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ASSESSMENT OF SPATIAL VARIABILITY AND MAPPING OF SOIL PROPERTIES USING GEO STATISTICAL METHODS IN A REGION OF KALAHANDI DISTRICT, ODISHA, INDIA

Ashutosh Sahu[1], Y.V. Singh[1], P.K. Bharteey[2]*, Ashok Kumar[3], Chandan A. S.[4] and Okram Ricky Devi[5]

[1]Department of Soil Science and Agricultural Chemistry, Institute of Agricultural Sciences, Banaras Hindu University, Varanasi-221005, India.

[2]Department of Agricultural Chemistry and Soil Science, C.C.R. (P.G.) College, Muzaffarnagar-251 001, Uttar Pradesh, India.

[3]Post Graduate College, Ghazipur-233001, Uttar Pradesh, India.

[4]Department of Crop Physiology, Assam Agricultural University, Jorhat-13, Assam, India.

[5]Department of Agronomy, Assam Agricultural University, Jorhat-13, Assam, India.

*Corresponding author E-mail: prembharti406@gmail.com ; **O**rchid id: 0000-0003-1832-8381

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ABSTRACT

Food security and ecosystem nutrient recycling depend on healthy soil. Soil quality has generally declined as a result of rapid infrastructure development projects involving the extraction of mineral resources. This study examines the spatial variability of important soil characteristics in the Indian state of Odisha's Kalahandi district. employing geostatistical techniques to enhance agricultural productivity and land management practices Thirty soil samples totalling about 1287.04 hectares were taken in December 2023 from three villages in the Kalahandi district. The pH, organic carbon, nitrogen, phosphorus, potassium, and sulfur content are among the soil properties that have been examined. Their coefficients of variation (CV) range from 3.19% to 13.78%. The predicted spatial distribution of these soil properties was calculated using standard kriging interpolation. Statistical measures like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Error (ME) were used to evaluate prediction accuracy. The results demonstrate that ordinary kriging yielded accurate predictions for most soil properties. Specifically, pH exhibited an RMSE of 0.217 and an ME of -0.013, organic carbon had an RMSE of 0.051 and an ME of 0.011, and nitrogen showed an RMSE of 0.510 and an ME of -0.082. These findings underscore the effectiveness of geostatistical techniques in mapping soil properties, providing valuable insights for optimizing agricultural practices and promoting sustainable development in the Kalahandi region.

***Key words*: Geostatistics, Ordinary Kriging, Spatial Variability and Soil Properties**

Introduction

Soil variability is a critical factor affecting agricultural productivity, environmental quality as well as land management techniques. The variation in texture, organic matter content, nutrient levels, and moisture availability across different areas of the soil significantly influences crop yields and ecosystem sustainability (Cambardella *et al.*, 1994). Understanding this variability is essential for optimizing resource use and improving land management strategies. The Kalahandi region of Odisha, known for its diverse soil types and agricultural potential, presents a unique case for studying soil variability using geostatistical techniques. The principal issue this study attempts to address is the deficiency of detailed information regarding the spatial variability of soil parameters in the Kalahandi region. Because traditional soil sampling techniques are unable to capture the spatial heterogeneity of soil properties, they frequently offer only a limited amount of insight. across large areas reported by Journel and Huijbregts 1978. Consequently, there is a need for advanced techniques that can provide detailed and accurate information on soil variability. In order to evaluate the spatial variability of soil parameters in the Kalahandi region, this study suggests using geostatistical techniques. Geostatistics provides strong tools for predicting unsampled locations based on spatial autocorrelation and analyzing spatial data. Key soil property distribution will be mapped using methods like variogram analysis and kriging. providing a comprehensive understanding of soil variability in the study area (McBratney *et al.,* 2003). Previous studies have demonstrated the effectiveness of geostatistical methods in assessing soil variability. Kravchenko and Bullock 1999 highlighted the utility of kriging for mapping soil properties and improving the precision of agricultural practices. Similarly, Journel and Huijbregts 1978 emphasized the importance of variogram analysis in characterizing spatial dependence and guiding soil sampling strategies. Studies have shown that geostatistical techniques can significantly enhance soil fertility management (Sharma *et al.,* 2004). The study will pay attention to important soil characteristics like pH, nutrient levels, organic matter, and texture. This study uses geostatistical methods to create detailed maps of soil properties that can be useful resources for land managers, farmers, and policy makers. This research addresses a critical need for detailed information on soil variability in the Kalahandi region of Odisha. By leveraging geostatistical techniques, the study aims to provide a comprehensive assessment of soil parameters, thereby supporting informed decision-making in agriculture and land management. The findings are expected to have significant implications for enhancing agricultural practices and promoting sustainable development in the region.

