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RESEARCH ARTICLE

Determination of soil fertility management zones in Veeranam Command for rice production using geostatistical methods, principal component analysis and fuzzy clustering

V Arunkumar[1], K Manikandan[2], Patil Santosh Ganapati[3], S Babu[1], D Dhanasekaran[1*], N Senthilkumar[1], T Balaji[1], M Vijayakumar[4] & K Ananthi[1]

[1]Department of Soil Science & Agricultural Chemistry, Agricultural College and Research Institute, Tamil Nadu Agricultural University, Vazhavachanur 606 753, Tiruvannamalai, Tamil Nadu, India

[2]Department of Soil Science & Agricultural Chemistry V.O.Chidambaranar Agricultural College and Research Institute, Tamil Nadu Agricultural University, Killikulam 622 104, Tirunelveli, Tamil Nadu, India

[3]Department of Physical Sciences and Information Technology, Agricultural Engineering College and Research Institute, Tamil Nadu Agricultural University, Coimbatore 641 003, Tamil Nadu, India

[4]Department of Soil Science & Agricultural Chemistry Anbil Dharmalingam Agricultural College and Research Institute, Tamil Nadu Agricultural University, Trichy 620 027, Tamil Nadu, India

*Correspondence email - dhansflora@gmail.com

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Abstract

Crop productivity can be enhanced while reducing environmental threats from excessive fertilization by fully comprehending the spatial variability of soil properties and delineating management zones (MZs). A field investigation was carried out in Veeranam Command area in Southern India to study the spatial variability of soil properties and the delineation of MZs. Grid wise 240 soil samples collected from the study area were analyzed for pH, available macronutrients and micronutrients. The coefficient of variation of the soils varied from low (6.34 %) to high (87.56 %). Geostatistical analysis showed differed spatial variability patterns for the studied soil properties with spatial dependence ranged from moderate to strong and the ordinary kriging method is used to map the distribution of soil properties. MZs were delineated by performing principal component analysis (PCA) and fuzzy K-means clustering. Four PCs with eigen values more than 1 dominated 52.65 % of the total variance, so they were retained for clustering analysis. Six MZs were delineated based on the two criteria modified partition entropy (MPE) and fuzzy performance index (FPI). The studied soil properties differed significantly among MZs. Thus, the methodology used for MZ delineation could be used effectively for soil site-specific nutrient management for avoiding soil degradation concurrently with maximizing crop production in the study area.

Keywords: fuzzy clustering; geostatistics; soil fertility management zones; spatial variability

Introduction

Soil is crucial for biodiversity and life, significantly contributing to the provision of key ecosystem services for humanity. Soil is a vital resource for food production, acting as the medium for crop growth. Recognizing soil characteristics and associated nutrient dynamics has significant consequences for soil fertility, agricultural production, food security and environmental health (1, 2). The soil properties exhibit significant temporal and geographical heterogeneity since they differ across time and space among various soil types (3, 4). Therefore, implementing a uniform management strategy across all gradients only results in excessive fertilization, resource waste and environmental contamination (5).

Soil fertility management zones entail partitioning target regions into several management zones (MZs) according to soil characteristics and particular needs. This method enables accurate fertilization and cultivation management techniques while successfully addressing the regional diversity of soil attributes (6). A management zone (MZ) can be considered as a subpartition of larger areas into smaller ones based on soil properties. Hence, a MZ has distinctive properties that distinguish it from other zones, allowing for specific management measures. In command areas, the implementation of soil fertility management zones emerges as an effective strategy for precision farmland management, aiming to maximize crop productivity (7). Precise soil-property distribution maps can be generated using ordinary kriging interpolation (8).

In geostatistics, the semivariogram parameters enable the analysis of intrinsic and extrinsic factors' impact on regional variables, the evaluation of the spatial variation characteristics of soil properties and the calculation of an appropriate sampling density, all of which contribute to precision in fertilization (9-12). However, when delineating MZs based on soil properties, there is often a specific correlation between different soil properties that could result in information duplication. Principal component analysis (PCA) can transform the original variables into new mutually independent principal components (PCs). Fuzzy c-means clustering (FCM) is a frequently employed unsupervised clustering method, often applied to delineate soil MZs (13, 14). Many studies have utilized PCA and FCM to categorize farmland soil into distinct areas with uniform soil properties, forming the basis for sustainable soil MZs (15-19).

This study aims to divide the study area into management zones (MZs) based on soil fertility characteristics, facilitating the classification of large, heterogeneous regions into manageable agricultural production areas. However, to prioritize sustainable agricultural production, the study does not account for local factors such as landforms and parent materials (20, 21).

The study area encompasses Veeranam Command area in the central part of Tamilnadu of Southern India and is characterized by a high level of agricultural development. Unfortunately, the misuse of fertilizers has resulted in the degradation of the soil environment. According to the main hypothesis, reducing the excessive use of agricultural chemical fertilizers requires a thorough understanding of the spatial distribution of soil attributes and the delineation of production management regions. Against this backdrop, the primary objectives of this study are, (a) employing geostatistics, the study aims to comprehensively analyse the spatial variability of soil properties. By utilizing ordinary kriging interpolation, the research endeavors to generate detailed soil fertility maps. These maps will offer valuable insights into the distribution of key soil properties, enabling a nuanced understanding of the local soil conditions, (b) utilizing PCA and FCM, the study seeks to delineate distinct agricultural production MZs within the Veeranam Command region. This approach is anticipated to facilitate a more informed and strategic allocation of resources, contributing to sustainable agricultural practices and mitigating the adverse environmental impacts associated with indiscriminate fertilization.

