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Assessment of Spatial Variability of Soil Properties Using Geo-Statistical Approach in Northern Transect of Bengaluru

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Abstract

This study was conducted in the Northern transect of Bangalore, Karnataka, India, aiming to map the spatial variability of soil properties using geospatial techniques. Surface soil samples (0-15 cm) were collected from two villages Kachahalli and Karanalu using GPS. Laboratory measurements were performed to determine the physico-chemical properties of the soil. The accuracy of various ordinary kriging methods was executed and compared in this research. Semivariogram analysis was employed to quantify the spatial variability of soil properties and surface maps were generated using ordinary kriging. The exponential model demonstrated a good fit with the experimental semivariograms of pH, organic carbon (OC), available nitrogen (N), phosphorus (P_2O_5), potassium (K_2O), sulfur (S) and zinc (Zn). The coefficient of variation for soil properties exhibited considerable variability, with the highest variation observed in K_2O (60.57). OC, N, P_2O_5 and K_2O displayed moderate spatial variation, while pH showed the smallest variation (13.43%). In the case of P_2O_5, the goodness of prediction (G) had a negative value, whereas N, P_2O_5, K_2O, pH, Zn and S displayed positive values. Cross-validation of the krigged maps demonstrated that spatial prediction of soil nutrients using semivariogram parameters outperformed assuming the mean of observed values for unsampled locations.

Keywords : Geospatial techniques, Semivariogram, Krigging, Soil properties, Northern transect

Soil is the soul of life and serves as the foundation of life and a deep understanding of its spatial characteristics, including location, extent, distribution and classification, is vital for successful agricultural practices. Conducting a soil resource inventory allows us to gain valuable insights into the possibilities and limitations of soil for effective utilization. The inherent spatial variability of soils is a result of diverse physical, chemical and biological processes, operating at varying intensities and scales (Wang and Shao, 2013). This knowledge enables decision-making and facilitates the adoption of sustainable approaches in soil management.

To achieve sustainable land management practices, it is crucial to have reliable information on the spatial distribution of soil properties. Traditional soil surveys typically involve recording soil properties at representative sites and assigning them to entire mapping units, which are determined based on physiographic and geopedologic approaches (Bhunia *et al*., 2016). However, this conventional approach fails to capture the spatial variability of soil properties adequately. Soil surveyors are well aware of the inherent variability of soil properties in nature, but the boundaries defined by soil units in traditional soil maps do not fully reflect this variability. In reality, soil properties exhibit high spatial variability across landscapes. Therefore, for accurate estimation of soil properties, it is essential to consider this continuous variability rather than relying solely on discrete mapping units. Considering the spatial heterogeneity of soil characteristics is essential in ensuring proficient land management approaches and the adoption of enduring soil conservation strategies (Nalina *et al*., 2017). This understanding enables land managers to make informed decisions tailored to specific soil conditions, leading to improved agricultural productivity, soil health and ecosystem sustainability. The traditional methods of soil analysis and interpretation have long been recognized as laborious, time-consuming and expensive. Consequently, there is a growing need for more efficient and cost-effective approaches in this field. Geostatistical techniques, particularly kriging, have emerged as highly valuable tools for spatial interpolation in land resource inventories.

Geostatistical techniques play a pivotal role in quantifying the spatial arrangement and variability of soil properties. These techniques consider the spatial extent of the study region, the intervals between sample points and the spatial pattern unveiled through the modeling of semivariograms (Vieira *et al*., 2007). They have found extensive applications in assessing spatial correlations in soils and analyzing the spatial variability of various soil properties, including physical, chemical and biological characteristics. By employing geostatistical techniques, researchers can extract valuable insights into the spatial patterns and variations of soil properties, enhancing our understanding of soil dynamics and aiding in effective soil management strategies (Behera and Shukla, 2015).