Materials and Methods

Study Area

Three villages in the Karlamunda block of the Kalahandi district in Odisha, India, were the sites of the study. The study area is roughly 1287.04 hectares and is located between latitudes 20°37'19.8" to 20°40'69.3" N and longitudes 83°48'50.8" to 83°54'03.9" E (Fig. 1). The region has an average annual rainfall of 1387 mm and an average temperature of 28°C. Its altitude ranges from 97 to 194 meters above sea level.

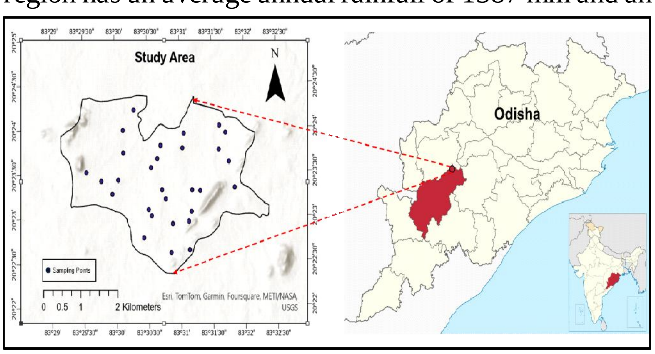

Fig. 1: The location of the study area in the Kalahandi district region of Odisha, India.

Soil Sampling and analysis

Throughout the research region, a methodical protocol for soil sampling was put in place. Using a stratified random sampling technique, thirty representative soil samples covering both agricultural and bare areas within three villages were taken from the 0–15 cm depth stratum. Samples were kept in cloth gunny bags and delivered to the agricultural chemistry lab and soil science department of Banaras Hindu University. To ensure homogeneity for chemical analysis, the sample was prepared by air-drying under controlled conditions, then mechanically grinding and standardizing through a 2 mm sieve. The available N, P, and K of the soil were determined using the alkaline permanganate method (Subbiah and Asija 1956), the 0.5 M $NaHCO_3$ method (Olsen *et al.*, 1954), and the ammonium acetate method (Jackson, 1973).

Ordinary Kriging

A basic geostatistical interpolation method called Ordinary Kriging (OK) is used to predict spatially distributed variables by yielding the best linear unbiased prediction. This method assumes a constant but unknown mean of the spatial process and employs a variogram to quantify spatial dependence. The experimental variogram γ(h) is defined as:

γ(h)=12N(h)i=1N(h)[z(xi)-z(xi+h)]2

Where z(xi) and z(xi+h) are the values of the variable at locations xi and xi+h respectively, and N(h) is the number of pairs of observations separated by distance h. This variogram is modelled by theoretical functions (*e.g.*, spherical, exponential, Gaussian) to inform the calculation of Kriging weights. The ordinary Kriging estimator for an unsampled location x0 is a weighted sum of observed values z(xi):

z*x0=i=1nλizxi

Evaluating the accuracy of spatial prediction

To test the predictive models' accuracy, eight of the thirty soil samples were taken at random from the dataset. As diagnostic metrics, the root mean square error (RMSE), mean absolute error (MAE), and mean error (ME) of residuals with kriging variance were computed as follows: Root Mean Square Error (RMSE):

RMSE=1ni=1nzi-zi2

Mean Absolute Error (MAE):

MAE=1ni=1nzi-zi

Mean Error (ME):

ME=1ni=1nzi-zi

Where, zi is observed values and zi is predicted values

Table 1: Descriptive statistical parameters of soil.