Materials and Methods

Study sites

The study region is spread around Kattumannarkoil and Chidambaram taluks falling under Cuddalore district of Tamil Nadu (Fig. 1). The extent of study site ranges between 79 ° 15' and 79 ° 32' N and 11 ° 05' to 11 ° 26' E. The total geographical area is 2400 ha. The climate of the study area is humid and receives an annual rainfall of 1110 mm, mostly during the monsoon period (October to December). The physiography of the study area falls under flat alluvial plain. The soil consists of coastal sands and alluvium derived from the cauvery of the quaternary period. Major soil orders of the study area are entisols, inceptisols and vertisols and the soil texture varies from coarse loamy to clayey. Agriculture is the predominant land use, mainly with a rice-rice - pulses cropping pattern.

The grid sampling, with a grid size of 1 km, was used to collect the soil samples (20, 16) from the study site, considering uniform underlying geology and lesser soil variability (Fig. 1). A total of 240 geocoded soil samples were collected at 0-15 cm depth during the summer season of May 2023 and before planting of the paddy crops. The soil samples were air-dried, crushed using a wooden pestle and mortar and sieved through a 2 mm mesh (0.2 mm mesh for organic carbon). Each sample was labelled and stored correctly. These samples underwent analysis for 10 chemical parameters, which included pH and electrical conductivity (EC); organic carbon; available nitrogen (N), phosphorus (P), potassium (K); available micronutrients like iron (Fe), zinc (Zn), copper (Cu) and manganese (Mn) using standard analytical procedures (22-27).

Statistical procedures

By adopting SPSS 19 software, statistical variables, viz., standard deviation (SD), coefficient of variation (CV), mean, skewness and kurtosis, were computed. The relationship between different soil properties was envisaged utilizing Pearson's correlation coefficient (28).

Geostatistical analysis

Geostatistical study of soil properties was carried out using ArcGIS 9.1 software for semivariogram modeling and fitting the best semivariogram model. Before geostatistical analysis, logarithm transformation was applied to skewed soil properties to get normally distributed data. The data were back transformed using the back transformation function during data interpretation. Variogram models viz., spherical and exponential were fitted to the empirical semi-variance. Semivariogram models were selected based on the coefficient of determination (R^2) and residual sum of squares (RSS). The fitted models were utilized to estimate various attributes at non-measured points as interpolated values for mapping using ordinary kriging technique (29). The cross validation was performed to assess the bias and accuracy of kriging interpolation. A spatial domain's measured points are individually removed from the domain and kriging estimates are made as if they were present (30). In this approach, the estimated and real values for each sample location can be compared.

Principal component analysis

PCA is a data reduction method without losing necessary information that uses correlated attributes to identify the best linear combination of the characteristics that extracts the primary sources of variability within data. Soil properties were used as input for PCA analysis. In this study, a large number of principal components (PC) variables are extracted. It has been observed that principal components (PCs) with high Eigen values (>1) would serve as the best representation of the field's characteristics and explain the maximum variability (30). Hence, in this study, PCs with Eigen values ≥ 1 were utilized to build the management zone for precise nutrient management.

Fuzzy clustering algorithm

The fuzzy c-mean was utilized to divide the field into distinct management zones. The fuzzy clustering statistically increases the among-group variations while decreasing the within-group variability to create homogeneous groups. A sample with various characteristics in fuzzy clustering may belong to multiple groups simultaneously when assigning membership to them, which might lessen the impact of outliers on the sample's overall results. Using the R programming language, the field was divided into 2-7 cluster groups using fuzzy c-mean, an unsupervised continuous classification approach (31). In this analysis, seven clusters were identified to be the most practicable management zones following the procedure outlined by researchers (32). An iterative procedure starting with a random set of cluster means was used to identify membership in each cluster. The closest of these means was

