 to 8.90, with a mean value of 7.555 and a coefficient of variance (CV) of 10.25%, which shows low variability and is predominantly neutral to slightly alkaline soil conditions. The soluble salts showed a high spatial variability with electrical conductivity (EC) ranging from 0.11-1.52 dS m-1, with a mean of 0.807 dS m-1 and the highest CV (50.43%). Soil organic carbon (OC) ranged from 0.21 to 0.89 per cent with a mean value of 0.4914 and a coefficient of variation (CV) of 30.30 per cent, showing moderate variability. Available nitrogen (N) ranged from 121.10 to 380.40 kg ha^{-1}, with a mean of 252.60 kg ha^{-1} and a CV of 29.04%, while available phosphorus (P) ranged from 7.12 to 25.23 kg ha^{-1}, with a mean of 16.18 kg ha^{-1} and a CV of 31.89%. Available potassium (K) ranged from 145.80 to 492.30 kg ha^{-1} with an average of 315.80 kg ha^{-1} and a coefficient of variation of 31.44% which implies moderate variation. Skewness values for all the parameters were found to be close to zero varying from −0.037 to 0.118 indicating nearly symmetric distributions. In general, the pH had the lowest variation, EC had the highest variation and OC, N, P and K had moderate variation. The data obtained variety in soil properties indicates the existence of spatial heterogeneity and the possibility of using spatial interpolation techniques such as Inverse Distance Weighting (IDW) and Kriging to map their spatial distribution.

Table 3: Descriptive statistics of the soil parameters

Descriptive Statistics	pH	EC (ds/m)	OC (%)	N (Kg ha^{-1})	P (Kg ha^{-1})	K (Kg ha^{-1})
Mean	7.555	0.807	0.4914	252.60	16.18	315.8
SD	0.775	0.407	0.1489	73.371	5.162	99.314
CV (%)	10.25	50.43	30.30	29.04	31.89	31.44
Min	6.20	0.11	0.21	121.10	7.12	145.80
Max	8.90	1.52	0.89	380.40	25.23	492.30
Skewness	-0.037	0.031	0.118	-0.008	0.012	0.056
Kurtosis	1.8305	1.7998	2.15	1.853	1.8464	1.8684

Min stands for minimum, Max for maximum, skew for skewness, SD for standard deviation, and CV for Coefficient of variation. Skewness (O) and kurtosis(O)

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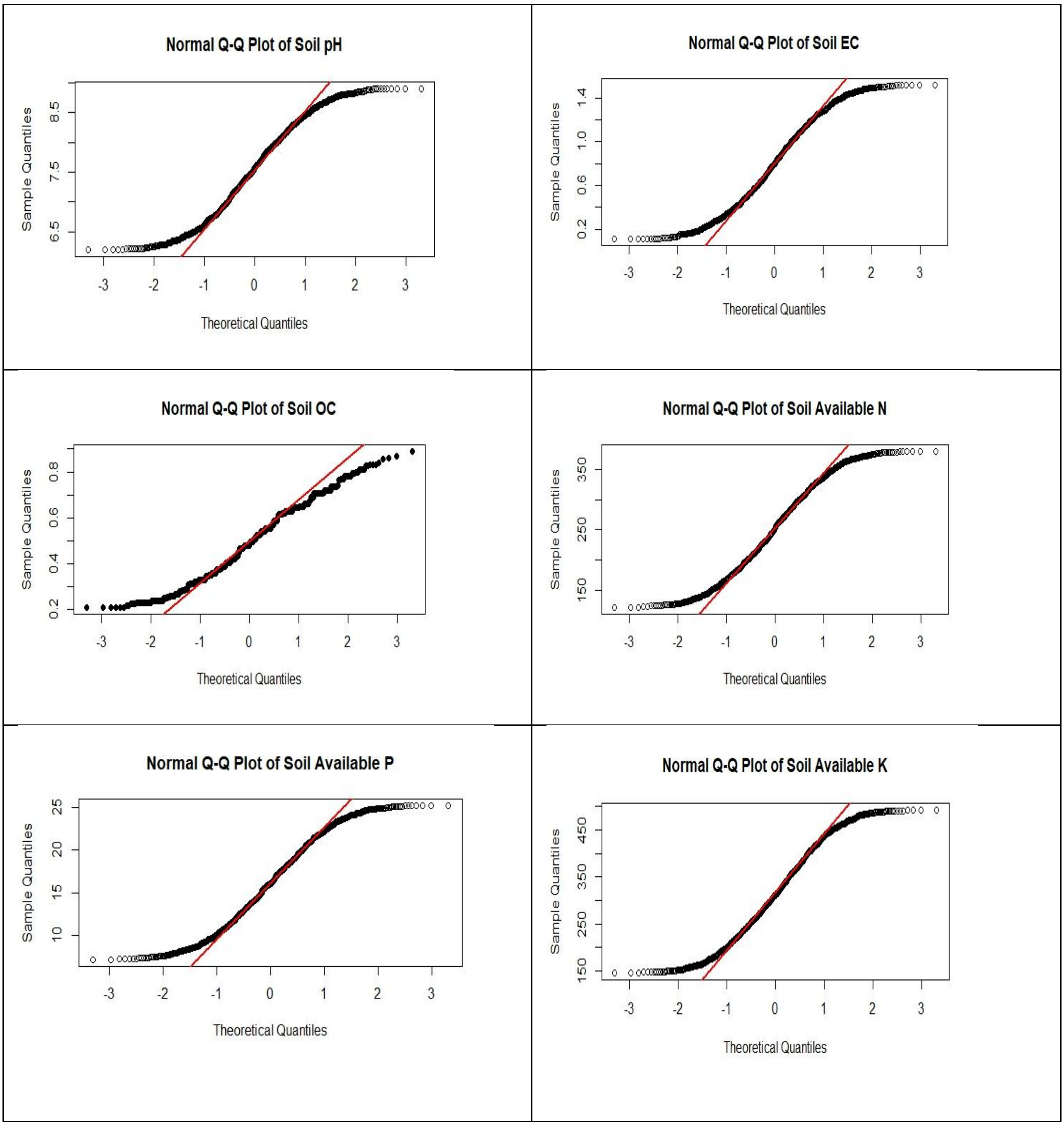


