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Research Article

Modeling the Spatial Variability of Soil Nutrients - A Case from Soil Health Card Project, India

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Abstract

Ascertaining and mapping soil nutrient data is crucial for governments to maintain soil health on farmlands. As part of the soil health card project, a total of 329 geo-referenced soil samples were collected from Thaticherla village, Anantapur mandal, Andhra Pradesh, India. These samples were analyzed for various soil properties such as soil pH, electrical conductivity (EC), organic carbon (OC), available nitrogen (N), available phosphorus (P), available potassium (K), available sulphur (S), DTPA extractable micronutrients (Fe, Mn, Zn, Cu), and hot water-soluble boron (B) at a depth of 0 to 15 cm. The results showed high variability (>35%) in coefficients of variation in Cu, EC, Zn, and B. The findings indicated positive correlation between Zn and Mn; N and OC; and OC and Zn. The data underwent logarithmic and Box-Cox transformations to achieve normalization. The ordinary kriging method was employed to analyze the spatial variability. The findings revealed that exponential model was appropriate for B, Fe, Mn, Zn, and OC; Gaussian for K; J-Bessel for N; K-Bessel for Cu, P, and S; stable for EC and rational quadratic for pH, respectively. The analysis showed a strong to weak spatial dependency. In the study area, the spatial variability maps exhibited deficiencies of 97%, 96% and 40% for N, OC and Zn, respectively. Therefore, it is urgent to apply suitable manures and fertilizers in the study area to address these issues. The study area exhibited significant variation in spatial patterns, emphasizing the importance of implementing field-specific plans for soil health and environmental management.

Keywords: Soil Fertility, Soil health Card project, Environment, Geostatistics, Interpolation

Introduction

Soil health is essential for food security, sustainable development, plants, animals, environment, and humans (Kibblewhite et al., 2007; Das et al., 2022; Behera et al., 2023). The depletion of soil nutrients can have adverse impacts on crop productivity and soil health, emphasizing the necessity for implementing measures to sustain and improve soil health (Kumar and Babel, 2011). Implementing appropriate soil management strategies can effectively address various challenges, such as land degradation, global warming, hunger, and poverty Behera et al. (2023). Moreover, utilizing limited agricultural land in an efficient way is one of the best soil management practices (Vasu et al., 2021).The lack of essential nutrients in soil is a significant global concern, as it can have adverse effects on yield and plant growth (Abdel-Mawgoud et al., 2011).The distribution of nutrients in soil can vary depending on several external and intrinsic factors such as rainfall, irrigation, soil type, fertilizer usage, climate, topography, human activities, parent material, physiography, and soil depth, which can impact ecosystems in various ways, and these factors may have effects in small agricultural areas (Bogunovic et al., 2017a; Li et al., 2016; Esetlili et al., 2018). Farmers play a significant role in maintaining soil health, which requires a complete understanding of their soil's nutrient status and appropriate agricultural practices for maintaining health and profit. Thus, cultivating crops without access to information on soil nutrient distribution and proper management practices can lead to unsustainable yields. Also, soil analysis-based nutrient management recommendations have proven to be beneficial for farmers, increasing crop yield and productivity (Wani and Singh, 2021).

Accurate maps representing the distribution of soil nutrient properties are important for farmers to reduce the costs of fertilizer use. Spatial variability of soil nutrients information may provide guidance to farmers for fertilizer recommendations (Jin and Jiang, 2002; Vasu et al., 2021) to specific fields to improve crop yields and sustainable land use development and planning (Reza et al., 2017; Eljebri et al., 2019; Chatterjee et al., 2015; Shukla et al., 2020; Koç and Karayiğit, 2022; Ngabire et al., 2022). Soil fertility changes over time and space due to natural and human factors, and mapping nutrient variability in specific fields is one way to manage soil health. Kriging, a geostatistical technique, can predict nutrient values by minimizing estimation errors and accounting for spatial correlation, saving time, reducing costs, and minimizing pollution. Maps of soil nutrients are essential for precision agriculture, and geostatistical methods are reliable in modeling soil property variation with distance (Goovaerts, 1999; López-Granados et al., 2002; Denton et al., 2017). Numerous researchers have applied geostatistics, particularly Kriging, which is widely employed for predicting nutrient levels (Goovaerts, 1999; Denton et al., 2017; López-Granados et al., 2002; Lipiec and Usowicz, 2018; Behera et al., 2023; Salem et al., 2024). Ordinary Kriging (OK), an interpolation method, is commonly used to predict spatial distribution of soil nutrients (Sanad et al., 2024; Zhang et al., 2015; Tang et al., 2017; Saleh, 2018). Behera and Shukla (2015) observed significant differences in organic carbon, soil pH, and electrical conductivity. Furthermore, environmental factors employ a noteworthy impact on the spatial distribution of zinc in acidic soils across India (Behera et al., 2011). Several scholars applied geostatistics and OK interpolation to examine spatial variability for different research objectives in various soil types in diverse regions of India (Nogiya et al., 2024; Reza et al., 2017; Behera et al., 2018; Vasu et al., 2017; Bhunia et al., 2018; Verma et al., 2021; Behera et al., 2023).

National soil heath card project

The Soil Health Card (SHC) project was initiated by government of India in 2015 to provide farmers with essential information to improve soil health, increase crop yields and farmers' income (SHC, 2023). The SHC data collection and laboratory analysis was done in three phases during the year from 2015 to 2020.Some scholars have done research on SHC data for various purposes. The SHC initiative at National level may empower farmers through public-private partnerships and participation (Das et al., 2022). Patra et al. (2017) studied various levels of potassium (K) in the soil in various districts of India using SHC data. Niranjan et al. (2018) evaluated the effectiveness and awareness using SHC data. Reddy (2019) explored the challenges and opportunities for other countries in implementing the SHC project. Fitzpatrick et al. (2022) discussed the relationship between SHC and zero-budget natural farming. Morton et al. (2023) reported that SHC data of India indicate a strong positive relationship between children's height development and the availability of zinc in the soil, as well as between soil iron availability and haemoglobin levels. Some scholar's generated spatial variability maps by applying IDW interpolation using SHC data (Pratibha et al. 2020; Velamala and Pant 2023; Velamala and Pant, 2024), however research on literature suggests that geostatistical analysis in particular kriging interpolation is best method. According to the literature review, geostatistical analysis for studying spatial variability in India, particularly in the Anantapur district of Andhra Pradesh, is either limited or unavailable in the literature.

To fill the gap in this study investigated parameters of soil namely a) soil-macronutrients:-nitrogen (N), potassium (K), phosphorus (P), and secondary nutrient sulphur (S), b) soil-micronutrients:-copper (Cu), zinc (Zn), manganese (Mn),boron (B), and iron (Fe), and c) soil-chemical parameters:-organic carbon (OC), soil pH, and electrical conductivity (EC), in the cultivated soils located at Thaticherla village of Anantapur mandal, Andhra Pradesh, India, it is a model village under SHC project of the Indian government with objectives are: i) identify characteristics and its relationships among various soil properties, and ii) to generate and evaluate spatial viability maps.

Data and methodology

Study area

The present area (Fig.1) is primarily comprised of red and black soils, with the soil composition being predominantly shallow and consisting of red sandy ferruginous loam. The farmers adopt monocropping as their agricultural practice, focusing on the cultivation of groundnuts, red gram, rice, and vegetables. The climate is tropical, characterized by hot and arid weather. On average, the study area experiences rainfall (annual) of 553 mm (DES, 2019).