Parameters	Min	Max	Mean	Median	Mode	Sd	%CV	Skewness	Kurtosis
pH	5.57	6.31	6.01	6.04	5.79	0.19	3.19	-0.53	-0.36
OC (%)	0.35	0.56	0.45	0.44	0.44	0.05	11.42	0.35	-0.25
N(kg ha^{-1})	278.16	349.09	309.38	307.08	278.16	18.01	5.82	0.43	-0.42
P(kg ha^{-1})	19.85	35.79	27.21	27.45	19.85	2.91	10.71	0.15	2.53
K(kg ha^{-1})	246.89	333.10	285.49	283.66	246.89	21.91	7.67	0.41	-0.35
S(kg ha^{-1})	25.59	44.73	35.47	36.13	25.59	4.89	13.78	0.02	-0.58

Min= minimum, Max= maximum, Sd=Standard deviation, % CV= Coefficient of variation

Data analysis

In order to characterize the spatial distribution of soil available S in the study area, the following descriptive statistical parameters were calculated using an Excel spreadsheet: mean, median, minimum, maximum, standard deviation (SD), percent coefficient of variation (%CV), skewness, and kurtosis. To investigate the arrangement of spatial structure and variability, a semi variogram was utilized. Ordinary kriging interpolation techniques were used to investigate the spatial distribution of soil properties. Every map was made using Arc GIS.

Results and Discussion

Descriptive statistics for soil

A thorough statistical analysis of the soil's composition, including pH, organic carbon (O.C.%), nitrogen (N), phosphorus (P), potassium (K), and sulfur (S), is shown in Table 1. With a mean of 6.01, a median of 6.04, and a mode of 5.79, the pH values range from 5.57 to 6.31. The coefficient of variation (C.V.) is 3.19% and the standard deviation is 0.19, which indicates low variability. A slight left skew is indicated by the negative skewness (-0.53), and a relatively flat distribution is indicated by the negative kurtosis (-0.36). With a mean of 0.45%, a median of 0.44%, and a mode of 0.44%, the organic carbon content ranges from 0.35% to 0.56%. Moderate variability is indicated by the %CV of 11.42% and the standard deviation of 0.05%. A distribution that is somewhat flat and slightly skewed to the right is suggested by the positive skewness (0.35) and negative kurtosis (-0.25) values. With a mean of 309.38 kg ha^{-1}, a median of 307.08 kg ha^{-1}, and a mode of 278.16 kg ha^{-1}, the range of nitrogen levels is 278.16 to 349.09 kg ha^{-1}. With a percentage CV of 5.82%, the standard deviation is 18.01 kg ha^{-1}. A slightly right-skewed and flat distribution is indicated by the positive skewness (0.43) and negative kurtosis (-0.42). With a mean of 27.21 kg ha^{-1}, a median of 27.45 kg ha^{-1}, and a mode of 19.85 kg ha^{-1}, the levels of phosphorus vary from 19.85 to 35.79 kg ha^{-1}. The %CV is 10.71%, and the standard deviation is 2.91 kg ha^{-1}. A more peaked distribution is indicated by the positive kurtosis (2.53) and the near-zero skewness (0.15), which both point to a symmetric distribution. With a mean of 285.49 kg ha^{-1}, a median of 283.66 kg ha^{-1}, and a mode of 246.89 kg ha^{-1}, potassium concentrations range from 246.89 to 333.10 kg ha^{-1}. The %CV is 7.67% and the standard deviation is 21.91 kg ha^{-1}. A distribution that is flat and skewed to the right is indicated by the positive skewness (0.41) and negative kurtosis (-0.35). In conclusion, the range of sulfur levels is 25.59 to 44.73 kg ha^{-1}, with a mean of 35.47 kg ha^{-1}, a median of 36.13 kg ha^{-1}, and a mode of 25.59 kg ha^{-1}. The %CV is 13.78%, and the standard deviation is 4.89 kg ha-1. The distribution appears to be flat, as indicated by the negative kurtosis (-0.58) and near-zero skewness (0.02).

The spherical model was applied to organic carbon and K, the exponential model to S, and the Gaussian model to the pH, N, and P spatial dependence. With a range of 345.23, a sill of 0.048, and a nugget of 0.012, the pH values showed moderate spatial dependence; this resulted in a nugget-to-sill ratio of 0.25 (Table 2, Fig. 2a). This result is consistent with that of (Cambardella *et al*., 1994),

Table 2: Ordinary kriging semi variance analysis of spatial structure in soil properties.

Parameters	Model	Range	Sill	Nugget	Psill	Nugget/sill ratio	Spatial Dependence
pH	Gau	345.23	0.048	0.012	0.036	0.25	Moderate
OC	Sph	985.47	0.019	0.0052	0.0138	0.2737	Moderate
N	Gau	268.34	393.45	28.47	364.98	0.0724	Strong
P	Gau	218.67	9.87	2.46	7.410	0.2497	Moderate
K	Sph	375.12	591.24	98.53	492.71	0.1666	Strong
S	Exp	892.32	117.36	29.58	87.78	0.252	Moderate

Sph=spherical, Exp=exponential, Gau=gaussian, Nugget/Sill ratio,Psill=Partial sill, <25% =Strong Spatial Dependence, 25-75%=Moderate Spatial Dependence, >75% =Weak Spatial Dependence.