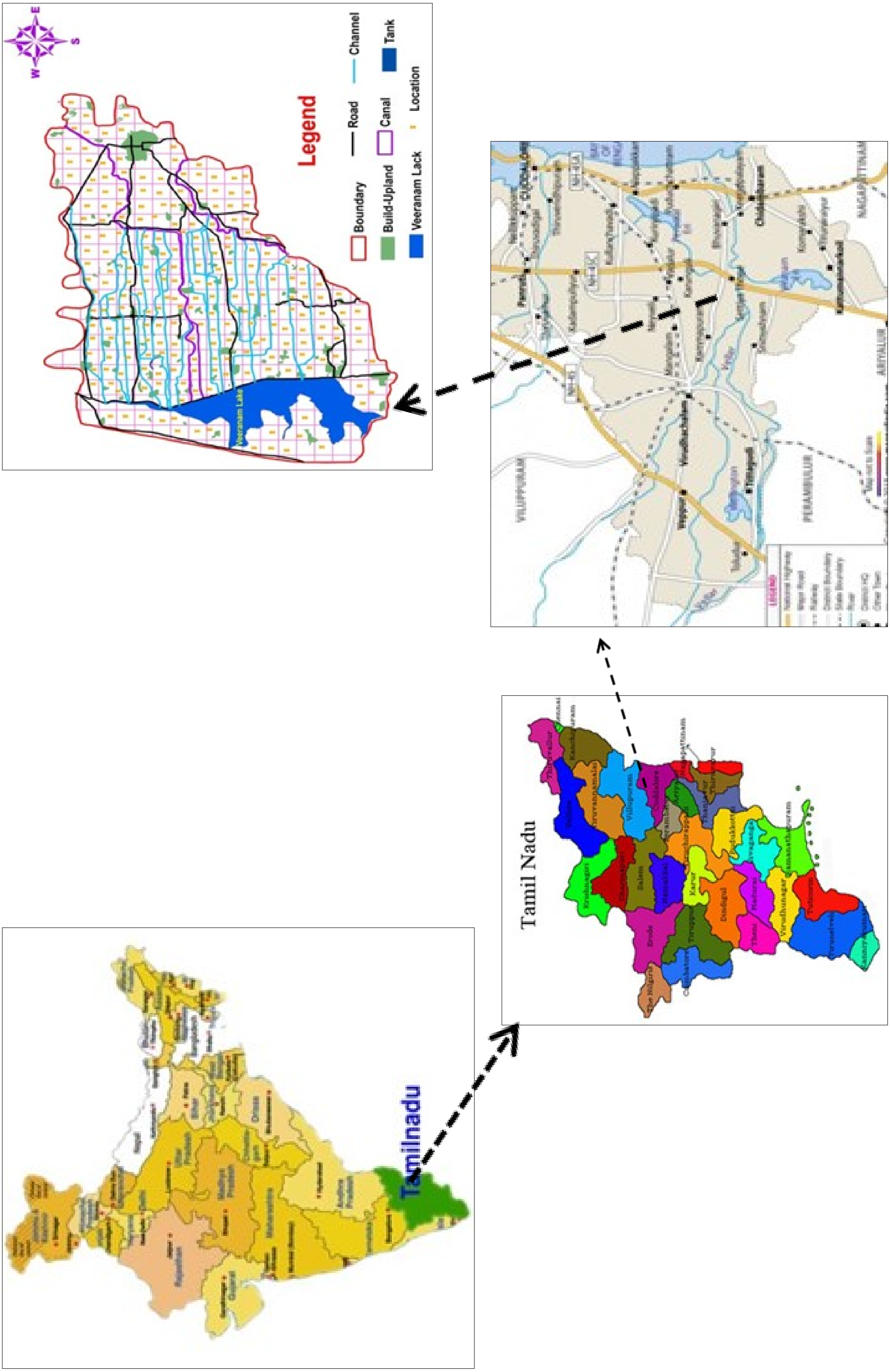


Fig. 1. Study region depicting soil sampled locations.

chosen for each observation. Based on the separation between the observation and the cluster mean, new means were generated for each cluster. According to equal variance and statistical independence, the distance between data points and cluster center points was calculated using the Euclidean distance. To determine the ideal cluster number, two cluster validity functions, the fuzzy performance index (FPI) and the normalized classification entropy (NCE) were used (33, 34) as follows:

$$\text{FPI} = 1 - \frac{c}{c-1}\left[1 - \frac{\sum_{i=1}^{c}\sum_{k=1}^{n}(\mu_{ik})2}{n}\right] \quad (1)$$

$$\text{NCE} = 1 - \frac{n}{n-c}\left[1 - \frac{\sum_{k=1}^{n}\sum_{i=1}^{c}\mu_{ik}\log_a(\mu_{ik})}{n}\right] \quad (2)$$

Where,

c is the number of clusters

n is the number of observations

μ_{ik} is the fuzzy membership

$\log_a$ is the natural logarithm

The FPI calculates the degree of fuzziness brought about by a particular number of classes. FPI values may vary between 0 and 1. While values close to 1 imply no distinct classes with a significant degree of membership sharing, values close to 0 indicate distinct classes with little membership sharing. The NCE calculates the degree of disorganization created by a specified number of classes. The ideal number of clusters for each computed index (FPI and NCE) is attained when the index is at its lowest value, which results in the least membership sharing (FPI) and most organization (NCE) because of the clustering process (35). The analysis of variance was utilized to demonstrate variation among various MZs.

Results

Descriptive statistics

The mean, standard deviation and other descriptive results of the sampling points (240) for a variety of soil properties in the study area are summarized in Table 1. The pH values range from 6.55 (slightly acidic) to 8.30 (moderately alkaline), with the median at 7.70, showing that most soils are near neutral. The pH values are relatively stable, with a low standard deviation (0.48). The data is slightly negatively skewed, meaning more samples have pH levels above the average showing very less CV of 6.34 %.

The soil samples have an average EC value of 0.67 dS/m, indicating low salinity, which is good for plant growth, as shown in Table 1. The EC values are quite consistent, with only small variations, as demonstrated by the low standard deviation (0.0754) and standard error (0.0066). The data is strongly skewed to the right (skewness of 2.00), meaning most samples have EC values lower than the average, with a few higher values affecting the mean. The high kurtosis (4.78) suggests extreme EC values are more common than usual. The EC values range from 0.15 to 2.34 dS/m having a moderate variation of 58.33 %.

The soil's average organic carbon content is 0.66 %, a key index of soil fertility and the source of various soil nutrients. The variation in organic carbon levels is not too wide, as reflected by the standard deviation (0.11). The organic carbon content ranges from 0.41 % to 0.75 %, with most soils having levels close to the median value of 0.66 %, essential for maintaining soil health. Table 1 shows that the soil samples have an average nitrogen content of 201.94 kg/ha, a moderate level needed for plant growth. Nitrogen deficiency in soil was prevalent in study area as evident from the low available nitrogen content in soil. The average phosphorus content in the soil is 16.33 kg/ha, which is a moderate level essential for root development. The data has a slight positive skew, meaning most samples have phosphorus levels below average. The average potassium content is 296.60 kg/ha, a moderate level necessary for plant health.

Among major soil nutrients, available Phosphorus had the highest CV. A high CV of 87.56 % for available Copper was recorded which varied from 1.58 to 3.12 $mgkg^{-1}$. Among all the ten soil variables, lowest CV (6.34 %) was recorded for pH, whereas DTPA- extractable Cu had the highest CV (87.56). Except available K, Fe and Cu, medians for all other variables were close to their means (Table 1).

Relationship among the soil properties and available nutrients

The degree of correlation among the soil properties is shown in Fig. 2. Almost all the properties except a few were significantly positively and negatively correlated with each other. Notably, the soil pH significantly correlates with all other soil properties; it exhibits a significant positive correlation with the OC, Fe and Mn, while showing a significant negative correlation with the remaining properties. The EC is a direct indication of nutrient availability because it measures amount of salt in the soil and correlated negatively with N and positively with P. Predictably, nutrient pairs that are significantly negatively correlated will have spatial patterns, which are mirror images (36). There is a high correlation between the soil OC and N, which has been confirmed by many scholars elsewhere (37, 38). Except for the pH, OC, Fe, Mn and Cu, P exhibits a significant positive correlation with the other properties. There was a significant positive correlation between any two of Fe, Mn, Cu and Zn. Correlations between Cu and other soil properties were mostly weak.