In India, the majority of soil maps have been prepared using conventional methods, with limited utilization of modern spatial prediction techniques. However, accurate estimation of the spatial distribution of soil properties, including soil pH, organic carbon (OC), electrical conductivity (EC), phosphorous, potassium and more, is crucial for precision agriculture and serves as a foundation for decision-making and policy formulation (Rajsetia and Verma, 2012). Therefore, there exists a requirement for research in the fields of environmental monitoring, modeling and precision agriculture to have access to high-quality and cost-effective soil data. The primary objective of this paper is to assess the potential of utilizing geostatistical methods in measuring soil properties, including pH, OC, nitrogen (N), phosphorus (P), potassium (K), sulphur (S), zinc (Zn) and while considering their spatial variability.

Geostatistical techniques offer a promising approach to analyze the spatial patterns and variations of soil properties, allowing for a better understanding of soil dynamics and the development of targeted soil management strategies. By employing geostatistics, researchers aim to provide valuable insights into the spatial distribution of soil properties, contributing to improved decision-making processes and precision agriculture practices.

Material and Methods

Description of the Study Area

The geographical region of interest is situated within the Eastern Dry Zone of Karnataka (Zone 5). This zone consists of an area of 1808 M ha. The annual rainfall ranges from 679.1 to 888.9 mm and the main cropping season is *kharif.* The elevation is 800 to 900 m above MSL. It is characterized by tropical climate with maximum (Max) temperature ranging from 30 to 36°C and minimum temperature ranging from 15 to 22°C. Area is classified under *ustic* soil moisture regime and iso hyperthermic soil temperature regime. South West monsoon contributes most for the rainfall. Major soil orders in the study area are *Alfisols and Inceptisols*. and the soils are red sandy loam in major areas and lateritic in the remaining areas. Geographically study area is located at 13.0614° to 13.4072° N latitude and 77.5632° E to 77.6112° E longitude and falls in major Survey of India toposheets on 1:50000 scale.

Soil Sampling and Analysis

Surface soil samples were collected from two villages (Kachahalli and Karanalu). The exact sample locations (latitude and longitude) were recorded with the help of a hand held GPS device. The soil samples were collected in polythene bags and transported with proper handling to the laboratory for analysis. The large lumps were broken and spread on drying sheet made of brown papers and then air-dried in shade. The air-dried soil samples were grinded using a wooden