Fig: 2

Q-Q plot is a useful graph for visualizing the data distribution and can help determine if there may need to be some data transformation before further analysis is conducted. The advantage of checking the distribution of soil properties for Kriging is that if the data is skewed, the variogram can be impacted and the performance of the prediction could suffer; IDW is not dependent on the soil data being normally distributed. Hence it is suggested that Q–Q plots be utilized as an important initial diagnostic tool when assessing the performance of spatial interpolation methods such as IDW and Kriging. The Q-Q plot for various soil parameters are shown in Fig 2.

Geo-statistics for soil chemical properties

In the present study, ArcMap version 10.8.1 was used to create the spatial maps as well as examine the spatial structures of various parameters of the soil. Spatial pattern analysis included in the study was ordinary kriging and IDW methods. In Ordinary Kriging, the different properties of soil were tested to find the best model and highest R^2 value and the corresponding semi-variogram was computed. The distribution of soils was different between the areas (Table 4). The Spherical model was found best fit for soil pH and available phosphorus (P) while the exponential model was best for available electrical conductivity (EC), organic carbon (OC), available nitrogen (N) and available potassium (K). The selected models were suitable for capturing the spatial variability of soil properties and appeared to be a good predictor of soil properties at the spatial level. All soil parameters showed high spatial dependence in terms of the nugget-to-sill ratio. If the nugget-to-sill ratio is less than 25%, variations in these soil properties are not caused by chance, but are primarily caused by soil-forming processes, parent material, topography and land management over the years which explains the spatial variability of soils. The algorithm of Leave-One-Out Cross-Validation (LOOCV) was used to evaluate the performance of the spatial interpolation models in predicting and reliability. One of the observations is temporarily removed from the data set and the model is calibrated by using the remaining data. The prediction error is calculated for the excluded observation and the fitted model is used to make prediction. This is repeated for each observation within the data set with each observation only used once for validation. The model accuracy was assessed from the following validation statistics: 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.

Table 4: Semivariogram Parameters of Ordinary Kriging

Parameter	Model	Nugget (C_0)	Partial sill (C)	Sill (C_0+C)	MSE	RMSE	R^2	N/S	Spatial Dependenc
pH	Spher	0.0039	0.0510	0.0550	0.0029	0.0537	0.938	7.3%	Strong
EC	Expo	0.0008	0.0114	0.0122	7.00E-04	0.0273	0.941	6.7%	Strong
OC	Expo	0.00	0.0086	0.0086	0.000018	0.00426	0.997	0.0%	Strong
N	Spher	27.24	494.03	521.28	24.1924	4.9186	0.953	5.2%	Strong
P	Expo	0.00	3.62	3.6271	0.0784	0.2801	0.977	0.0%	Strong
K	Expo	50.18	783.55	833.73	42.8614	6.5468	0.942	6.0%	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 R^2, MSE, and RMSE. With a very low RMSE of 0.0021 and an R^2 of 0.966 for soil EC, the IDW model demonstrated a high degree of agreement between observed and predicted values. Similarly, with an R2 of 0.964 and an RMSE of 0.008, pH showed excellent accuracy. Additionally, with an R^2 value of 0.9833 and an RMSE of 0.0001, 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	R^2
pH	IDW	0.0893	0.008	0.9643
EC	IDW	0.0462	0.0021	0.966
OC	IDW	0.01369	0.00018	0.9833

N	IDW	8.3807	70.2346	0.9658
P	IDW	0.5768	0.3327	0.9628
K	IDW	11.4223	130.469	0.9642

AREAS OF THE STUDY LAND USING GEO-STATISTICAL TECHNIQUES

Areas under different soil categories based on soil fertility parameters are shown in Table-5

Table 5: 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		6.0-6.5	Slightly Acidic	0.00	0.00	3549.65	0.71
		6.5-7.3	Neutral	61103.50	12.16	134754.62	26.82
		7.3-7.8	Slightly Alkaline	380373.90	75.69	223215.20	44.42
		7.8-8.4	Moderatory Alkaline	61004.45	12.14	128315.72	25.53
		8.4-9.0	Strongly Alkaline	33.02	0.01	12679.68	2.52
		>9.0	Very Strongly Alkaline	0.00	0.00	0.00	0.00
EC	dS m^{-1}	≤ 2.0	Non-Saline	502514.87	100%	502514.87	100%
OC	%	≤ 0.5	Low	248112.27	49.37	248360.31	49.42
		0.5-0.75	Medium	254402.6	50.63	251315.21	50.01
		≥ 0.75	High	0.00	0.00	2839.35	0.57
N	Kg ha^{-1}	≤ 280	Low	151875.49	30.23	186909.71	37.19
		280-560	Medium	350639.38	69.77	315605.16	62.81
P	Kg ha^{-1}	≤ 10	Low	0.00	0.00	8568.69	1.71
		10-25	Medium	502514.87	100	493896.65	98.28
		≥ 25	High	0.00	0.0	49.53	0.01