Geostatistical analysis of soil properties

Semivariograms were computed and the best models were determined for different soil properties as shown in Fig. 3. Table 2 shows the results of the semivariogram analysis. The best-fit theoretical models were spherical for most of the soil properties except for pH and available phosphorous where exponential models were fitted. Additionally, researchers observed that spherical models provided the best representation of the majority of soil attributes (39-42). The results showed that there was spatial autocorrelation in soil parameters. It is attributed to environmental factors such as crop management practices, fertilizer application and farming systems (42).

The nugget/sill ratio was compared for soil variables (Table 2). The nugget/sill ratio showcases the spatial dependency of soil properties (43). A ratio of < 25 % expresses strong spatial dependence, between 25 % and 75 % signifies moderate spatial dependence and > 75 % signifies weak spatial dependence. In the present study, pH recorded strong spatial dependency whereas all the other properties recorded moderate spatial dependency. Soil pH exhibited strong spatial autocorrelation, indicating that extrinsic factors predominantly influenced the spatial variation. The remaining soil properties demonstrated moderate spatial autocorrelation, indicating that a combination of intrinsic and

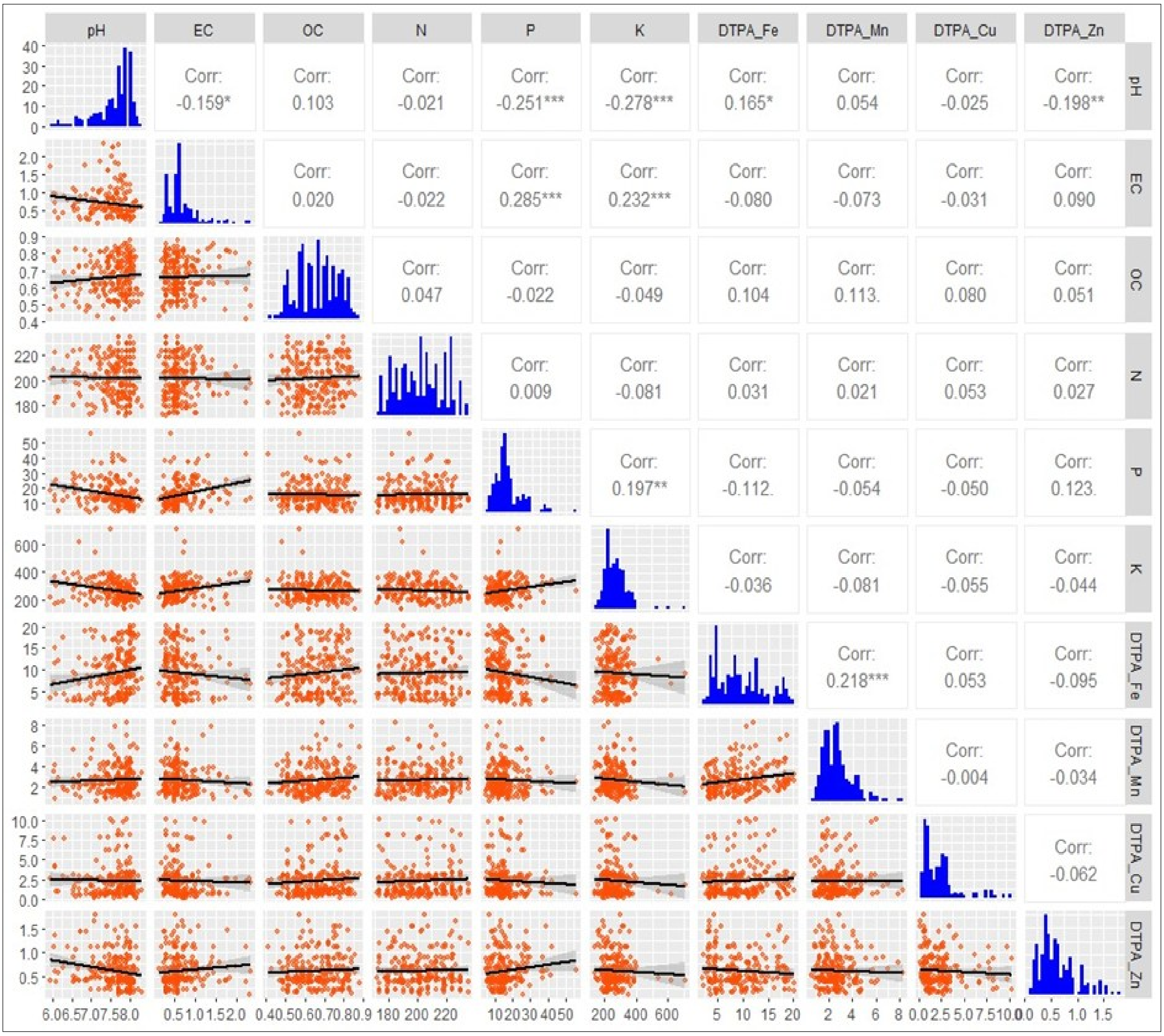


Fig. 2. Correlation coefficient plot showing relationship among soil properties of the study area.