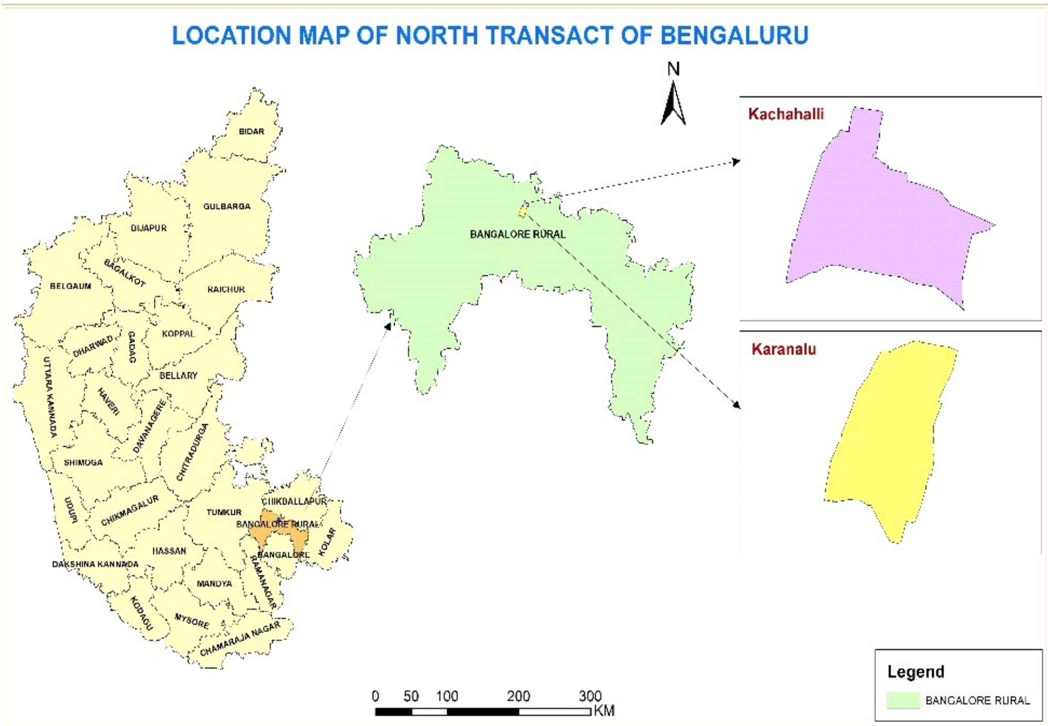


Fig. 1 : Location map of the study area

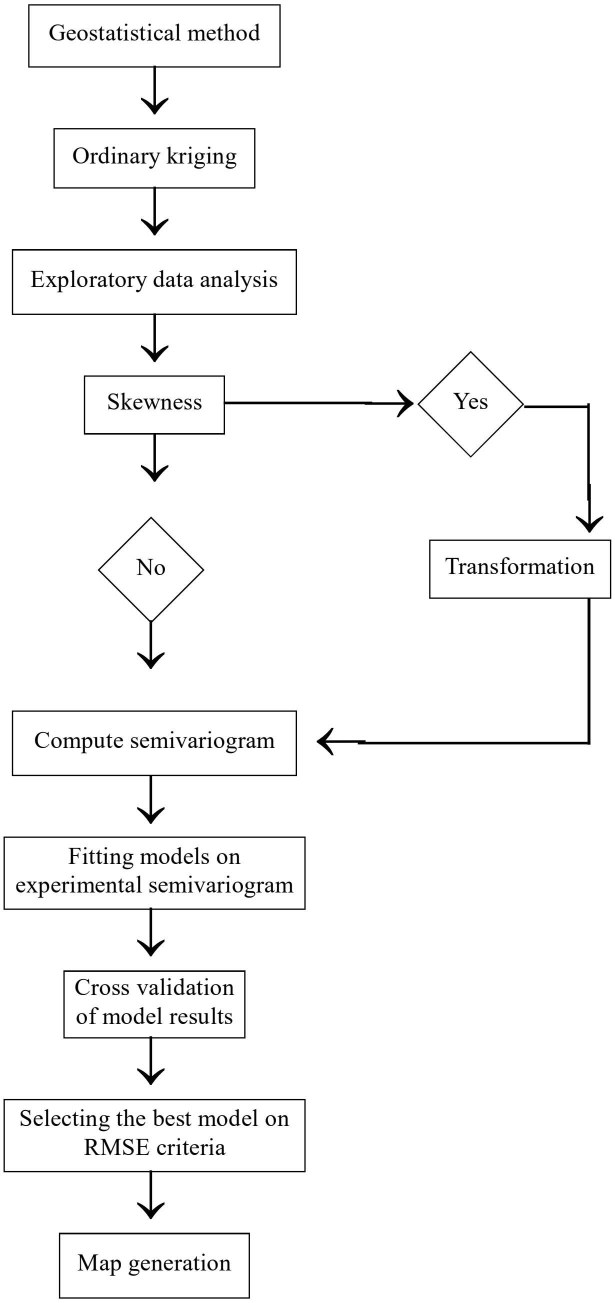
pestle and mortar, followed by sieving through a 2 mm mesh to remove larger particles (materials exceeding 2 mm in size).

In the laboratory, soil pH was determined by using potentiometric method (Jackson, 1973), in organic carbon determination, wet digestion method (Walkley and Black, 1934) was followed, available nitrogen in soil was determined by alkaline potassium permanganate method as described by Subbaiah and Asija (1956), phosphorus determined by Bray's method as described by (Jackson, 1973), Potassium content was quantified through the utilization of a flame photometer (Jackson, 1973). The determination of available sulfur in the soil involved an extraction process employing 0.15 per cent $CaCl_2.2H_2O$ solution, with subsequent reaction of the extract with barium chloride crystals. The degree of turbidity formed was quantified using a spectrophotometer at a specific wavelength of 420 nm (Jackson, 1973). The estimation of zinc was executed utilizing an Atomic Absorption Spectrophotometer (AAS).