Sampling and analysis

A total of 329 soil samples were obtained from agricultural fields at a depth of 0 to 15 cm. These samples were sent to a designated public soil testing lab for air-drying, processing, and nutrient analysis. A conductivity meter and a pH meter, respectively, were used to measure the EC and pH, using a 1:2.5 soil and water ratio (Jackson, 1967). The soil OC content was estimated by Walkley and Black, 1934 method. The N was quantified using the alkaline $KMnO_4$ technique (Subbiah and Asija, 1956), while P was extracted by 0.5 M sodium bicarbonate (pH 8.5) solution and assessed using ascorbic acid method (Olsen et al., 1954). The K was extracted through a neutral ammonium acetate solution (pH7.0), and the flame photometry technique was employed to determine its availability (Hanway and Heidel, 1952). The S was extracted using a 0.15% $CaCl_2$ solution (Williams and Steinbergs, 1959). Micronutrients such as Fe, Zn, Mn, and Cu were extracted using a 0.005 M DTPA (diethylenetriaminepentaacetic acid) (pH-7.3) solution (Lindsay and Norvell, 1978), and their concentration was measured through atomic absorption spectrophotometry. The availability of B was determined using the azomethine-H method, and a UV/VIS spectrophotometer was used for assessment (Gupta, 1967). The categorization of soil fertility for OC, K, P, and N was based on three levels: low, medium, or high. The soil S, B, Mn, Cu, Fe, and Zn were accurately interpreted as deficient or sufficient (Arora, 2002).

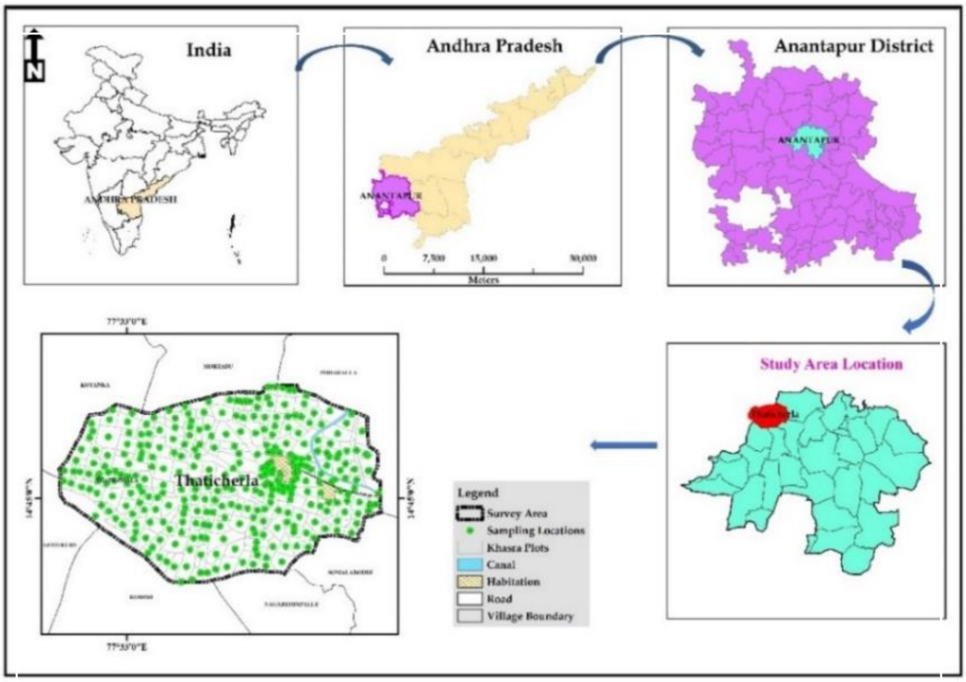


Fig. 1 Location map of study area

Data Analysis

Classical statistical analysis

Present study examined 329 soil samples for 12 soil parameters. The study calculated descriptive statistics for these parameters, including the minimum (min), maximum (max), median, mean, kurtosis, skewness and correlation Pearson's correlation coefficients. The data was analyzed for outliers, and its normality was tested using statistical software packages such as IBM SPSS (version 28.0.1.1) and R Core Team (2023) in the windows environment.

Data outliers' detection

The study area data outliers were dictated based on most commonly used formula given in the equation (1).

$$x = (\bar{x} \pm \delta * SD) \qquad (Eq. 1)$$

Where $\bar{x}$ and SD are mean and standard deviation respectively, δ values range from 2 to 3 and y is outlier if it is lies more than δ standard deviations (Jones, 2019). According to the equation (1) and δ=3, the study area data did not find any outliers and considered n=329 observations for this study.

Data normality and Transformation

The geostatistical analysis may be affected by distribution asymmetry, as environmental data often exhibits an asymmetric distribution (Barnett and Lewis, 1994; McGrath et al., 2004). In some cases, non-normality of the distribution (p>0.05) can impact the spatial variogram analysis of the dataset, leading to unsatisfactory results (McGrath et al., 2004; Kerry and Oliver, 2007; Goovaerts et al., 2005). One dimensional K-S-Test (Kolmogorov-Smirnov) was utilized to examine data distribution, thereby ensuring accurate spatial interpolation. The kurtosis and skewness values are analyzed to determine if the data follows a normal distribution. In soil survey research, scholars employed data transformation techniques, such as the Box-Cox-Transformation (BCTN) and logarithmic transformation (LTN) methods, to bring data to normal-distribution (ND) (Bogunovic et al., 2017b). Previous literature suggests that a logarithmic transformation is often applied when the data is positively skewed or has a skewness value greater than one (Webster and Oliver, 2001; McGrath et al., 2004 ;). However, a LTN may not always apply to every dataset (Fu et al., 2013). Therefore, BCTN is recommended for improving normality (Box and Cox, 1964) in present study. Equation (2) illustrates the mathematical form of the BSTN.

$$x(\alpha) = \begin{cases} \dfrac{x^{\alpha} - 1}{\alpha}, & if\ \alpha \neq 0 \\ \log(x), & if\ \alpha = 0 \end{cases} \qquad (Eq. 2)$$

Where, x is data to be transformed and αis transformation exponent its values range from –5 to 5 (Asar et al., 2017). If λ equals zero, the BSTN takes on a logarithmic form. The R-Language software (R Core Team, 2023) was utilized to compute the value of lambda (λ). Accordingly, LTN for EC and Cu and BCTN for remaining soil parameters applied.

Geostatistical analysis

The Geostatistical Assistant of ArcMap 10.8.3 is utilized to calculate semivariogram (SV) and ordinary-kriging (OK) interpolation to analyze the SV of soil properties in the study area. Equation (3) (Goovaerts, 1999; ESRI, 2001) was used to calculate the SV.

$$\gamma(u) = \frac{1}{2N(u)} \sum_{i=1}^{N(u)} [z(a_i) - z(a_i + u)]^2 \qquad (Eq. 3)$$

Where $z(a_i)$ and $z(a_i + u)$ are values of variables at observed sample-locations a_i and $a_i + h$ respectively, γ(u) is the function of SV for u (lag distance), N(u) refers to the no. of pairs of points of samples separated by u (distance-of-lag).