K	Kg ha^{-1}	≤120	Low	0.00	0.0000	0.00	0.0000
		120-280	Medium	48539.40	9.6593	135646.16	26.99
		>280	High	453975.47	90.3407	366868.71	73.01

pH

Soils in the study area were mostly moderately alkaline with a pH range of 6.20 to 8.90 with an average value of 7.55. The coefficient of variation (CV) was 10.25%, 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 = 0.9643) with RMSE (0.0893) than Ordinary Kriging (R^2 = 0.938, RMSE = 0.0537). The maps of the spatial distribution (Fig 4 and 5) showed that most of the study area was moderately alkaline with a small portion neutral and strongly alkaline. From these results, it is suggested that nutrient availability may require a change in the pH in high pH areas. The majority area (75.69%) soils have slightly alkalinity of 7.3-7.8 pH by OK method, while 44.42% area soils have slightly alkalinity based on IDW method. The moderate alkaline category (7.8 to 8.4) comprises 12.13% by OK and 25.53% by IDW method while strongly alkaline (8.4 to 9.0) represents 0.0066% by OK and 2.52% by IDW of the study area and very strongly alkaline (>9.0) area was found 0% by both OK and IDW. The neutral area was just 12.15% by OK and 26.81% by IDW. In high pH areas, and for better nutrient absorption, the proper implementation of corrective measures becomes necessary.

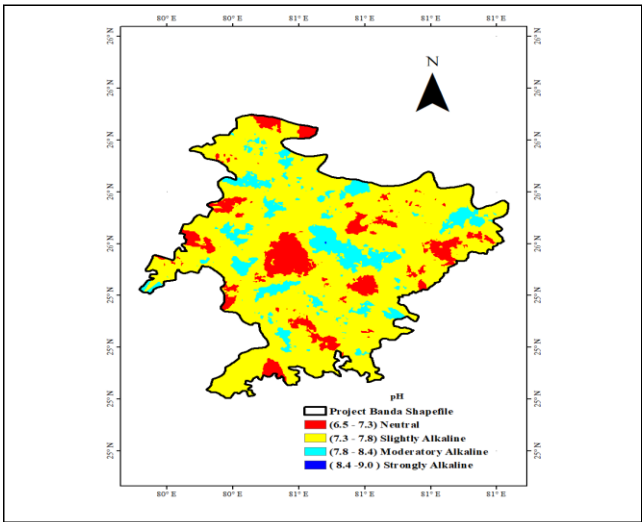


Fig. 4: pH (OK)

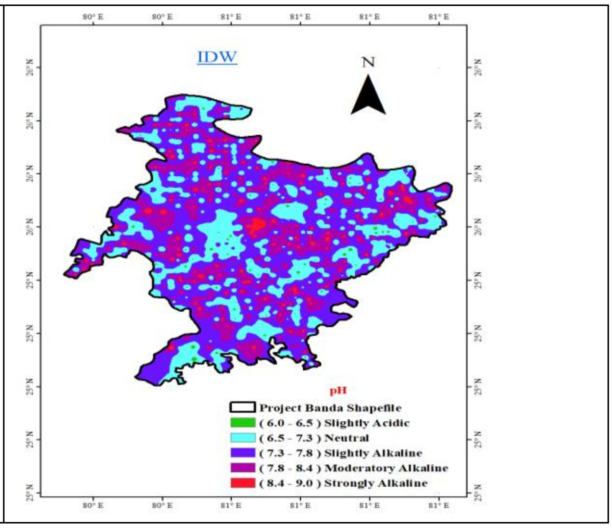
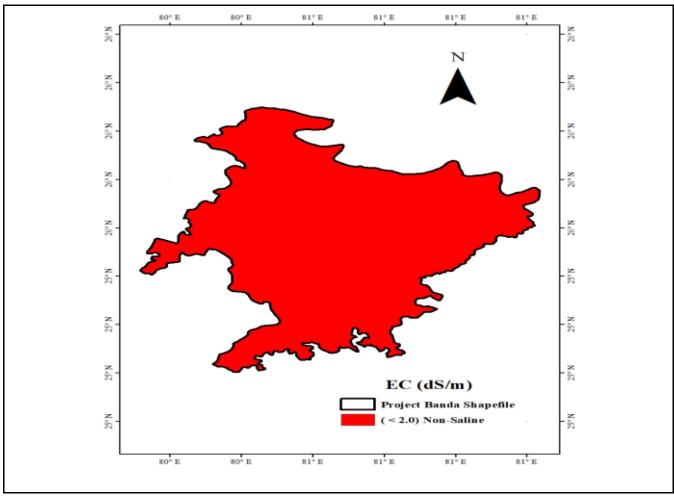


Fig. 5: pH (IDW)

ELECTRICAL CONDUCTIVITY (EC)