Statistical and Geostatistical Analysis

The essential statistical parameters used to evaluate central tendency and data spread, such as mean, median, standard deviation (SD), variance, coefficient of variance, maximum and minimum values, were examined. In addition, a correlation coefficient matrix was generated by estimating the Pearson correlation coefficients for all possible paired combinations of the response variables. These statistical calculations were performed using microsoft excel.

The semi-variogram model serves as an approximation of the spatial variability of the measured conditions. In this study, an omni directional semi-variogram was calculated for each soil property, as no significant directional trend was observed. The best-fit model was determined by selecting the one with the minimum root mean square error (RMSE) and root mean square standardized (prediction) errors (RMSSE) close to 1 for each soil property. By employing this selection process, ensured that the selected model closely aligned with the observed data, offering dependable predictions (Dey *et al*., 2017).



$$RMSE = \sqrt{\frac{1}{n} \sum_{j}^{n} = (Y_j - \hat{Y}_j)^2}$$

Where $\hat{Y}_j$ is the predicted value, Y_j the observed value and n the number of values in the dataset Finally, the cross-validation method was applied to validate the parameters of the model.

For each soil property, five commonly used semivariogram models were fitted: Circular, Spherical, Exponential, Tetraspherical and Gaussian models. The exploratory variogram analysis was conducted using the ArcGIS geostatistical analyst extension in the GIS domain. This analysis served as a preliminary step to understand the spatial characteristics of the data. Subsequently, the exploratory approach was extended to spatial interpolation using kriging. Geostatistical analysis, which involved the calculation of semi-variograms, kriging and mapping, was conducted using the Geostatistical Analyst extension of ArcGIS 10.8.

Validation of Soil Maps

The accuracy of the soil maps was assessed using a cross-validation approach. In this study, two different evaluation indices were utilized: mean absolute error (MAE) and mean squared error (MSE) (Dey *et al*., 2017). MAE and MSE were employed to gauge the accuracy of the predictions, while, MAE quantifies the sum of the residuals (*i.e.,* the predicted values minus the observed values), providing an indication of the average prediction error.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} Z\,[(X_i) - (X_i)]$$

In this context, (Xi) represents the predicted value at a specific location i. A smaller MAE value indicates a lower number of errors in the predictions. However, the MAE measure does not provide information about the magnitude of potential errors at individual points. Therefore, to assess the magnitude of errors, the mean squared error (MSE) were calculated.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} [Z_1\,(X_i) - Z_2(X_i)]$$

By squaring the difference at each point, we obtain an indication of the magnitude of the errors. For instance, smaller MSE values suggest more accurate estimation on a point-by-point basis. This allows for a more detailed assessment of the accuracy of the predictions at individual locations.

Results and Discussion

Descriptive Statistics

These summary statistics offer important information about the range, central tendency, variability and

TABLE 1

Descriptive statistics of soil parameters (0-15 cm depth) of soil samples

Parameters	Minimum	Maximum	Mean	Median	SD	Skewness	Kurtosis	CV
pH	4.03	6.62	5.09	5.04	0.68	0.40	-0.54	13.43
OC(%)	0.24	0.96	0.76	0.81	0.18	-1.02	0.42	23.36
N (kg ha^{-1})	112.89	275.96	187.64	185.03	36.16	0.30	-0.27	19.27
P (kg ha^{-1})	36.40	65.49	47.32	46.80	8.47	0.37	-1.18	17.90
K (kg ha^{-1})	60.48	512.88	196.39	147.60	118.96	1.07	0.09	60.57
S (mg kg^{-1})	10.20	24.36	16.70	16.90	3.55	0.05	-0.74	21.26
Zn (mg kg^{-1})	0.33	1.92	0.84	0.78	0.38	0.96	0.58	45.68