Table 3: Prediction accuracy of ordinary kriging.

Parameters	RMSE	MAE	ME
pH	0.217	0.174	-0.013
OC	0.051	0.040	0.011
N	0.510	0.358	-0.082
P	0.462	0.242	0.018
K	0.321	0.256	0.006
S	0.348	0.310	0.074

who in their investigation of soil properties across diverse landscapes reported a similar moderate spatial dependence of pH. Consistency in the spatial variability of pH in various environments indicates influences from elements including land use, parent material, and management techniques. With a range of 985.47, a sill of 0.019, and a nugget of 0.0052, organic carbon also showed moderate spatial dependence. This resulted in a nugget-to-sill ratio of 0.2737 (Table 2, Fig. 2b). This suggests that the distribution of organic carbon in the study area exhibits a significant spatial structure. With a range of 268.34, a sill of 393.45, and a nugget of 28.47, nitrogen (N) showed strong spatial dependence. This resulted in a nugget-to-sill ratio of 0.0724 (Table 2, Fig. 1c). The significant spatial dependence for nitrogen that has been observed is in line with Goovaerts' (1998) findings. Who stated that strong spatial structures were indicated by low nugget-to-sill ratios. Such a strong spatial dependence implies that localized factors like microbial activity and fertilization techniques have a significant impact on nitrogen distribution.. With a range of 218.67, a sill of 9.87, and a nugget of 2.46, phosphorus (P) displayed a moderate degree of spatial dependence, yielding a nugget-to-sill ratio of 0.2497 (Table 2, Fig. 2d). This observation is consistent with the geostatistical analysis conducted by McBratney and Webster (1983), which also found a moderate spatial dependence for phosphorus. The application of phosphate fertilizers is one soil management practice that frequently affects the spatial variability of phosphorus and adds to its moderate spatial dependence. With a range of 375.12, a sill of 591.24, and a nugget of 98.53, potassium (K) showed strong spatial dependence, resulting in a nugget-to-sill ratio of 0.1666 (Table 2, Fig. 2e). Zhang *et al.*, (2011), who reported comparable strong spatial structures for potassium in agricultural soils, provide support for this conclusion. The distribution of potassium is significantly impacted by both natural soil properties and soil management techniques, as indicated