To assess the soil characteristics, an examination of the properties of Nugget (Nu), Partial Sill (PS), Sill (Si), and the range was conducted. The Nu value was obtained from the y-axis SV intercept, and the Si was identified as the point where model exhibited flattening. The range indicated the distance over which spatial correlation was present, and the partial sill denoted the disparity between Si and Nu. The spatial interdependence of individual soil properties was ascertained by evaluating the ratio between Nu and Si. The classification of the spatial dependency of each soil property was done based on the criteria recommended by Cambardella et al. (1994) as weak (>75%), moderate (25% to 75%), or strongly dependent (less than 25%). The most suitable SV model cannot be determined by a single, universal standard. To choose the best fit model, researchers use a variety of software packages that offer different parameters for evaluation, and they also depend on personal expertise. In this study, the geostatistical assistant of ArcMap10.8.3 software (ESRI) to assess eleven semivariogram models, namely Stable, K-Bessel, Hole Effect, Exponential, Spherical, Gaussian, J-Bessel, Circular, Tetraspherical, Rational Quadratic, and Penta spherical was utilized and selected the best-fit model. This study's approach to model selection and error validation is similar to other studies (Foroughifar et al., 2013).

Ordinary Kriging

Many researchers commonly employed the Ordinary Kriging (OK) method to estimate semivariogram parameters and create surface maps of soil properties. This technique is preferred because it provides reliable and unbiased predictions of unsampled sites while minimizing the effect of outliers (Cressie, 1993; Fu et al., 2013; ESRI, 2001). The Ordinary Kriging interpolation is expressed in equation (4).

$$X(v_0) = \sum_{i=1}^{n} \mathrm{w}_i \, X(v_i) \qquad (4)$$

Here, unknown sampling point is $X(v_0)$ determined by the value of a known point $Z(v_i)$ and w_i is weight unknown of the sampling point at i^{th} location, with n representing the number of known observed values.

Cross Validation

In cross-validation, values are estimated by subtracting one sample at a time and calculating the value from remaining observations. This technique was applied to test the accuracy and performance of various semivariogram models for different soil properties. The models tested include K-Bessel, Circular, Tetra-spherical, Spherical, Penta-spherical, Exponential, Rational quadratic Gaussian, J-Bessel, Hole Effect, and Stable. Cross-validation techniques namely Root mean square standardized error (RMSSE), Root mean square error (RMSE), Mean standardized error (MSE) and Average standard error (ASE) equations for these techniques, as denoted by (5), (6), (7), and (8), are presented in Table 1 to select the best-fitted model. These techniques were applied using the geostatistical assistant of ArcMap 10.8.3. The best-fitted model was selected based on the results of cross-validation techniques. These techniques were employed in choosing best-fit models with low RMSE values, ensuring that ASE and RMSE values were almost equal, MSE values nearly to zero, and determining RMSSE values approximately to one. It noted that overestimation occurs when RMSEE exceeds one, while underestimation occurs when it is less than one (Yumin et al., 2022; ESRI, 2023; Reza et al., 2019).

Table 1 The Statistical Indices used for assessment of models

Index	Equation
Mean Square Error (MSE)	$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{z^*(x_i) - z(x_i)}{\sigma^2(x_i)}\right]$ (5)
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[z^*(x_i) - z(x_i)]^2}$ (6)
Root Mean Square Standardized Error (RMSSE)	$RMSSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[\frac{z^*(x_i) - z(x_i)}{\sigma^2(x_i)}\right]^2}$ (7)
Average Standard Error (ASE)	$ASE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\sigma^2(x_i)}$ (8)

Where $z^*(x_i)$, $z(x_i)$ are estimated and observed values at a study area and $\sigma^2(x_i)$ *is kriging variance.*

Results and Discussion

Descriptive Statistics

The details of classical statistics of study area (n=329) given in Table 2. The mean values of OC, EC, Cu, Zn, B, Mn, Fe, pH, S, P, N, and K are 0.289,0.331,0.658,0.725,0.996,4.114,4.773,7.496,29.348 ,32.216,181.453 and 337.064, respectively. Among these, the highest is for K (337.064), and the lowest means for OC (0.289). The mean and median values are almost equal for pH and OC compared to the other parameters. According to Wilding (1985), variability in the CV% is classified as moderate (15%-35%), high (above 35%), and low (below 15%). The CV% of pH, N, P, Fe, OC, K, S, Mn, B, Zn, EC, and Cu are 0.06, 0.21, 0.24, 0.31, 0.32, 0.33, 0.33, 0.34, 0.39, 0.51, 0.55 and 0.69. These results indicate that pH was low; N, P, Fe, OC, S, K, and Mn were moderate; Cu, EC, Zn, and B had high variability. Because of the logarithmic scale of soil proton concentration, studies from all around the world have documented low CV values in soil Ph (Bhunia et al., 2018; Behera et al., 2021; Li et al., 2019). Among the micronutrients, Fe and Cu have low (0.31%) and high (0.69%) variability, respectively. Micronutrient fertilizers are used to improve soil health and productivity, but the quantity is affected by multiple factors such as parent material, pH, rainfall, and organic matter (Dimkpa and Bindraban, 2016). Therefore, it is essential to understand these factors to develop effective soil health management strategies.

Table 2 Classical statistics (n=329) for study area soil properties

Soil parameter	Minimum	Maximum	Mean	Median	SD	CV%
N	128	295	181.453	172	37.705	0.21
P	15	48	32.216	32	7.797	0.24
K	152	670	337.064	325	110.896	0.33
pH	6.25	8.21	7.496	7.53	0.418	0.06
EC	0.1	0.812	0.331	0.28	0.181	0.55
OC	0.1	0.56	0.289	0.28	0.091	0.32
B	0.18	1.93	0.996	0.96	0.393	0.39
Zn	0.04	1.779	0.725	0.678	0.373	0.51
Fe	0.342	6.85	4.773	4.916	1.461	0.31
Mn	0.586	6.904	4.114	3.894	1.411	0.34
Cu	0.113	1.82	0.658	0.512	0.452	0.69
S	14	47	29.348	28	9.625	0.33

N= Available N (kg ha^{-1}), P= Available P (kg ha^{-1}), K= Available K (kg ha^{-1}), pH= Soil pH, EC= Electrical conductivity (dSm^{-1}), OC= Organic Carbon (%), B= Hot Water-Soluble B (mg kg^{-1}) Zn= DTPA Extractable Zn (mg kg^{-1}), Fe= DTPA Extractable Fe (mg kg^{-1}), Mn= DTPA Extractable Mn (mg kg^{-1}), Cu= DTPA Extractable Cu (mg kg^{-1}), S= 0.15% $CaCl_2$ Extractable S (mg kg^{-1}), SD-Standard deviation and CV-Coefficient Variation.

Data transformation

After examining the raw data (Table 3), the soil characteristics N, EC, OC, Zn, Cu, K, and B had an asymmetrical right-skewed shape distribution, and pH and Fe had an asymmetrical left-skewed distribution. In contrast, P, Mn, and S had a symmetrical distribution. Skewness of N, EC, and Cu was more than one, and all the soil parameters analyzed had p-values below 0.001. The range of kurtosis values observed for the studied soil properties was between -1.024 and 1.426. These results indicate soil parameters of the study area not exhibited a normal distribution, thus necessitating data transformation before conducting geostatistical analysis. The data of the study area was analyzed using logarithmic transformation. Afterward, a normality test was applied, which showed that only soil EC passed the test with a p-value of 0.181. The use of LTN significantly reduced the high skewness and kurtosis. Also, the values of p for the other parameters improved, except for Cu. A Box-Cox transformation is applied to reduce skewness and bring it closer to zero to address this issue.