distribution characteristics of the analyzed soil parameters. They help in understanding the variations and relative stability of these parameters, aiding in the assessment and management of soil quality and fertility (Ananthakumar and Meghana, 2022). Table 1 presents the summary statistics for the analysis of soil samples, highlighting various soil parameters. These statistics include the minimum and maximum values, standard deviation (SD), skewness, kurtosis and coefficient of variation (CV), which collectively describe the distribution of soil properties. The coefficient of variation (CV) is particularly useful as it represents the ratio of the standard deviation to the mean, providing a measure of overall variability. It is worth noting that differences in the CV of soil properties were observed, indicating variations in the degree of variability across different soil parameters (Niranjana and Sathish, 2011).

Recorded pH values range from a minimum of 4.03 to a maximum of 6.62. Organic carbon (OC), data indicates a minimum value of 0.24 per cent and a maximum value of 0.96 per cent. Nitrogen (N) concentrations vary from a minimum of 112.89 kg ha^{-1} to a maximum of 275.96 kg ha^{-1}. The range for phosphorus (P) lies between 36.40 kg ha^{-1} and 65.49 kg ha^{-1}, while potassium (K) exhibits a wider range of 60.48 kg ha^{-1} to 512.88 kg ha^{-1}. Sulfur (S) content falls between 10.2 mg kg^{-1} and 24.36 mg kg^{-1}, while zinc (Zn) concentrations range from 0.326 mg kg^{-1} to 1.92 mg kg^{-1}. The greatest variation was observed in potassium (60.57%) followed by zinc (45.68%) where, as the smallest variation of soil pH (13.43%).

Semi-variogram of Soil Properties

Root Mean Square Error (RMSE) is shown in Table 2 for various theoretical semivariogram models used to fit the experimental semivariogram values for each soil property. After testing different models, it was observed that the spherical model best fitted for pH and OC where, as circular model fit best for N and

TABLE 2

RMSE for different theoretical semi variogram models

Models	Soil properties						
	pH	OC(%)	N (kgha^{-1})	P (kg ha^{-1})	K (kg ha^{-1})	S (mg kg^{-1})	Zn (mg kg^{-1})
Circular	0.6538	0.097	5.96	2.27	5.20	8.06	1.097
Spherical	0.6207	0.096	6.30	2.28	4.90	8.04	1.095
Exponetial	0.6505	0.098	6.35	2.20	3.40	7.07	1.087
Gaussian	0.7127	0.102	6.55	2.49	5.40	8.03	1.099
Tetraspherical	0.6318	0.097	6.28	2.25	4.90	8.09	1.093

Exponential model emerged as the most suitable fit for P, K, S and Zn. The RMSE and RMSSE values provide insights into the accuracy and precision of the model's predictions, allowing for a comparison of the different models' performance.

In the realm of spatial interpolation for soil characteristics and nutrients, various methods are commonly employed but ordinary kriging found to be the best (Sathish *et al*., 2017). Pandu *et al*. (2022) highlighted that ordinary kriging is emerges as the most suitable interpolation technique. The assessment of spatial interpolation methods commonly centers on predictive inaccuracies, exemplified by metrics like the Root Mean Square Error (RMSE). In the comparative analysis of spatial interpolation methods for soil nutrient distribution, the exponential model demonstrated superior performance, the outcome aligned with the discoveries of Gotway *et al*. (1996). Generally, geostatistical methods, particularly kriging, were more commonly recommended compared to non-geostatistical methods like basic statistics. In the present study, the exponential model yielded the smallest RMSE values, which aligns with the findings of Reza *et al.* (2012) study conducted on similar soil textures in the Brahmaputra plain of North-Eastern India. These findings highlight the importance of selecting appropriate interpolation methods tailored to specific soil characteristics and nutrients (Robinson and Metternicht, 2006).