**Correlation is significant at the 0.01 level,

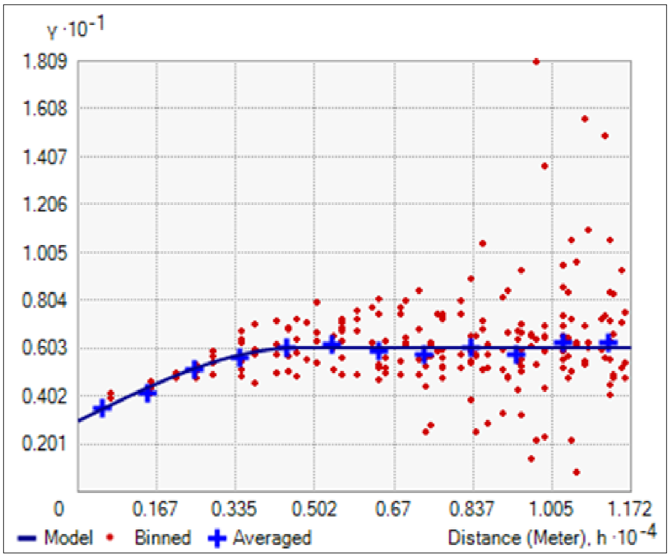
*Correlation is significant at the 0.05 level

Table 1. Descriptive data about the study area's soil characteristics

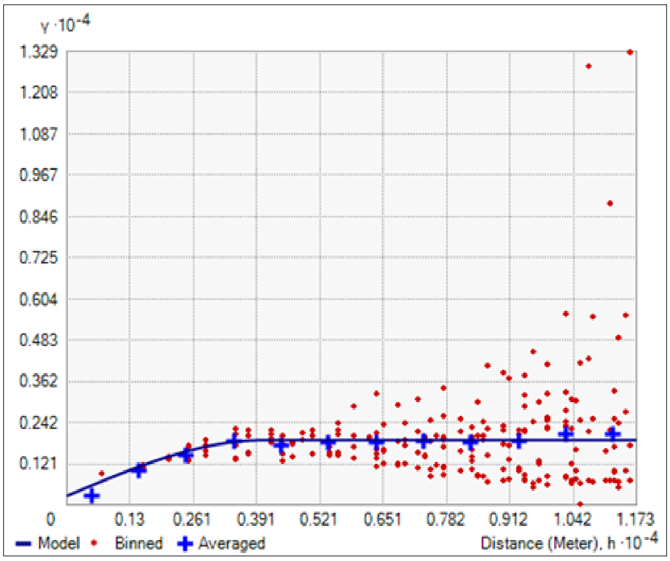
Soil Parameters	Minimum	Maximum	SD	Median	Mean	CV (%)	Skewness	Kurtosis
pH	6.55	8.30	0.48	7.70	7.59	6.34	-1.37	1.55
EC (dSm^{-1})	0.15	2.34	0.39	0.60	0.67	58.33	2.00	4.78
SOC (%)	0.41	0.75	0.11	0.66	0.66	15.92	-0.06	-0.96
N (kg/ha)	171.60	235.20	16.30	201.60	201.94	18.07	0.03	-1.02
P (kg/ha)	4.40	26.30	8.90	14.10	16.33	54.50	1.71	3.61
K (kg/ha)	81.90	458.30	137.80	260.00	296.70	46.44	2.35	5.88
Fe ($mgkg^{-1}$)	2.02	20.16	4.87	8.40	9.31	52.29	0.52	-0.77
Mn ($mgkg^{-1}$)	0.59	4.52	1.29	2.44	2.66	48.35	1.35	2.56
Zn ($mgkg^{-1}$)	0.12	1.79	0.34	0.54	0.61	55.42	1.07	0.89
Cu ($mgkg^{-1}$)	1.58	3.12	2.04	1.82	2.33	87.56	1.91	3.75

*SD-Standard Deviation

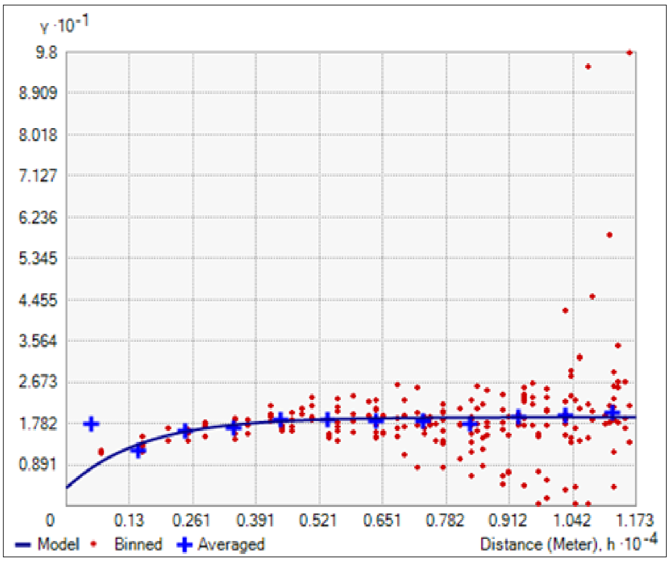
*CV- Coefficient of variation



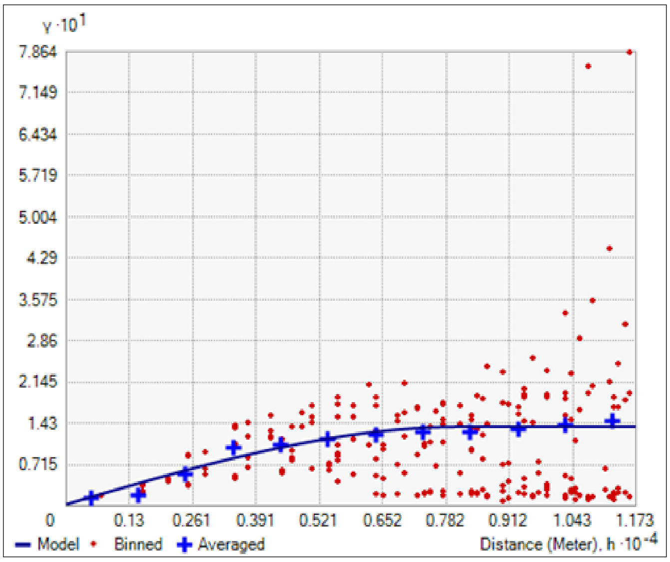
V(OC)