The BSTN was employed for all soil parameters (except soil EC) to select a suitable power parameter (Lambda=λ) and skewness nearer to zero. After the BSTN, normality tests passed for N, K, pH, Zn, and Fe. Furthermore, skewness, kurtosis, and p-values were reduced further, except for soil P (p=0.002) and Boron (p = 0.17). Even after applying LTN and BSTN, the normality test did not pass for soil P, B, Mn, OC, Cu, and S. Also, p-values for these soil parameters improved to more than 0.001, except for soil OC (p=0). After applying LTN for Soil EC and BSTN for N, K, pH, Zn, and Fe, the dataset of the study area exhibited normality and improved kurtosis and skewness values. The K-S test values have improved compared to the original raw data. Despite undergoing BSTN and natural LTN, the datasets of the study area still do not exhibit a normal distribution. Zhang et al. (2005 and 2008) have observed that environmental data often exhibit distributions that are not normal or log-normal but previous studies (McGrath and Zhang, 2003; Zhang, 2006) suggest that the data will closely approximate normality. Similar findings have also been reported by Fu et al., 2010; and Bogunovic et al., 2017b. Therefore, the transformed dataset of the study area can be effectively analyzed using geostatistical analysis.

The relationships between different soil parameters were analyzed using Pearson's correlation coefficient (Table 4). Positive correlation identified between N and OC (r=0.167), similar findings were observed by Chatterjee et al. (2015), OC and Zn (r=0.15), similar results found by Behera et al. (2011). The soil organic carbon (OC) has direct impact on physical, biological, and chemical properties which directly affects soil nutrients and crops. Zn and Mn (r=0.186), and Fe and Cu (r=0.153) showed positive correlations. Negative correlations were also found between K and organic OC (r=-0.147), K and Zn (r=-0.170), EC and Fe (r=-0.145), Zn and Fe (r=-0.334), Zn and Cu (r=-0.206), and Mn and Cu (r=-0.208) at $p<0.01$. Additionally, negative correlations were found between P and Cu (r=-0.132) and Zn and S (r=-0.117) at $p<0.05$. This study highlights the lack of correlation between Soil pH, and B with other soil parameters.

Table 3 Skewness, kurtosis and normality test results of Kolmogorov–Smirnov of raw, log transformed and Box–Cox transformed data

Soil Parameter	Raw data				Log-Transformed				Box-Cox Transformed				
	Skewness	Kurtosis	K-S test		Skewness	Kurtosis	K-S test		Power Parameter (Lambda=λ)	Skewness	Kurtosis	K-S test	
			D-Statistic	*p*			statistic	*p*				D-Statistic	*p*
N	1.223	3.897	0.17	< .001	0.823	3.051	0.13	0.00004	**-1.92**	**0.078**	**-0.564**	**0.06**	**0.174**
P	0.097	2.619	0.11	< .001	-0.6482	3.663	0.082	0.0232	**0.8**	**-0.02**	**-0.29**	**0.1**	**0.002**
K	0.618	3.219	0.09	< .001	-0.232	2.708	0.51	0	**0.26**	**-0.014**	**-0.293**	**0.07**	**0.072**
pH	-0.353	2.837	0.06	< .001	-0.503	3.12	0.068	0.00084	**2**	**-0.21**	**-0.357**	**0.07**	**0.077**
EC	1.138	3.683	0.14	< .001	**0.024**	**2.4**	**0.042**	**0.181**					
OC	0.851	4.386	0.14	< .001	-0.44	4.02	0.15	0	**0.34**	**0.018**	**0.778**	**0.13**	**0**
B	0.814	3.194	0.14	< .001	-0.3	3.5	0.74	0.053	**0.22**	**-0.003**	**0.1**	**.085**	**0.017**
Zn	0.965	3.872	0.08	< .001	-0.867	5.22	0.76	0.0411	**0.38**	**0.012**	**0.187**	**0.04**	**0.701**
Fe	-0.676	2.96	0.1	< .001	-2.39	11.513	0.19	0	**1.59**	**-0.225**	**-0.707**	**0.07**	**0.075**
Mn	-0.009	2.499	0.11	< .001	-1.395	6.099	0.16	0	**0.95**	**-0.057**	**-0.439**	**0.11**	**0.001**
Cu	1.217	3.199	0.25	< .001	**0.427**	**2.2877**	**0.13**	**< .001**	-0.34	0.046	-0.579	0.13	0.004
S	0.147	1.973	0.1	< .001	-0.37	2.16	0.1	0.0019	**0.59**	**-0.06**	**-1.007**	**0.09**	**0.015**

N= Available N (kg ha^{-1}), P= Available P (kg ha^{-1}), K= Available K (kg ha^{-1}), pH= Soil pH, EC= Electrical conductivity (dSm^{-1}), OC= Organic Carbon (%), B= Hot Water-Soluble B (mg kg^{-1}) Zn= DTPA Extractable Zn (mg kg^{-1}), Fe= DTPA Extractable Fe (mg kg^{-1}), Mn= DTPA Extractable Mn (mg kg^{-1}), Cu= DTPA Extractable Cu (mg kg^{-1}), S= 0.15% $CaCl_2$ Extractable S (mg kg^{-1}) and K-S test - Kolmogorov Smirnov test. Note - Transformed Data used for interpolation are given in Bold.

Table 4 Pearson's correlation coefficient among soil properties in the study area

Soil parameter	N	P	K	pH	EC	OC	B	Zn	Fe	Mn	Cu	S
N	-											
P	-0.050	-										
K	-0.008	0.020	-									
pH	-0.095	0.060	0.017	-								
EC	-.192**	-0.020	-0.004	0.089	-							
OC	.167**	-0.003	-.147**	0.056	-0.046	-						
B	0.030	-0.059	-0.088	0.014	-0.050	0.005	-					
Zn	0.010	0.042	-.170**	0.054	-0.021	.150**	0.032	-				
Fe	0.003	0.051	0.047	-0.088	-.145**	0.011	-0.010	-.334**	-			
Mn	-0.096	0.107	0.040	-0.002	0.023	-0.053	-0.027	.186**	-.0153**	-		
Cu	0.016	-.132*	-0.053	-0.017	0.069	-0.108	0.073	-.206**	.153**	-.208**	-	
S	-0.079	0.029	-0.016	0.023	0.069	-0.101	-0.087	-.117*	-0.035	0.052	0.064	-

**. Correlation is significant at the 0.05 level (1-tailed), **. Correlation is significant at the 0.01 level (1-tailed) N= Available N (kg ha^{-1}), P= Available P (kg ha^{-1}), K= Available K (kg ha^{-1}), pH= Soil pH, EC= Electrical conductivity (dSm^{-1}), OC= Organic Carbon (%), B= Hot Water-Soluble B (mg kg^{-1}) Zn= DTPA Extractable Zn (mg kg^{-1}), Fe= DTPA Extractable Fe (mg kg^{-1}), Mn= DTPA Extractable Mn (mg kg^{-1}), Cu= DTPA Extractable Cu (mg kg^{-1}), S= 0.15% $CaCl_2$ Extractable S (mg kg^{-1})*