The semi-variogram parameters, specifically the nugget and sill values, as well as the nugget-to-sill ratio, for each soil property with the best-fitted model presented in Table 3. These parameters play a significant role in capturing the spatial variability and correlation patterns within the soil. As indicated by Lin *et al*. (2005), the nugget component signifies variability at an extremely close distance scale, frequently linked to measurement errors or localized influences. The sill, on the other side, represents the maximum level of variability observed for a given soil property. It signifies the range of spatial dependence, beyond which the correlation diminishes significantly. The nugget-to-sill ratio provides insights into the relative contribution of the nugget effect to the total variability.

The strength of spatial dependence can be assessed based on the nugget-to-sill ratio. A ratio of less than 25 per cent indicates a strong spatial dependence, while a ratio between 25 per cent and 75 per cent suggests a moderate spatial dependence. Conversely, a ratio above 75 per cent indicates a weak spatial dependence. The pH, nitrogen (N), Potassium (K), Sulphur (S) and Zinc (Zn) variables exhibit a moderate spatial dependence, as their nugget-to-sill ratios fall within the range of 25 per cent to 75 per cent. This indicates that these characteristics have a moderate level of spatial correlation and can be influenced by neighbouring samples. On the other hand, the OC (Organic Carbon) and phosphorous (P) variables demonstrate a weak spatial dependence. The nugget-to-sill ratios for these properties exceed 75 per cent, indicating a lesser degree of spatial correlation. This

TABLE 3

Semi variogram parameters of soil nutrients

Parameters	Model	Nugget	Partial sill	Sill	Nugget/Sill (%)
pH	Spherical	0.16	0.31	0.47	33.33
OC	Spherical	0.59	2.93	3.52	16.72
N	Circular	0.93	0.39	1.33	70.29
P	Exponential	0.10	0.38	0.48	21.05
K	Exponential	1.15	0.44	1.59	72.33
S	Exponential	1.33	0.08	1.41	94.17
Zn	Exponential	0.84	0.34	1.18	70.95

suggests that the values of these variables may not be strongly influenced by the proximity of neighbouring samples, similar result was obtained by Zhang *et al*. (2010).

The nugget-to-sill ratio, quantifies the spatial variability within data, with the nugget representing fine-scale variations and measurement errors and the sill indicating overall variability. This ratio is integral to map preparation, as a high nugget-to-sill ratio suggests abrupt changes over short distances in spatial maps, while a low ratio implies gradual transitions (Sun *et al*., 2019). Moreover, in the context of sample size determination, a high nugget-to-sill ratio signals the need for closely spaced samples to capture fine-scale variations, whereas a low ratio may indicate that larger sampling distances are sufficient to account for spatial structure, ultimately guiding the optimal collection and representation of data in spatial analysis (Kerry and Oliver, 2008).

Ordinary Kriging and Cross-validation

The outcomes of cross-validation for the spatial maps generated using ordinary kriging with the Exponential model and the semi-variogram parameters are presented in Table 4. To perform the cross-validation, 10 per cent sample was left out and predictions were made for those sample locations based on the remaining samples. This process allows for the evaluation of the predictive accuracy of the spatial maps. This also shows that semi variogram parameters obtained from fitting of experimental semi variogram values were fairly reasonable to describe the spatial variations. Spatial maps of soil properties prepared through ordinary kriging are presented in Figs. 2 to 8.

TABLE 4

Evaluation of ordinary kriging map of soil nutrients through cross-validation

Nutrient	MAE	MSE	G
pH	0.07	0.64	36.88
OC	0.14	0.03	16.23
N	3.04	6.00	15.68
P	2.89	2.96	12.21
K	4.65	5.90	23.05
S	6.06	48.93	22.41
Zn	0.68	1.56	12.68