The electrical conductivity of the soil in the study area was found to be 0.11 to 1.52 dS m-1 and mean value was 0.80 dS m-1, which was non-saline. The CV was observed as 50.43%, highlighting the high variability. The IDW model provided better prediction accuracy (R^2 = 0.966, RMSE = 0.0462) than OK (R^2 = 0.941, RMSE = 0.0273). Spatial distribution map showed the whole of the study area was non-saline indicating that there is no salinity constraint to crop production. The results of electrical conductivity measurements showed that the entire study area (100%) falls within the non-saline range (≤ 2.0 ds/m) by both methods. There are no salinity issues in all the areas of soil surveyed and these soils are suitable for different agricultural crops as salt stress is not an issue. In all of the study area, there are no saline segments in the very slightly saline range (2.0 to 4.0 ds/m), in the slightly saline range (4.0 to 8.0 dS/m), moderately saline range (8.0 to 16.0 dS/m), and strongly saline range (≥ 16.0 dS/m).The result of the interpolation map created for the EC is shown in Fig. 6 and 7.

Natural Resources for
Human Health
eISSN: 2583-1194



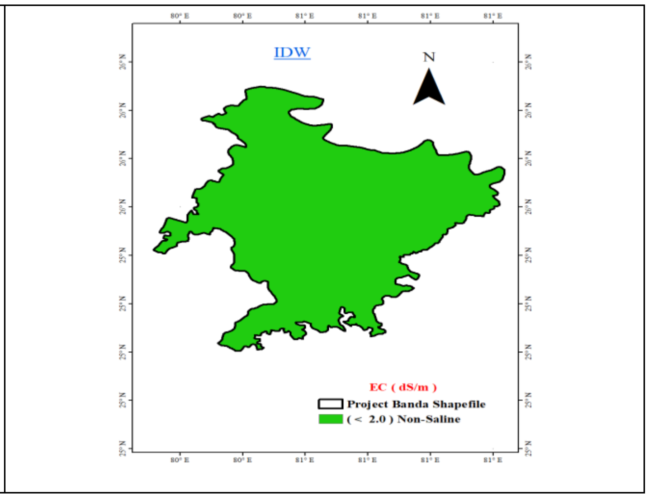
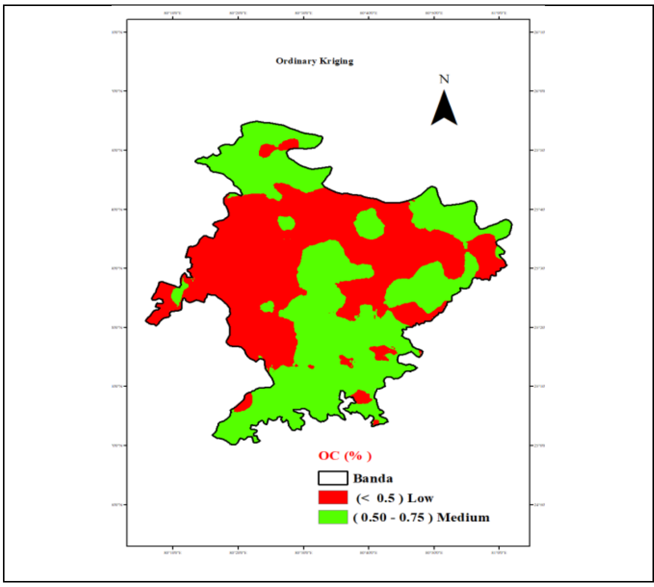


Fig. 6: EC (OK) **Fig. 7:** EC (IDW)

ORGANIC CARBON (OC)

The range of organic carbon content was lying between 0.21 and 0.89% with an average of 0.491% which is generally low. The CV was 30.3% which was high in the study area. OK produced more accurate predictions (R^2 = 0.997, RMSE = 0.004) than IDW (R^2 = 0.9833, RMSE = 0.013). The majority of the study area was in low to medium class of organic carbon which shows application of farmyard manure/compost/crop residues and green manure to improve soil fertility. This shows that there is a huge difference in the levels of soil organic carbon (OC); 49.37% of the area had low OC (≤ 0.5%) using the OK method and 49.42% using the IDW method, which suggests that the soil condition was poor due to intensive farming and low organic input. These soils are usually well compacted, have low water-holding capacity and low nutrient levels. Medium OC levels (0.5 – 0.75%) are observed over 50.63% area by OK and 50.01% area by IDW, indicating moderate fertility either due to good management or natural factors. The optimal soil health and sustainable land use category (high OC, ≥ 0.75%) was proposed only by only IDW with an area of 0.57%. This distribution underscores the importance of soil restoration measures such as organic amendments and conservation tillage to improve soil productivity and facilitate climate change mitigation by sequestering carbon. The result of the interpolation map created for the OC is shown in Fig. 8 and 9.