Geostatistical Analysis

The analysis of classical statistics alone cannot determine spatial variability of soil nutrients necessary to utilize semivariance function to assess these characteristics. The results of the semivariogram examination are given in Table 5. Scholars have conducted several studies to determine the most suitable models for different soil parameters. The results indicate suitable model was exponential for B, Zn, OC, Fe, and Mn, with distances of 538.93, 689.84, 760, 1283.6, and 3972 meters, respectively and it was recognized as the most appropriate for properties of soil (Vieira and Gonzalez, 2003). The model of Gaussian for soil K at a distance of 1236 meters. K-Bessel model was the best fit for P, Cu, and S, with ranges from 598.43, 1332.5, and 1838 meters, respectively. J-Bessel model was the most suitable for describing Soil N, with a distance of 850.59 meters. The stable model for soil EC, while the rational-quadratic model appropriate for soil pH, with ranges of 2573.8 and 621.24 meters, respectively. The Gaussian model has been identified as the best model for soil parameter K, as observed in other studies conducted by Abbas et al. (2023.The exponential model is the most effective for Zn, as indicated by Laekemariam et al. (2018). Hegde et al. (2019) confirmed that the exponential model also works well for Mn and Fe. Furthermore, Reza et al. (2016), Hegde et al. (2019) provided evidence for the effectiveness of the exponential model for OC. The K-Bessel model has received support from Tripathi et al. (2015) for soil P and Shukla et al. (2020) for Sulphur (S). The range is used to ascertain an attribute's similarity range. This study displays (Table 5) the ranges of various soil parameters, including B, P pH, Zn, OC, N, Fe, K, Cu, S, EC, and soil Mn are 538.93, 598.43, 621.24, 689.84, 760, 850.59, 1236, 1283.6, 1332.5, 1838, 2573.8, and 3972 meters, respectively. In this study, the value of a high range of Soil Mn results was in line with Tamburi et al. (2020). The range vary in this study area might be due to factors including parent material, ecological processes, climatic conditions, soil management practices, and anthropogenic factors (López-Granados et al., 2002).

The percentage of Nugget (Nu) and Sill (Si) was examined to ascertain the spatial relationship of soil properties. Cambardella et al. (1994) classified spatial dependence as weak (above 0.75), moderate (between 0.25 and 0.75), and strong dependency (below 0.25). In the current study, the results (Table 5) found strong for N, Cu, and S, moderate for P, and a weak spatial distribution for B, Fe, OC, pH, EC, Mn, K, and Zn. The similar results for strong and moderate spatial dependency recorded by Tagore et al. (2015), and Verma et al. (2021), respectively. The weak spatial dependency of Soil pH was also reported by Behera et al. (2018). The Soil EC findings are consistent with Abdu et al. (2023). The soil Mn and OC had weak spatial dependencies, supported by Vasu et al. (2021). The spatial dependence is classified according to a number of factors. The inherent soil characteristics of topography, minerals, and agricultural techniques of fertilization and irrigation are the causes of the strong spatial dependency (Gökmen et al., 2023). The combination of internal elements like parent material and soil texture and external variables like fertilizer and irrigation cause moderate spatial dependence (Vasu et al., 2017). Weak dependence and a high percentage of nugget (Nu) and sill (Si) ratio are caused by activities of humans, soil and crop management practices (Vasu et al., 2016; Vasu et al., 2021; Gökmen et al., 2023). A lower percentage of nugget (Nu) and sill (Si) indicate that topography, parent material, and climate are structural elements that influence spatial variability.

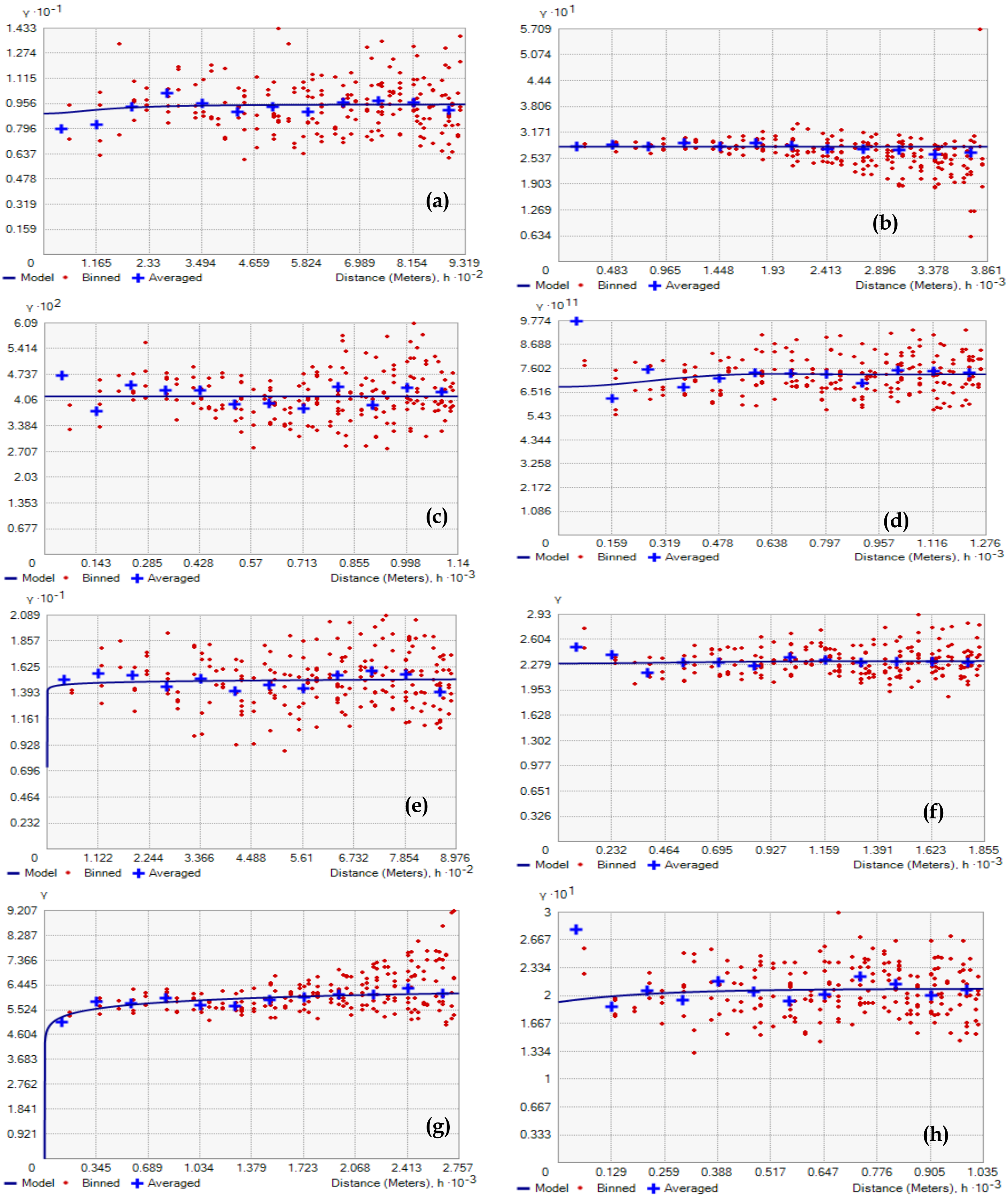
The nugget (Nu) effect for N, OC, Cu, and S was the lowest, indicating low variance in the study area among soil parameters. It implies similar and different values for near and distant observations. The results (Table 5 and Fig. 2) show the soil properties B, P, pH, Zn, OC, and N have a spatial correlation that extends up to a distance of 0.5 kilometres. Fe, K, Cu, and S exhibit a spatial correlation range from one to 2.5 kilometres. EC and Mn show a spatial correlation range from 2.5 to 3.9 kilometres and no correlation beyond these distances. It is advisable to use a sampling interval smaller than half of the range (Kerry et al., 2010) to ensure accurate sampling, the range of spatial autocorrelation for soil nutrients extends from 0.5 to 3.9 kilometres, indicating the presence of ecological processes operating at different scales. Hence, a sampling strategy employing a distance of 0.2 kilometres is appropriate for examining the spatial distribution.