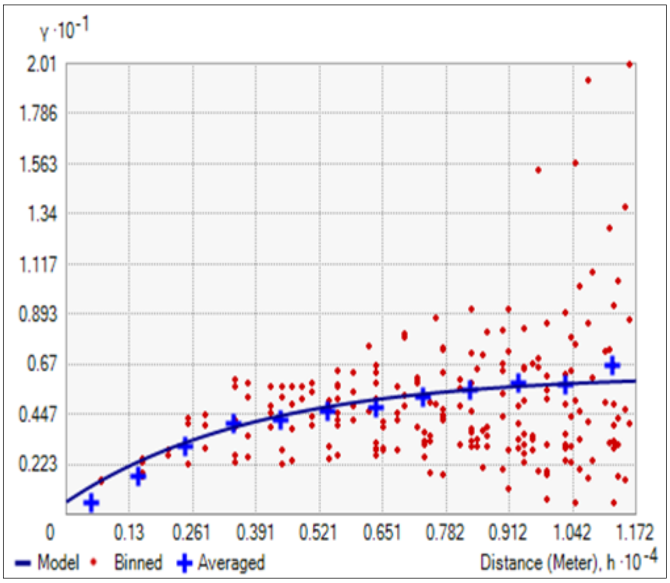
V(N)



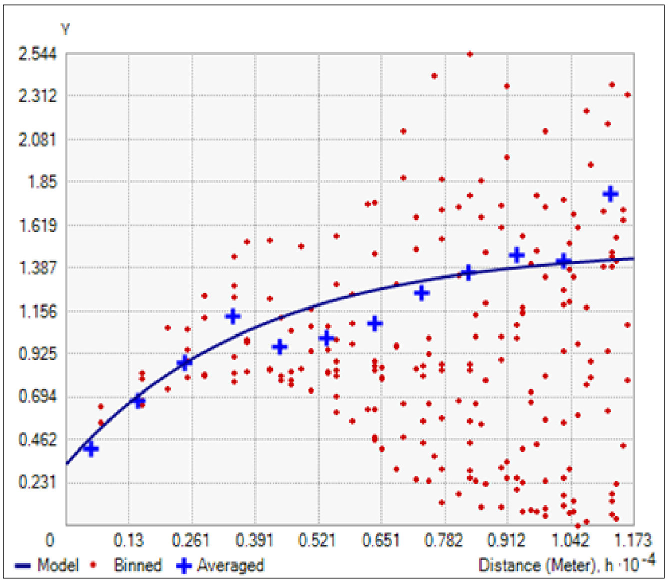
V(P)



V(K)



V(Ca)



V(Mg)

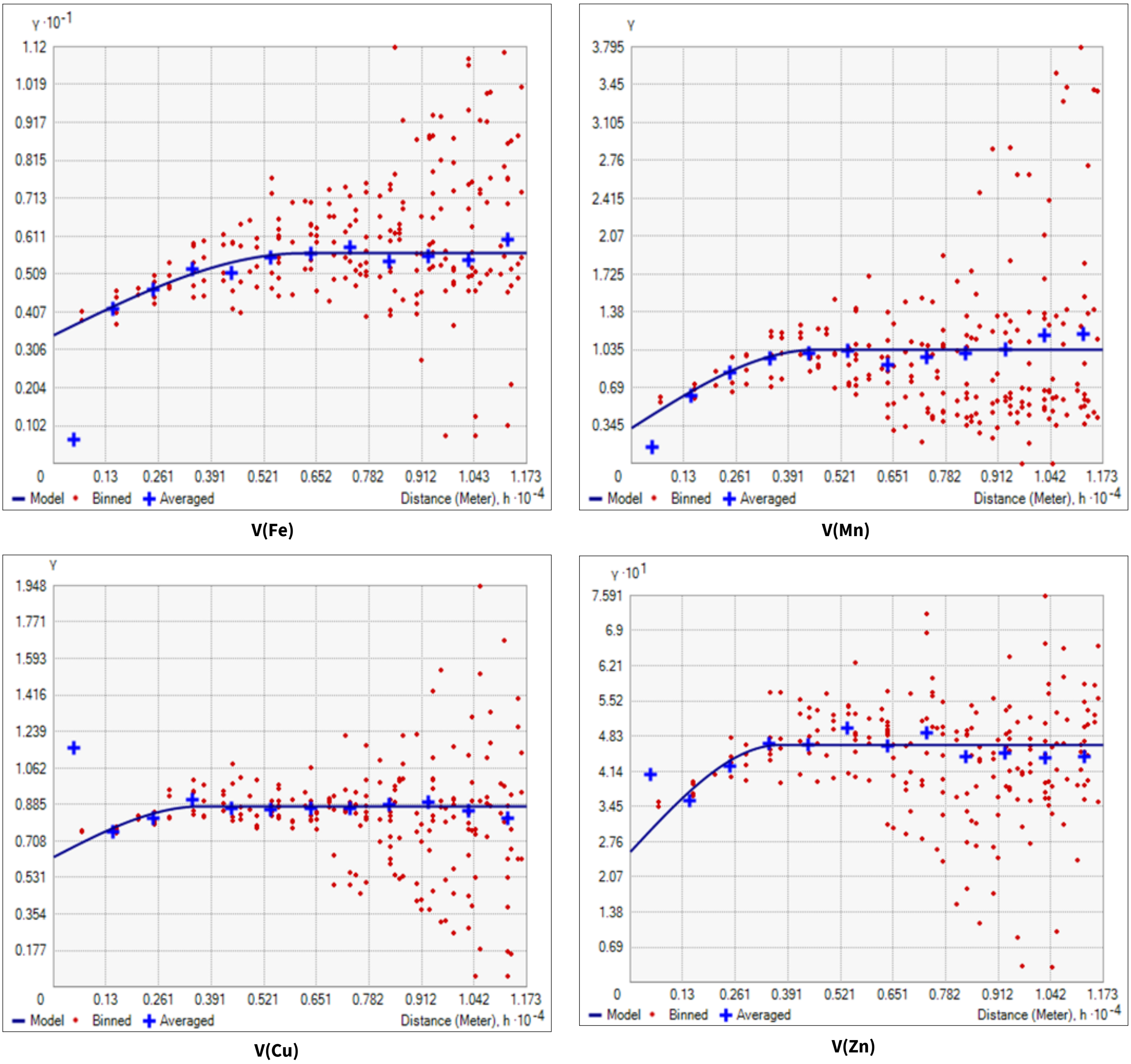


Fig. 3. Semivariogram of soil properties in the study area, experimental semivariance and the fitted semivarigram models (lines).