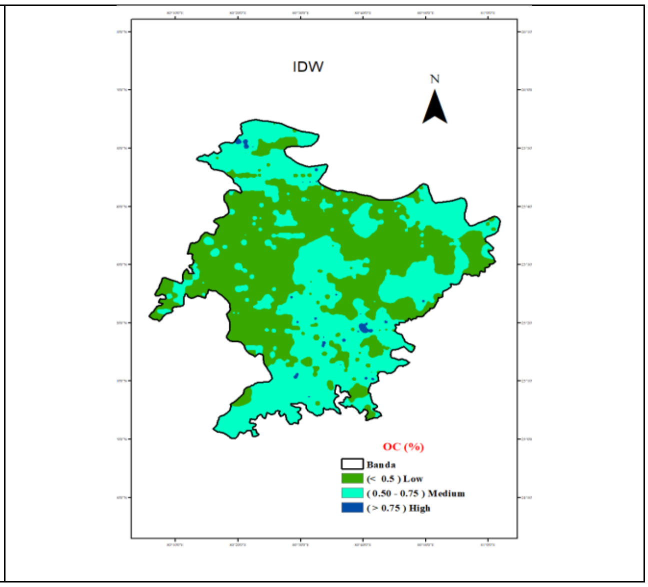


Fig. 8:OC (OK) **Fig. 9:** OC (IDW)

Natural Resources for Human Health

eISSN: 2583-1194

Nitrogen (N)

The available nitrogen (kg ha-1) in the study area ranged from 121.10 to 380.4 kg ha^{-1} and the mean value was 252.6 kg ha^{-1} indicating that majority of soils were nitrogen deficient. There was moderate variability with a CV of 29%. The R^2 of the IDW model was slightly higher (0.965) than OK (0.953), while the RMSE for OK was lower (4.91) than IDW (8.38). Spatial distribution map showed that the majority of the area was in low nitrogen category suggesting the need for balanced nitrogen fertilization and increased application of organic amendments. The findings revealed that nitrogen deficiency is present in majority of the study area as available N in OK (98.62%) and IDW (91.87%) is below 280kg/ha. 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 indicates that the study area needs specific soil fertilization strategies that involve green manure, legume rotation and organic fertilizers as well as the application of nitrogenous fertilizers. Protection is needed to restore N in the soil for sustainable farming practices and to increase soil fertility. The result of the interpolation map created for the nitrogen is shown in Fig. 10 and 11.

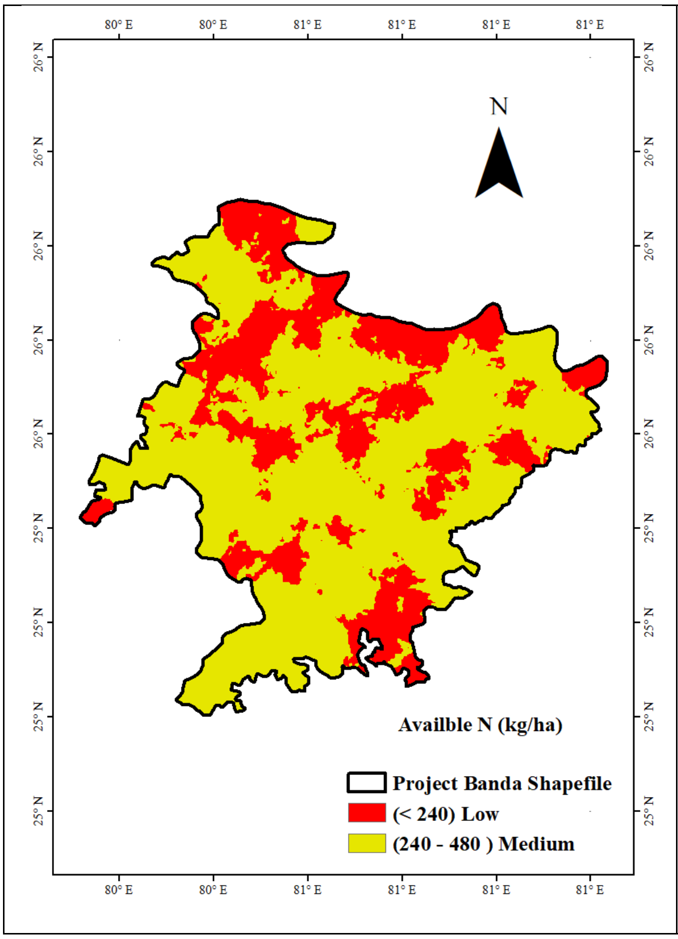


Fig. 10: N (OK)

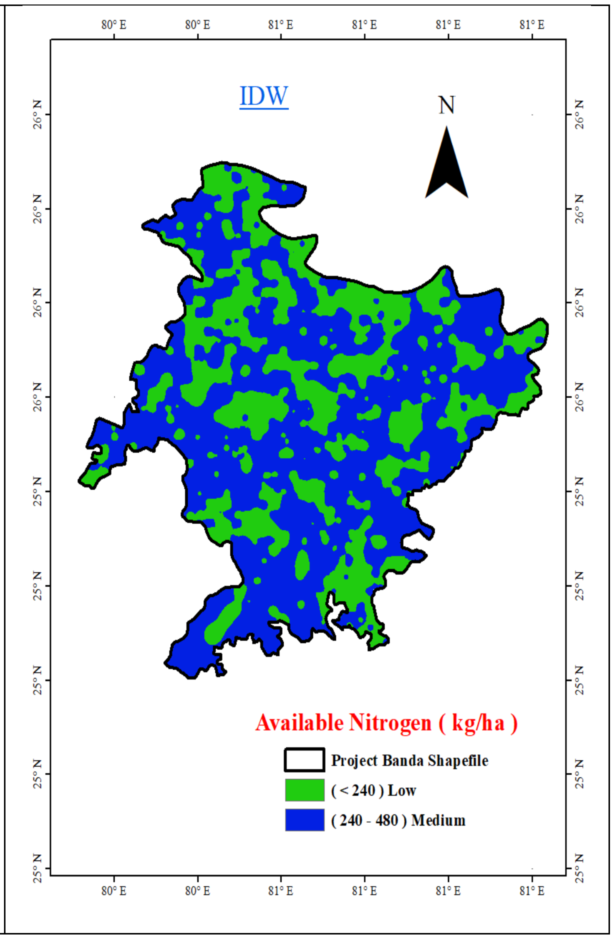


Fig. 11: N (IDW)