Cross validation and comparing models

The study conducted cross-validation techniques such as MSE, ASE, RMSE, and RMSSE (Table 5) to select the best models based on accuracy. The results indicated that the ASE and RMSE values were generally similar, except for soil K. The MSE values were close to zero, while the RMSEE ranged from 0.91 to 1. Based on the accuracy of the cross-validation techniques, the K-Bessel, Circular, J-Bessel, Spherical, Tetraspherical, Hole Effect, Pent spherical, Exponential, Stable, Gaussian, and Rational Quadratic models were found to be the best.

Spatial variability maps

The twelve soil properties were mapped using OK interpolation (Figure 3). The pH levels (Figure 3a) ranges between 6.5 and 8.5. Approximately 47.76% of the soil had a pH within the normal range (6.5-7.5), which is best for crop growth and 42.08% of the soil had a slightly alkaline pH (7.5-8.5), requiring specific management strategies for crop cultivation.


γ ·10-1
1.433
1.274
1.115
0.956
0.796
0.637
0.478
0.319
0.159
0
1.165
2.33
3.494
4.659
5.824
6.989
8.154
9.319
(a)
Model
Binned
Averaged
Distance (Meters), h ·10-2
γ ·10¹
5.709
5.074
4.44
3.806
3.171
2.537
1.903
1.269
0.634
0
0.483
0.965
1.448
1.93
2.413
2.896
3.378
3.861
(b)
Model
Binned
Averaged
Distance (Meters), h ·10-3
γ ·10²
6.09
5.414
4.737
4.06
3.384
2.707
2.03
1.353
0.677
0
0.143
0.285
0.428
0.57
0.713
0.855
0.998
1.14
(c)
Model
Binned
Averaged
Distance (Meters), h ·10-3
γ ·10¹¹
9.774
8.688
7.602
6.516
5.43
4.344
3.258
2.172
1.086
0
0.159
0.319
0.478
0.638
0.797
0.957
1.116
1.276
(d)
Model
Binned
Averaged
Distance (Meters), h ·10-3
γ ·10-1
2.089
1.857
1.625
1.393
1.161
0.928
0.696
0.464
0.232
0
1.122
2.244
3.366
4.488
5.61
6.732
7.854
8.976
(e)
Model
Binned
Averaged
Distance (Meters), h ·10-2
γ
2.93
2.604
2.279
1.953
1.628
1.302
0.977
0.651
0.326
0
0.232
0.464
0.695
0.927
1.159
1.391
1.623
1.855
(f)
Model
Binned
Averaged
Distance (Meters), h ·10-3
γ
9.207
8.287
7.366
6.445
5.524
4.604
3.683
2.762
1.841
0.921
0
0.345
0.689
1.034
1.379
1.723
2.068
2.413
2.757
(g)
Model
Binned
Averaged
Distance (Meters), h ·10-3
γ ·10¹
3
2.667
2.334
2
1.667
1.334
1
0.667
0.333
0
0.129
0.259
0.388
0.517
0.647
0.776
0.905
1.035
(h)
Model
Binned
Averaged
Distance (Meters), h ·10-3

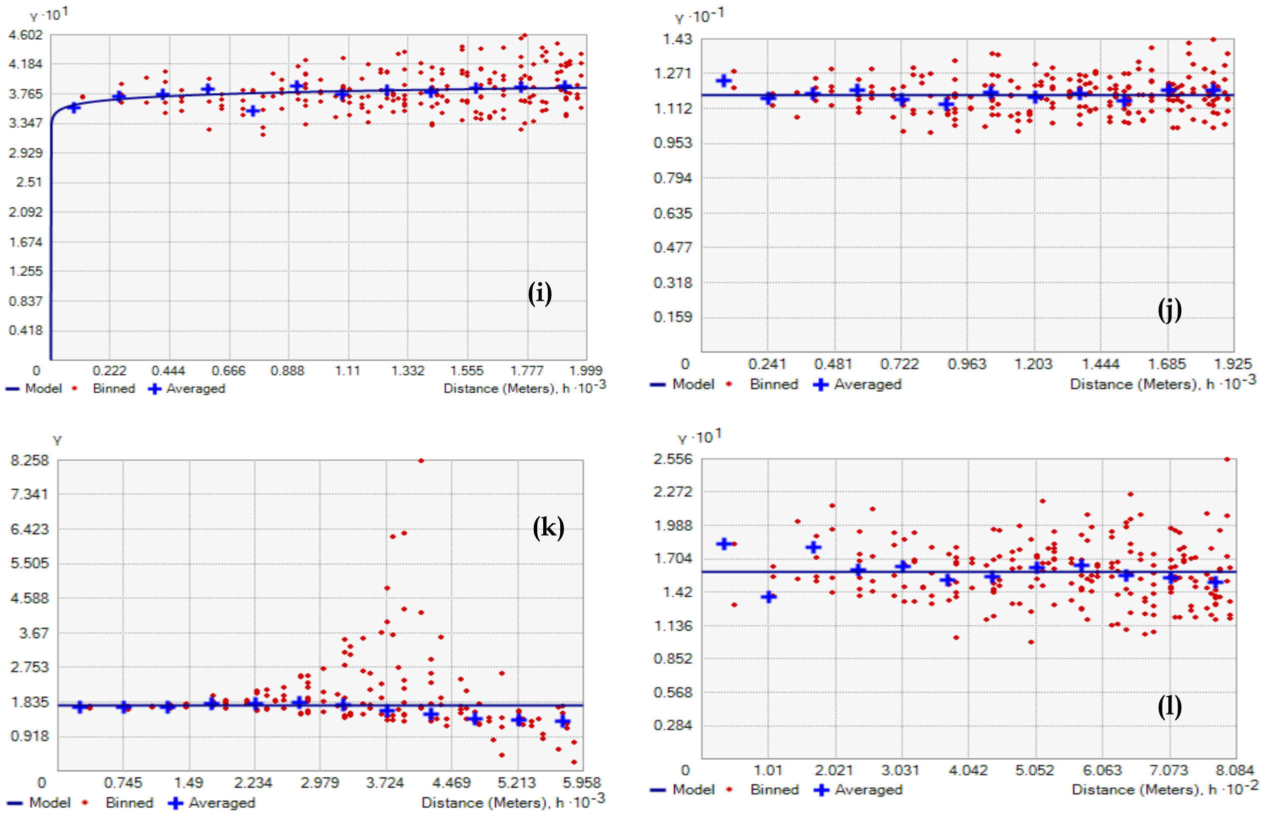


Fig. 2 Semivariograms with fitted models for soil properties, (a) Soil pH, (b) EC (dSm^{-1}), (c) Organic Carbon (%) (d) Available N (kg ha^{-1}), (e) Available P (kg ha^{-1}), (f) Available K (kg ha^{-1}), (g) 0.15% $CaCl_2$ Extractable S (mg kg^{-1}), (h) DTPA Extractable Zn (mg kg^{-1}), (i) DTPA Extractable Cu (mg kg^{-1}), (j) DTPA Extractable Fe (mg kg^{-1}), (k) DTPA Extractable Mn (mg kg^{-1}), (l) Hot Water Soluble B (mg kg^{-1})

This variation due to multiple factors, including the geological conditions, the composition of the soil, and the inconsistent application of fertilizers and manures (Kumar et al., 2019).Similar findings were also found in Tatrakallu-village, Anantapur-district, and Andhra Pradesh-state (Sashikala et al., 2019).About 40% of soil EC values are less than 0.25 dSm-1, 45% of the area had values between 0.25 and 0.5 dSm-1, and 15% had values between 0.51 and 0.81 dSm-1(Fig. 3b).The soil in the study region was found to be non-saline and similar results reported by Sashikala et al. (2019) and Gorji et al. (2019).