Table 2. Semivariogram models for soil parameters

Soil properties	Model	Sill	Nugget	Nugget/Sill	Range (m)	RMSE	Nugget (%)	Spatial Dependence class
pH	Exponential	1.135	0.275	24.23	1498	0.57	19.50	Strong
EC(dSm^{-1})	Spherical	1.156	0.858	74.22	4468	0.13	42.60	Moderate
Organic carbon (%)	Spherical	1.163	0.769	66.12	2805	0.90	39.80	Moderate
Available N (kgha^{-1})	Spherical	1.016	0.643	63.29	2884	3.65	38.76	Moderate
Available P (kgha^{-1})	Exponential	1.166	0.586	50.26	4753	3.40	33.45	Moderate
Available K (kgha^{-1})	Spherical	1.104	0.863	78.17	6077	2.05	43.87	Moderate
DTPA-Fe (ppm)	Spherical	0.994	0.956	96.18	2328	2.06	49.03	Moderate
DTPA-Mn (ppm)	Spherical	1.109	0.7971	71.88	1264	2.12	41.82	Moderate
DTPA-Cu (ppm)	Spherical	0.629	0.874	62.91	2196	0.61	36.41	Moderate
DTPA-Zn (ppm)	Spherical	1.083	0.886	81.81	2838	2.19	45.00	Moderate

extrinsic factors influenced the spatial variation. Similar results from the geostatistical analysis of the soil properties were obtained by several studies (19,16). The strong spatial correlation was exhibited by pH (percent nugget of 24 and range of 1498 m: exponential model. The other properties pH, SOC, Fe, Mn, Cu and Zn had moderate nugget (50-96 %) with varied ranges (1264-6077 m).

After determining the fitting model, spatial distribution map was made through ordinary kriging for the ten properties of the study area as shown in Fig. 4. A heterogeneous pattern was observed for different soil parameters. The low soil-available nitrogen in the study site was due to continuous cropping with imbalanced fertilization and tropical climatic conditions. The low content and varied distribution of SOC owed to the tropical weather and adopted land use, in addition to differing biological properties during the cultivation and decomposition of litter (44). Soil P was low-to-high and was low around the fringe of Veeranam lake area and northwest of the block. The available soil K was high surrounding the Veeranam lake area and in the northwest of the study region. The low values of K in the study area were due to prolonged extensive rice farming without applying K fertilizer (45). The maps provided valuable details regarding the variation in nutrient content across the study.

Principal component analysis

Significant correlations existed between the majority of the soil properties. PCA was performed to summarize and aggregate the variability in soil properties. The first four principal components (with > 1 Eigen values) explaining 52.65 percent variability were considered for the final analysis. The variance exhibited by PC1, PC2, PC3 and PC4 were 18.77, 12.18, 11.29 and 10.42 %, respectively (Table 3).

The variables that had the biggest effects on PC1 were pH, EC, N and OC P, K, Fe and Zn. In PC2, K and Zn contributed more (Table 4). In PC3, the contribution of P and Mn was high. In PC4, Cu made the most significant contribution. Hence, the PCA aggregated ten variables into four PCs to account for gross spatial variability in these properties.

Clustering analysis for delineating management zones

The first four principal component values were used as inputs for management zone analysis in the R programming environment to perform Fuzzy C, which means cluster algorithm to segregate three PCs into management zones. The FPI and NCE cluster validity indices were plotted against the number of classes as shown in Fig. 5. Therefore, the optimal number of clusters was calculated when each index reached its minimum value, which corresponded to the minimum membership sharing (FPI) or maximum organization (NCE) (35). The kriged map (Fig. 6) describes six fertility management zones as MZ1, MZ2, MZ3, MZ4, MZ5 and MZ6. The PCA and fuzzy cluster algorithm were used to define management zones and the combined effectiveness was assessed using analysis of variance.

Table 3. Details of PCA for soil parameters

Principal component	Eigen value	Component variability (%)	Cumulative loading %
PC1	1.88	18.77	18.77
PC2	1.22	12.18	30.95
PC3	1.13	11.29	42.24
PC4	1.04	10.42	52.65
PC5	0.96	9.61	62.26
PC6	0.92	9.19	71.45
PC7	0.80	8.02	79.48
PC8	0.78	7.81	87.29
PC9	0.70	7.00	94.28
PC10	0.57	5.72	100.00

The analysis of variance (Table 5) showed that the soil chemical properties varied among the six delineated management zones. Among these management zones, there was a significant variation (p 0.05) for each soil property. The soils of management zone 1 with lower K, P, N, Fe, Zn, Cu and Mn values showed lower fertility potential than others.

Discussion

Among the soil properties, the CV values for available Cu, EC, Zn, Fe and P were greater than those for available Mn, K, N and OC content. High variations in soil micronutrients may be attributed to the depletion of micronutrients as a result of nutrient mining (50). The soil parameters showed high spatial variation within the study region and the need for appropriate nutrient management, according to spatial variability to optimize crop management. Significant correlations existed between the majority of the soil properties. The SOC is considered as an important property that influences availability of nutrients. A study reported a positive correlation between SOC and N and P (39). Correlation studies on soil properties revealed that PCA is the ideal tool for figuring out the primary causes of variability in data.