PHOSPHORUS (P)

The available phosphorus content of the soils was found to range from 7.12 to 25.23 kg ha^{-1} with 16.18 kg ha^{-1} as the average, which shows that most of the soils have medium available phosphorus contents. The CV is 31.89% which indicated low to moderate variability. The OK interpolation method outperformed IDW, with a higher R^2 (0.977) and lower RMSE (0.2801) than IDW (R^2 = 0.962, RMSE = 0.5768). 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. The available P in the soil shows promising results with

Natural Resources for Human Health
eISSN: 2583-1194

majority of the lands (100 area by OK and 98.28 area by IDW) under medium category (10-25 kg/ha). The level of phosphorus availability throughout the study area is moderate, providing good conditions for plant growth, root development, flowering function and energy transfer in crops. The study area only covers 1.71% area by IDW for low phosphorus land (<10 kg/ha). The total area with high phosphorus content (idw>25 kg/ha) is only 0.01 % by IDW. Therefore, a targeted intervention is required in the low phosphorus areas to increase nutrient concentration and careful nutrient management is essential in the high phosphorus areas to prevent environmental risk. Long-term soil fertility and yield is recommended with abalanced phosphorus fertilization, based on soil testing. The output of the interpolation map that was made for the phosphorus is displayed in Fig. 12 and 13.

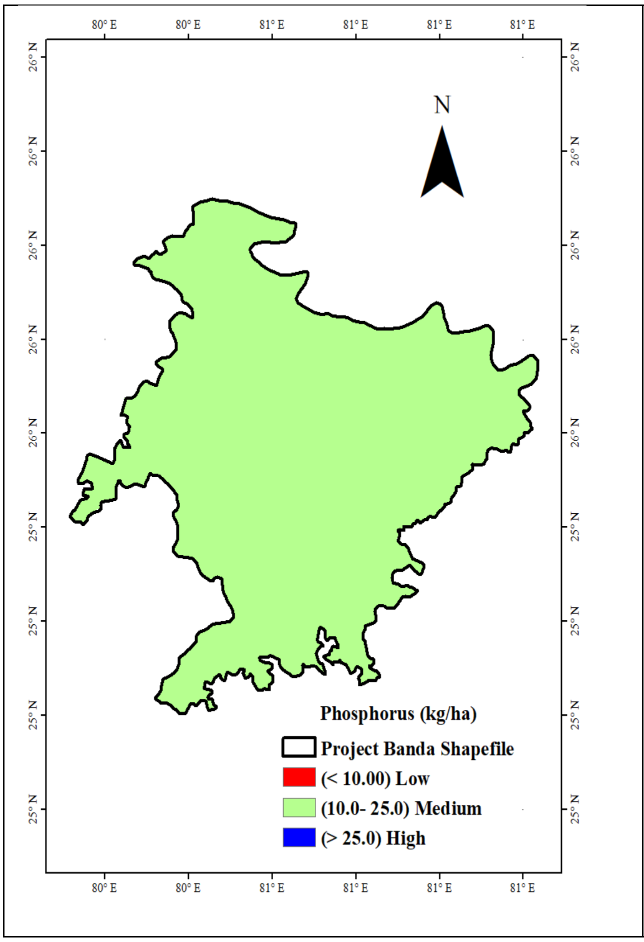


Fig. 12: P (OK)

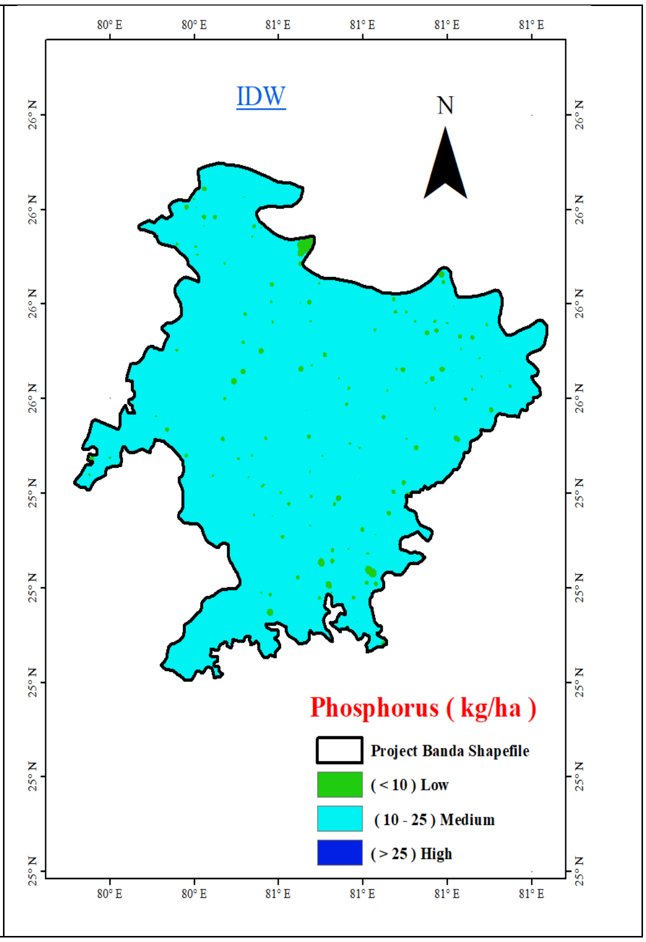


Fig. 13: P (IDW)