The OC varied from low to medium levels (Fig. 3c). Approximately 96% area exhibited lower OC values (< 0.50%), and 4% had medium values (0.50 -0.75%). The results revels that a significant portion of study area had a low OC content. According to Kumar et al. (2019) OC is poor generally in sub-humid soils in India, with an average value of 0.5%. In this study, the low organic carbon content may be due to inadequate crop management practices, biomass production (Nadal-Romero et al., 2016), low rainfall, and high temperatures (Kumar and Babel, 2011). Similar findings were also observed in the soils of the dry zone of Andhra Pradesh State under semi-arid conditions (Sashikala et al., 2019). Therefore, it is recommended to incorporate composts or animal manures, introduce legumes, and implement green manuring practices in the present research area to enhance OC content to improve soil health (Chan, 2008).
Figure 3d shows that the majority, around 97%, of the study area had critically low levels of available nitrogen.

The southeastern part had sufficient nitrogen for soil management practices. This low availability of nitrogen could be due to various factors such as semi-arid conditions, low rainfall, and low application of nitrogen fertilizers, organic manures, excess temperature and geology (Moharana et al., 2017; Kumar et al. (2019; Sashikala et al. (2019). In Fig.3e, it was observed that the western and eastern parts had a significant amount (79%) of P (> 25). This could be attributed to excessive use of fertilizers and low rainfall and low rainfall. The northwest and south parts had a moderate level (21%) of P (10–25). Similar findings were observed by Moharana et al. (2017) and Sashikala et al. (2019). The K (Fig. 3f) map reveals that southern and southwestern parts (30%) had a medium (120–280) and 70% had a high level of K (> 280), which implies a supply of accessible K in the study area. The current research area had enough S accessible, with a concentration of more than 10.0 mg kg-1(Fig. 3g), it ensures a sufficient amount of S for plants growth.

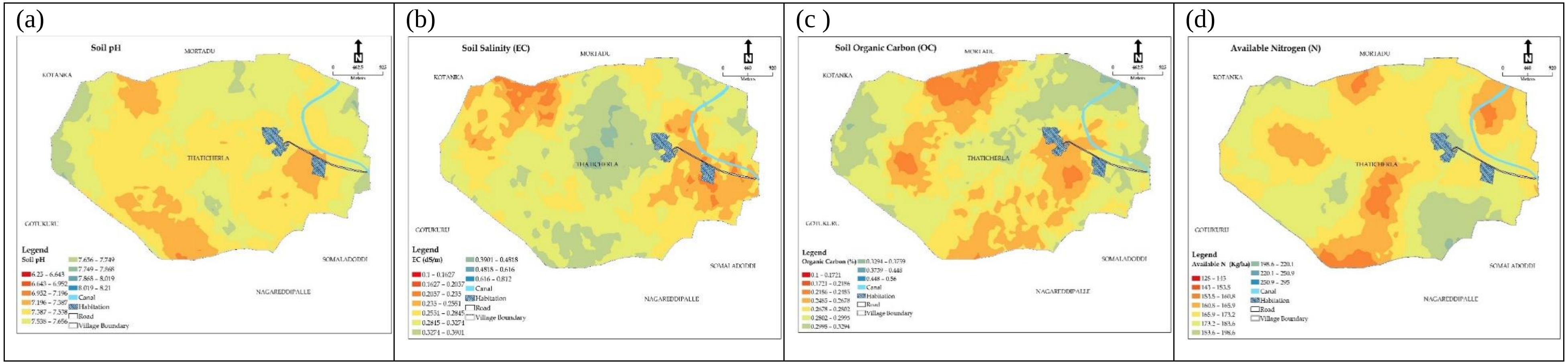
The map in Fig. 3h shows that zinc deficiency was present in 40% of the western, southwestern, and eastern parts, with levels below 0.6. The remaining 60% of the area had sufficient zinc levels, with values above 0.6.

The village of Tatrakallu-Village in Andhra Pradesh State was found to have zinc deficiency as reported by Sashikala et al., 2019.The study area's soils are alkaline, and low soil OC could be the reason for low Zn.

Table 5 The semivariogram models for soil properties and cross-validation errors

Soil parameter	Best fitted Model	Nugget	Parcel Sill	Sill	Nugget/Sill	Range (Meters)	Spatial Dependency	Cross Validation Errors			
								RMSE	ASE	MSE	RMSSE
N	J-Bessel	0	0	0	0.00	850.59	Strong	38.17	38.16	-0.035	1
P	K-Bessel	7.3	8.21	15.51	0.47	598.43	Moderate	7.98	7.96	-0.007	1
K	Gaussian	2.29	0.032	2.322	0.99	1236	Weak	113.79	116.62	-0.013	0.98
pH	Rational Quadratic	8.93	0.58	9.51	0.94	621.24	Weak	0.43	0.42	0	1
EC	Stable	0.28	0	0.28	1.00	2573.8	Weak	0.18	0.19	-0.002	0.94
OC	Exponential	0.04	0	0.04	1.00	760	Weak	0.09	0.09	-0.002	1
B	Exponential	0.159	0	0.159	1.00	538.93	Weak	0.41	0.42	-0.011	0.99
Zn	Exponential	0.19	0.02	0.21	0.90	689.84	Weak	0.38	0.38	-0.022	0.99
Fe	Exponential	11.74	0	11.74	1.00	1283.6	Weak	1.51	1.67	0.008	0.91
Mn	Exponential	1.74	0	1.74	1.00	3972	Weak	1.45	1.45	0.002	1
Cu	K-Bessel	0	0.4	0.4	0.00	1332.5	Strong	0.46	0.46	-0.047	1
S	K-Bessel	0	6.35	6.35	0.00	1838	Strong	9.86	9.56	-0.008	1.03

N= Available N (kg ha^{-1}), P= Available P (kg ha^{-1}), K= Available K (kg ha^{-1}), pH= Soil pH, EC= EC (dSm^{-1}), OC= Organic Carbon (%), B= Hot Water-Soluble B (mg kg^{-1}) Zn= DTPA Extractable Zn (mg kg^{-1}), Fe= DTPA Extractable Fe (mg kg^{-1}), Mn= DTPA Extractable Mn (mg kg^{-1}), Cu= DTPA Extractable Cu (mg kg^{-1}), S= 0.15% $CaCl_2$ Extractable S (mg kg^{-1})