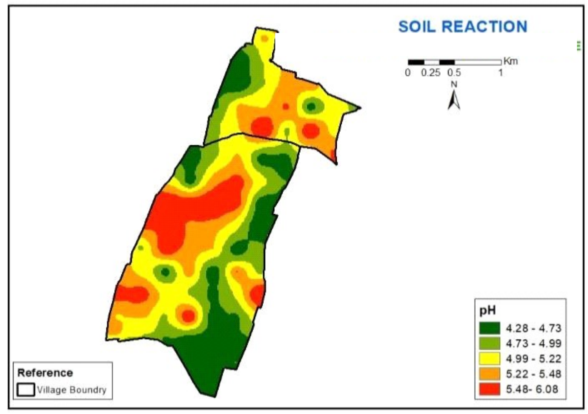


Fig. 2 : Spatial variability map of soil pH

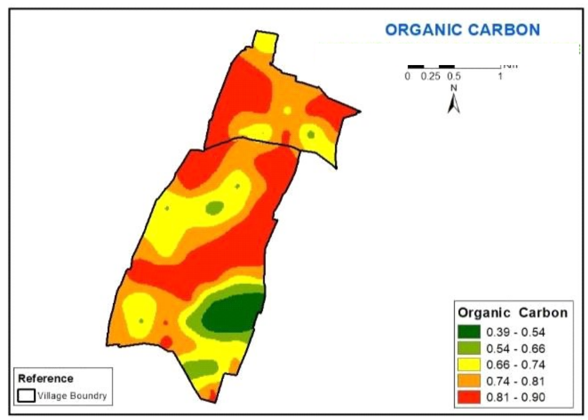


Fig.3 : Spatial variability map of soil OC (%)

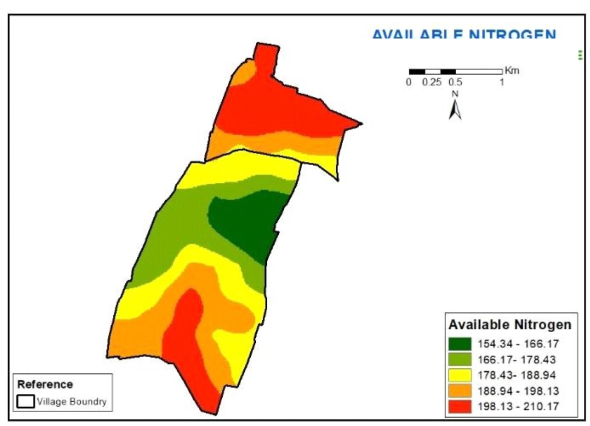


Fig. 5: Spatial variability map of soil nitrogen (kg ha^{-1})

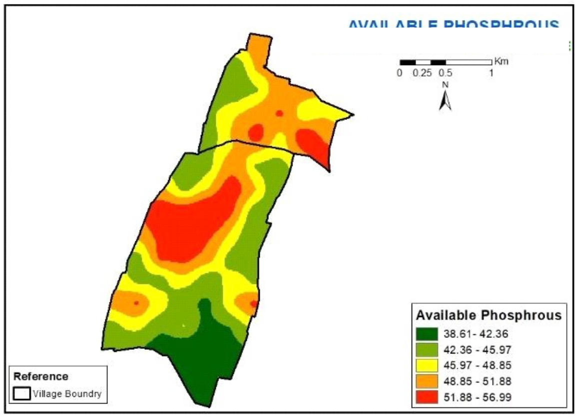


Fig. 5 : Spatial variability map of soil phosphorus (kg ha^{-1})

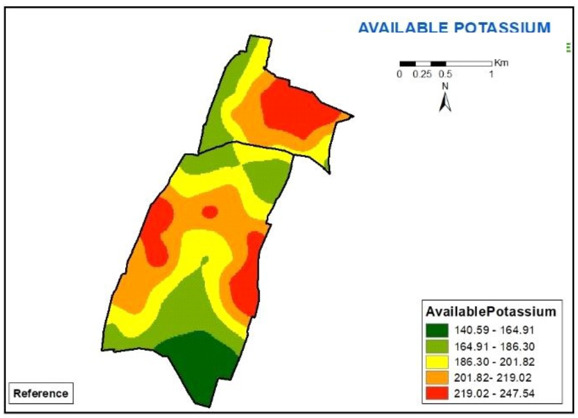


Fig. 6 : Spatial variability map of soil potassium (kg ha^{-1})