POTASSIUM (K)

The available potassium level ranged from 145.80 to 492.30 kg ha^{-1} with an average of 315.8 kg ha^{-1}, which is considered medium to high. The CV was 31.44% which was considered as moderate variability. In the case of the interpolation of potassium, IDW could give a higher R^2 (0.964) than OK (0.942) while having a larger RMSE (11.42) than OK (6.54). 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. Potassium deficiency is not a problem at the investigation site as there are adequate potassium levels in all areas. Medium potassium (120 to 280 kg/ha) indicates 9.65% by OK and 26.99% by IDW of land area with medium nutrients supply that is adequate for most crops. The high potassium category (90.35% of the region by OK and 73.01% by IDW) is made up of soil potassium content > 280 kg/ha. Although the entire region has sufficient potassium levels, recommendations for effective nutrient management need to be maintained to ensure that soil health is not compromised. This soil has a high base level of potassium and therefore good plant growth and plant resistance. This favorable condition is recommended to be maintained and balanced fertilization practices are recommended to avoid nutrient imbalance. The result of the interpolation map created for the potassium is shown in Fig. 14 and 15.

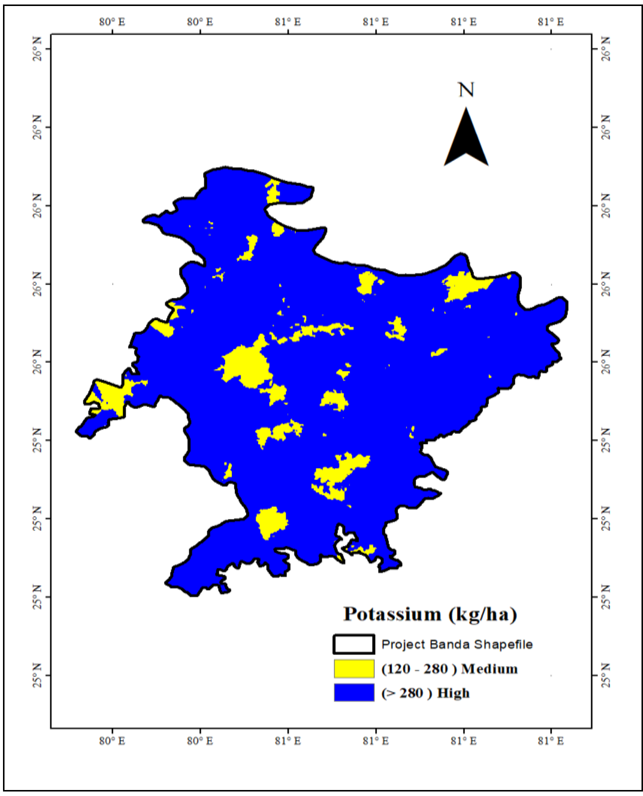


Fig. 14: K (OK)

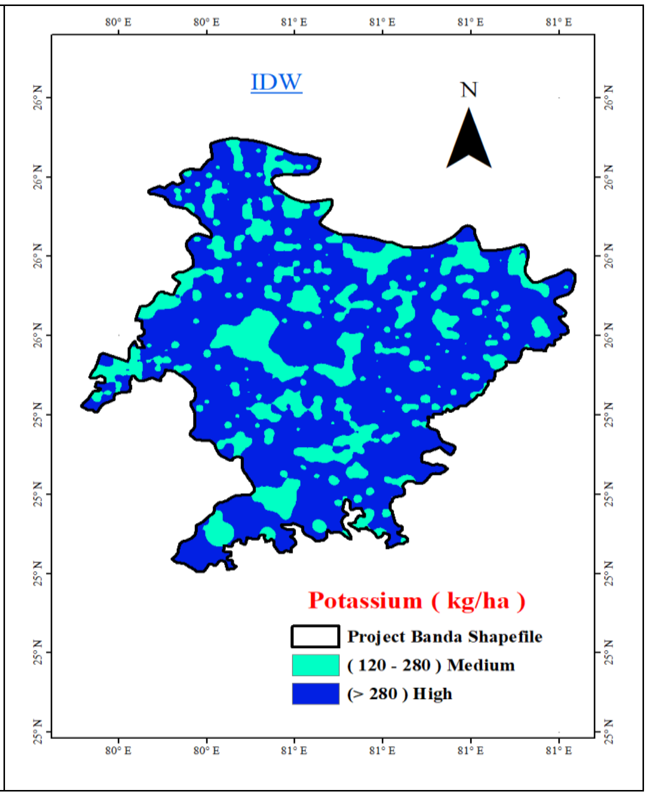


Fig. 15: K (IDW)

DISCUSSION

It was observed from the present study that there was a high spatial variability in soil fertility characteristics in the study area hence, site specific soil management is needed for sustainable agricultural production. The descriptive statistics revealed that most of the soils were moderately alkaline, non saline, low in organic carbon, low in organic nitrogen, medium in phosphorous and high in potassium content. These nutrient variations in soil fertility have been also reported in semi-arid regions of Bundelkhand and other parts of India where nutrient leaching occurs due to low rainfall, continuous cultivation and low organic matter content in soil that creates a spatial variability in the soil (Vasu et al., 2017; Chaubey et al., 2022).