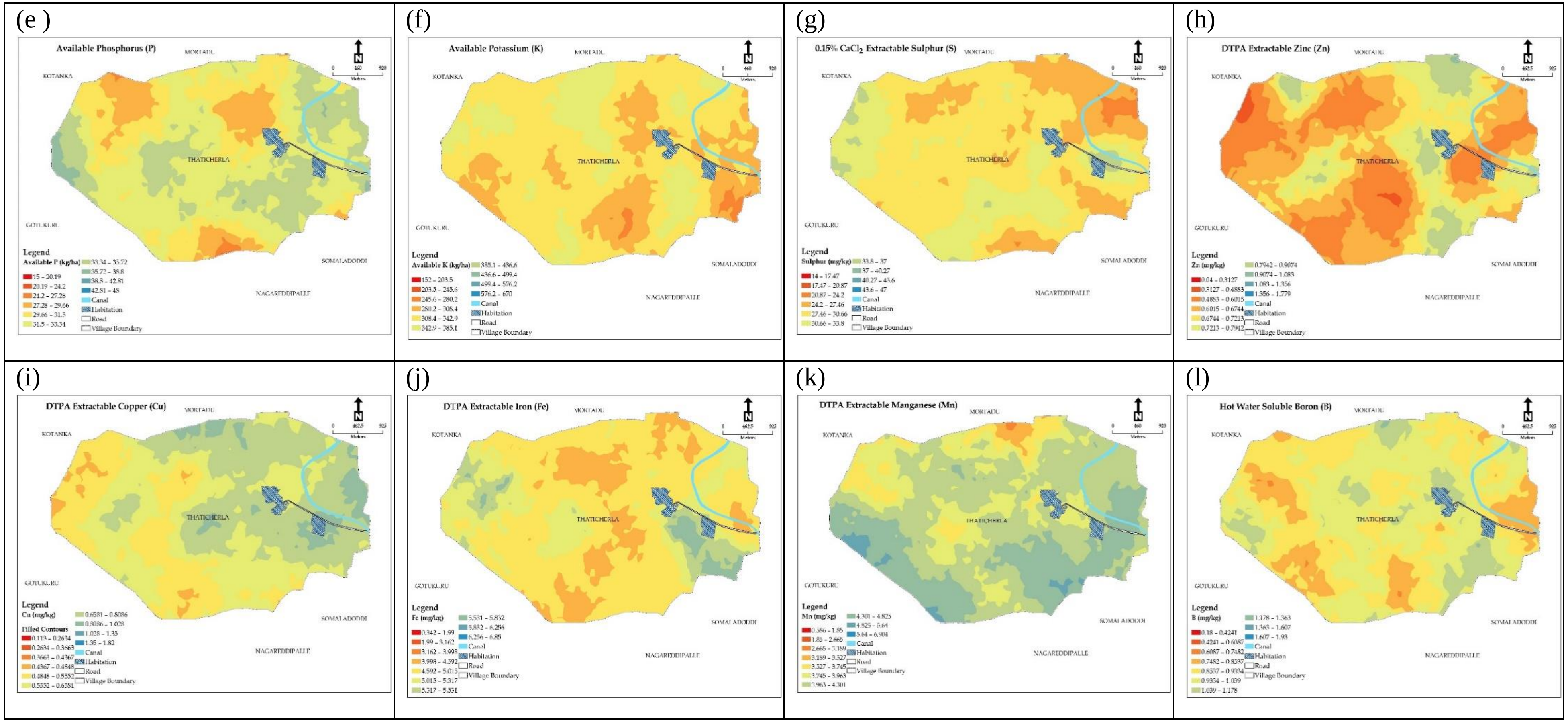


Fig. 3 Spatial Distribution of Soil Properties, (a) Soil pH, (b) EC (dSm^{-1}), (C) Organic Carbon (%), (d) Available N (kg ha^{-1}), (e) Available P (kg ha^{-1}), (f) Available K (kg ha^{-1}), (g) 0.15% $CaCl_2$ Extractable S (mg kg^{-1}), (h) DTPA Extractable Zn (mg kg^{-1}), i) DTPA Extractable Cu (mg kg^{-1}), (j) DTPA Extractable Fe (mg kg^{-1}), (k) DTPA Extractable Mn (mg kg^{-1}), (l) Hot Water Soluble B (mg kg^{-1})

The excessive use of NPK fertilizers without incorporating micronutrients, has worsened the deficiency of zinc (Arunachalam et al., 2013). Studies by Shukla et al. (2014) and Arunachalam et al. (2013) report that in India, zinc shortage was found in 43% of 97,464 and 48.5% of 256,000 soil samples, respectively. Insufficient zinc availability in the soil has led to suboptimal crop yields and reduced nutritional value (Khan et al., 2022). This study's findings are consistent with the generally low micronutrient content of Indian soil. These issues highlight the pressing need to take proactive measures to protect soil and human health (Das et al., 2022). Regarding soil Cu content (Fig. 3i), the study showed that 99% of the regions within the study area have adequate levels (> 0.2), and only 1% of the area exhibits low Cu concentration (<0.2). The study reveals that 35% of northern, southern, central, and eastern regions exhibits a deficiency in soil Fe, with levels below 4.5 (Fig 3j). Conversely, around 65% of the area shows satisfactory levels of Fe, with values above 4.5 mg kg^{-1}. This insufficiency in Fe content negatively impacts growth of crops. The water stress condition in India is the main cause of low levels of Fe (Sashikala et al., 2019). The study reveals that Mn levels were adequate (>2.0) in 94% of the study area, while only 6% of the region had levels below the desired threshold (<2.0) (Fig 3k). The results suggested sufficient levels across the study area, with some areas in the northern region displaying lower than ideal Mn concentrations. Additionally, the study revealed that 95% of the study area had sufficient hot water-soluble B content (> 0.5), while only 5% of the area had lower B concentrations (< 0.5) (Fig. 3l). The surface map indicated sufficient B content in most areas, but the east, west, south, and southwest displayed deficiency. Various land management techniques, such as the use of fertilizers, have resulted in different soil property distribution patterns in the research region (Sharma et al., 2011). These patterns are depicted through geographical maps that show significant differences in soil properties across the region. Policymakers and farmers can benefit from the study's findings by adopting site-specific soil nutrient management techniques, such as improved soil organic matter and targeted nutrient supplementation. This approach can help maximize agricultural production and mitigate specific deficiencies.

Conclusion

The study found that the coefficient of variation was high in copper (Cu) and low in soil pH. A positive association was found between N and OC, Zn and Mn, and OC and Zn, indicating a positive correlation. The data was normalized using Log and Box-Cox transformations. The ordinary Kriging interpolation is an effective geostatistical technique for generating soil nutrient distribution maps. The study concluded that the exponential model was suitable for B, Fe, Mn, Zn, and OC. The Gaussian and J-Bessel are best-fit-model for potassium (K) and Nitrogen (N) respectively. The K-Bessel model was suitable for Cu, P, and S. Stable and rational quadratic models best fitted models for EC and pH, respectively. The study area identified that it has a strong to weak spatial dependency. The present study area identified significant deficiencies of 96% and 97% in organic carbon and available nitrogen, respectively. The study suggests that it is essential to consider specific nutrient deficiencies when applying manures and fertilizers to improve crop production and maintain health of soils. These results can help to create field-specific plans for making informed decisions regarding the environment, soil, and human health. Governments and policymakers must prioritize the issues discussed in this research to ensure the achievement of sustainable development.

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