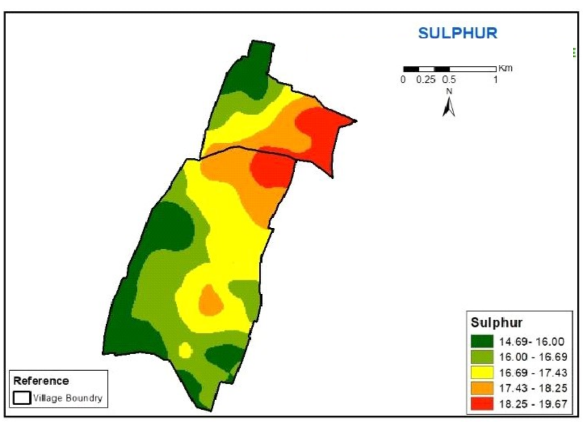


Fig. 7 : Spatial variability map of soil sulphur (ppm)

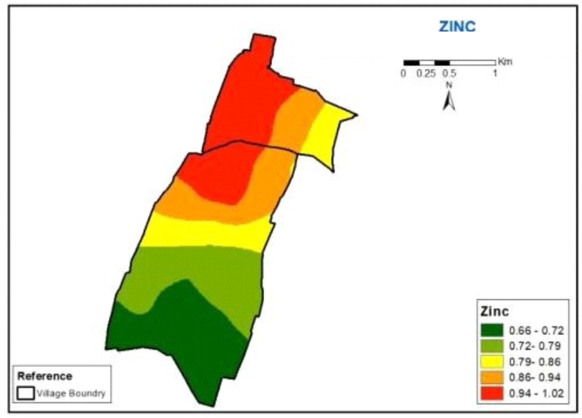


Fig. 8 : Spatial variability map of soil zinc (ppm)

Among all the soil parameters analysed, the highest Mean Absolute Error (MAE) and Mean Square Error (MSE) were observed for the potassium (K) parameter, followed by nitrogen (N), phosphorus (P), sulphur (S), zinc (Zn), organic carbon (OC) and pH.

While evaluating the goodness of fit (G) values, positive values were obtained for all soil nutrients except P. The pH parameter exhibited the highest G value, followed by K, S, OC, N and Zn. For all soil nutrients, the G values were greater than zero, except for P. This suggests that spatial prediction provides a better alternative to assuming the mean of observed values for unsampled locations. Consequently, spatial prediction offers a suitable and accurate method for estimating the chemical properties of soil at unmeasured positions, compared to direct measurement, which is often associated with time and cost constraints.

The Goodness of Prediction (G) values revealed that phosphorus (P) was the only soil nutrient for which the prediction would have been more reliable using sample means (basic statistics) instead of the interpolation model. Given the lack of spatial arrangement and the absence of clear patterns in the exploratory analysis, it would have been prudent to exclude P from further analysis. However, the positive G values for the other soil properties indicated that the interpolation model used for nutrient mapping was appropriate. To minimize errors and uncertainties in the prediction maps, it is advisable to adjust kriging parameters instead of relying on default values, potentially leading to improved results. Moreover, it would be valuable to explore different sampling strategies and compare the outcomes, while also considering parameters such as slope gradient, soil type and land use patterns, which significantly influence soil nutrient concentrations and their spatial distribution.

The descriptive statistics of soil nutrients shows that in the raw data sets of pH, N, P, K, S and Zn are strongly positively skewed, where, as organic carbon is negatively skewed and the application of logarithmic transformation was used for normalization, which affects the data. Among different models tested for analyzing the spatial variability of soil nutrients, the spherical model fits well for pH and OC whereas circular model is best for N and exponential model fits well for P, K, S and Zn. Soil properties showed large variability with greatest variation observed in K (60.57 %) whereas, the smallest variation was in pH (13.43%). In case of P, the goodness of prediction (G) had a negative value while N, P, K, pH, Zn and S shows positive value.

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