Soil EC is generally most highly influenced by inherent soil forming processes (parent material and climate) and has the lowest coefficient of variation, whereas the variability in soil organic carbon, soil phosphorus and soil nitrogen are associated with agricultural management processes (cropping history, distribution of organic matter, fertilizer application). Moderately alkaline soils may have limited concentrations of several essential nutrients which may affect the productivity of crops. The same has been observed by Chandra et al. (2026), Gehlotet al. (2019) and Emadi et al. (2009).

The organic carbon values obtained during the study area were low indicating low soil quality and biological activity of the soils. The role of organic carbon in soil structure, water holding capacity, nutrient availability and microbial activity are important. The low status of organic carbon in the study area is likely related with heavy cultivation, low incorporation of crop residues and low application of organic manures. The same result was reported by Cambardella and Elliott (1994), Singh et al. (2022) and Vasu et al. (2017) who pointed out that frequent cultivation without proper organic amendments results into rapid depletion of soil organic matter (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). The low to moderate nitrogen percentage can be related to low organic matter, continuous cropping, failure to turn the crop residues into the soil, removal of nutrients from the soil by crops, erosion, and insufficient organic manure application. The spatial variation in nitrogen status can also be due to variation in soil type, moisture, preceding crops, and fertilizer application practices.This finding is in line with the previous study that proposes that nitrogen is the most limiting nutrient in the rain fed agricultural system of Bundelkhand. Therefore, it is necessary to encourage the use of integrated nutrients management (balanced use of nitrogen, green manure, crop residues incorporation and legumes cropping systems) for improving soil fertility and productivity (Raghuvanshi et al., 2026).

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. Generally, phosphorus was not limiting, but there were some areas which were phosphorus-deficient and needed balanced fertilization of phosphorus as recommended from soil phosphorus testing. For sustainable crop production, there needs to be an optimum level of phosphorus and potassium.

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 (Mueller et al, 2004; Cambardella and Karlen, 1999)

This comparison of interpolation methods showed that Inverse Distance Weighting (IDW) was the most accurate interpolation method for soil pH, EC, N and K, while Ordinary Kriging (OK) was the most successful interpolation method for soil OC and P. 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. Phosphorus and OC, 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

Agriculture is a significant sector of the Indian economy and is grappling with various challenges, such as climate change, water scarcity, and nutrient deficiencies. Minimization of these problems can be achieved by improved fertilizer and soil management. Growth of the soil and production of crops has been shown to be linked to good health and is supported by recent research that backs government programs. The soil quality is influenced by the choice of crop, the soil ph and the village- level fertility indicator (OC and P). The classification of soil nutrients, such as nitrogen, phosphorus, potassium and EC, aids in their optimization for analysis and reduces the amount of time and chemicals used. The measurement range is greater than what's necessary for good fertilizer recommendations. Therefore, the level of their low, medium and high is foreseen by using a massive number of distinct classes. Spatial assessment of soil parameters in the study area provides basic soil productivity data, which helps interpret the agricultural productivity rates. The soil analysis results of the essential indicators (pH, EC, N and K) were significantly different in favor of IDW for all of the soil parameters, except for P and OC, for which OK was more useful. Moderate alkaline pH values of soils across the study area prevented salinity from becoming a problem, though it did impact nutrient uptake with good quality being maintained in the crops. Where soils are low in organic carbon and nitrogen it is a matter of concern that must be addressed with focus in the regions where there are low levels of organic carbon and nitrogen, as these can be ameliorated by the inputs of green manure, organic materials and nitrogen fertilizers. Strategic fertilization practices are important due to the favorable levels of phosphorus and potassium in most of the area. The research suggests that sustainable management strategies need to align soil needs and ensure successful agriculture and environmental health. Addressing important agricultural issues in india, especially in areas with limited resources regions like bundelkhand, can greatly benefit from this research. By integrating geo-statistical techniques with GIS technology, the study builds a robust framework and serves as a stepping stone towards precision soil fertility management, crucial for sustainable agriculture.

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AUTHOR CONTRIBUTIONS

G.S.: Supervision, Conceptualization, Writing-Original Draft, Writing-Review and Editing Investigation. U.C.: Conceptualization, Writing-Original Draft, Writing-Review and Editing Investigation. AKC: Soil Testing, Writing-Review and Editing Investigation. H.M: Conceptualization, Writing-Review and Editing Investigation. A.M: Soil Testing Writing-Review and Editing. B.P.M.: Conceptualization, Writing-Original Draft, Writing-Review and Editing Investigation. A.P: Soil Testing, Soil Sampling and Investigation.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Not applicable

DATA AVAILABILITY STATEMENT

Not applicable

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