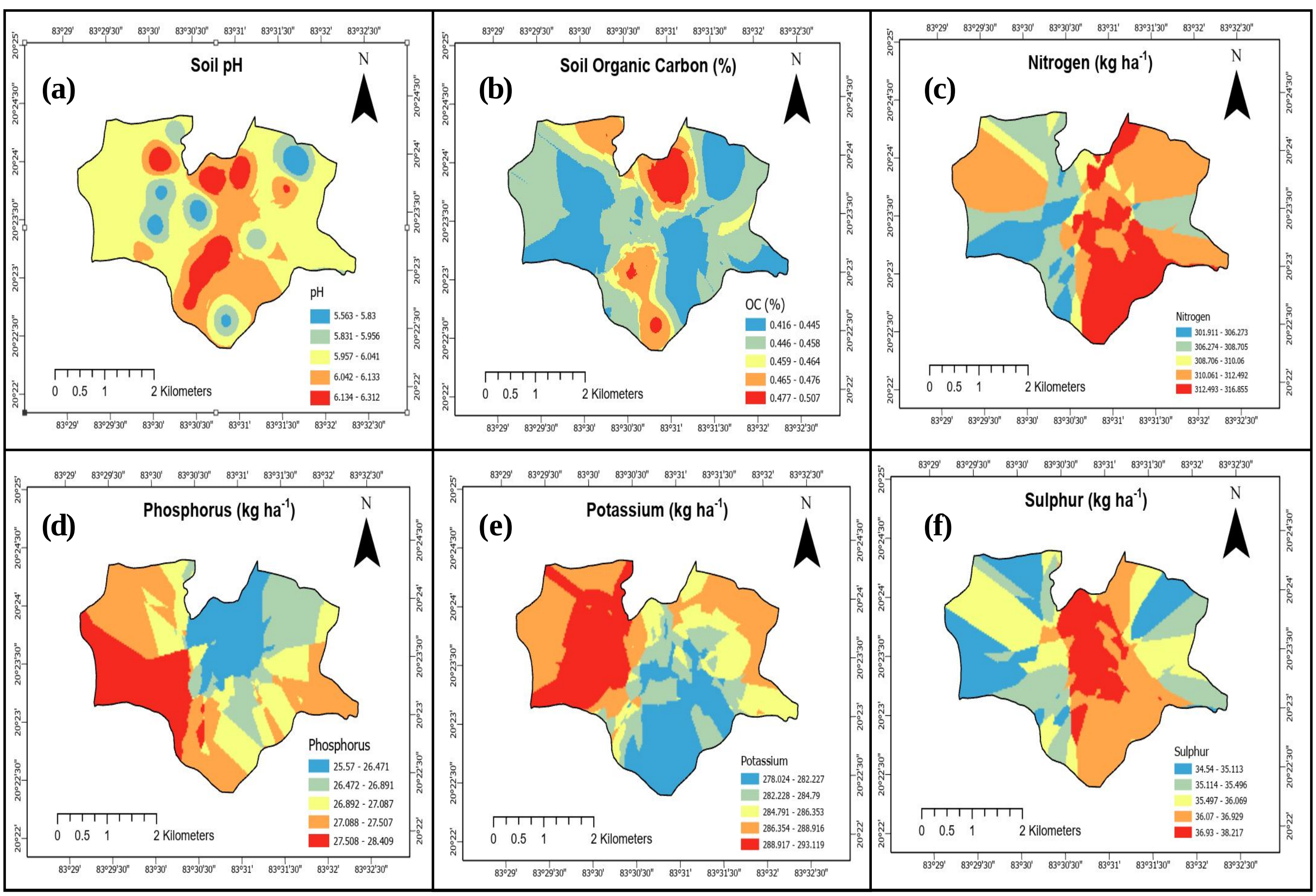

Fig. 2: Spatial distribution map of soil; **(a)** pH; **(b)** Organic Carbon; **(c)** Nitrogen; **(d)** Phosphorus; **(e)** Potassium; **(f)** Sulphur using ordinary kriging technique.

by the strong spatial dependence. Based on an exponential model analysis, sulfur (S) showed a moderate spatial dependence, with a nugget-to-sill ratio of 0.252, a range of 892.32, a sill of 117.36, and a nugget of 29.58 (Table 2, Fig. 2f). The moderate spatial dependence of sulfur indicates soil variability impacted by both anthropogenic and natural soil features. Table 3 shows the prediction accuracy of the standard kriging model for several soil properties, such as pH, organic carbon, nitrogen, phosphorus, and sulfur.

The spatial distribution of soil properties was estimated using ordinary kriging, and the prediction accuracy was assessed using mean error (ME), mean absolute error (MAE), and root mean square error (RMSE) pH exhibited the lowest RMSE (0.217) and MAE (0.174), indicating high prediction accuracy, while nitrogen (N) had the highest RMSE (0.510) and MAE (0.358), suggesting lower prediction accuracy for this parameter (Table 3). The ME values, which measure prediction bias, were close to zero for most properties, indicating minimal systematic error, with pH at -0.013, organic carbon (OC) at 0.011, and phosphorus (P) at 0.018 (Table 3). However, N displayed a more pronounced negative bias (ME = -0.082), implying under-prediction, while sulphur (S) showed a slight positive bias (ME = 0.074) (Table 3). Kriging has the potential to be an efficient method for modeling the spatial variability of soil pH and organic carbon, resulting in minimal bias and high prediction accuracy (Cambardella *et al*., 1994). According to McBratney and Pringle (1999), kriging is especially helpful for soil properties that have a moderate to strong spatial dependence because it produces low RMSE and MAE values. Oliver and Webster (2014) also discovered that regular kriging yields trustworthy estimations with little bias for a variety of soil parameters, though some parameters, like nitrogen, may show larger prediction errors because of their higher spatial variability.

Conclusions

Important new information about the spatial variation of soil properties in the study area was provided by the study. Significant variability in soil properties was highlighted by classical statistical analysis. The spatial structure of these properties was best described by the exponential model, according to geostatistical analysis. The spatial interpolation map for soil properties was successfully produced by the ordinary kriging (OK) technique. In order to improve management practices in the study area, this map can be a helpful guide.

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