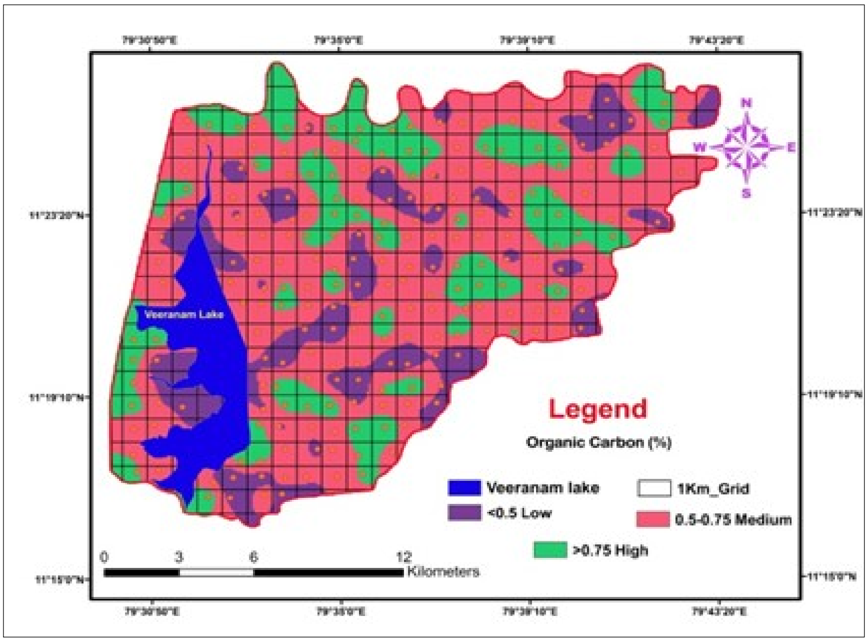
Table 4. Principal component loading for soil parameters

Parameters	pH	EC	K	P	N	OC	Fe	Zn	Cu	Mn
PC1	**0.644**	**-0.565**	0.200	0.076	**-0.623**	**-0.552**	0.424	0.321	0.141	-0.318
PC2	0.128	-0.295	**-0.602**	-0.279	-0.272	-0.111	-0.466	**-0.532**	-0.222	-0.195
PC3	-0.113	-0.174	0.135	**0.490**	-0.022	-0.516	-0.360	-0.190	0.142	**0.612**
PC4	0.122	-0.011	0.032	-0.285	0.044	-0.159	0.039	0.309	**-0.805**	0.414

Table 5. Soil nutrient properties in management zones

Management zone	pH	EC (dSm^{-1})	OC (%)	N ($Kgha^{-1}$)	P ($Kgha^{-1}$)	K ($Kgha^{-1}$)	Fe ($mgkg^{-1}$)	Mn ($mgkg^{-1}$)	Cu ($mgkg^{-1}$)	Zn ($mgkg^{-1}$)
1	6.72^{d}	0.17^{c}	0.73^{c}	103.89^{d}	4.95^{c}	111.68^{d}	1.54^{b}	0.20^{c}	0.39^{b}	0.17^{c}
2	7.68^{b}	1.26^{b}	0.42^{a}	234.51^{a}	14.07^{a}	434.24^{b}	5.71^{a}	3.27^{a}	1.91^{a}	1.50^{a}
3	8.21^{a}	0.57^{a}	0.75^{b}	180.01^{c}	18.13^{a}	439.88^{a}	5.73^{a}	2.90^{b}	1.76^{a}	1.20^{b}
4	7.24^{c}	0.20^{c}	$0.66a^{b}$	214.46^{b}	12.59^{b}	300.75^{c}	4.87^{a}	3.61^{b}	1.81^{a}	1.09^{b}
5	7.12^{a}	1.84^{a}	0.31^{b}	164.01^{c}	19.56^{a}	175.46^{a}	6.90^{b}	1.84^{b}	1.95^{a}	1.14^{b}
6	7.14^{c}	1.45^{b}	0.25^{b}	194.56^{a}	18.24^{a}	248.65^{c}	7.20^{c}	3.96^{b}	1.65^{b}	0.48^{b}

Values in a column followed by different letters are significantly different at $P < 0.05$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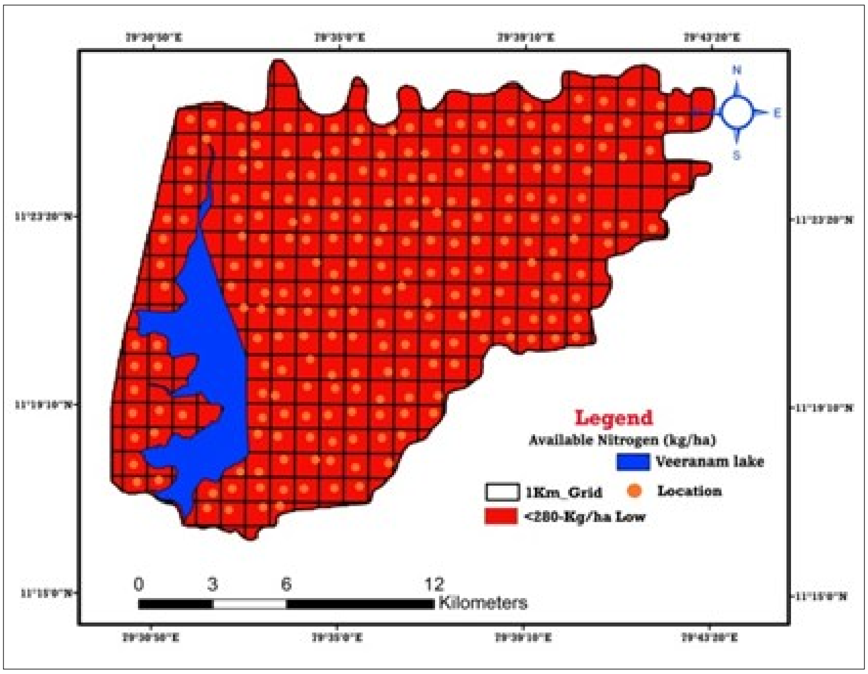
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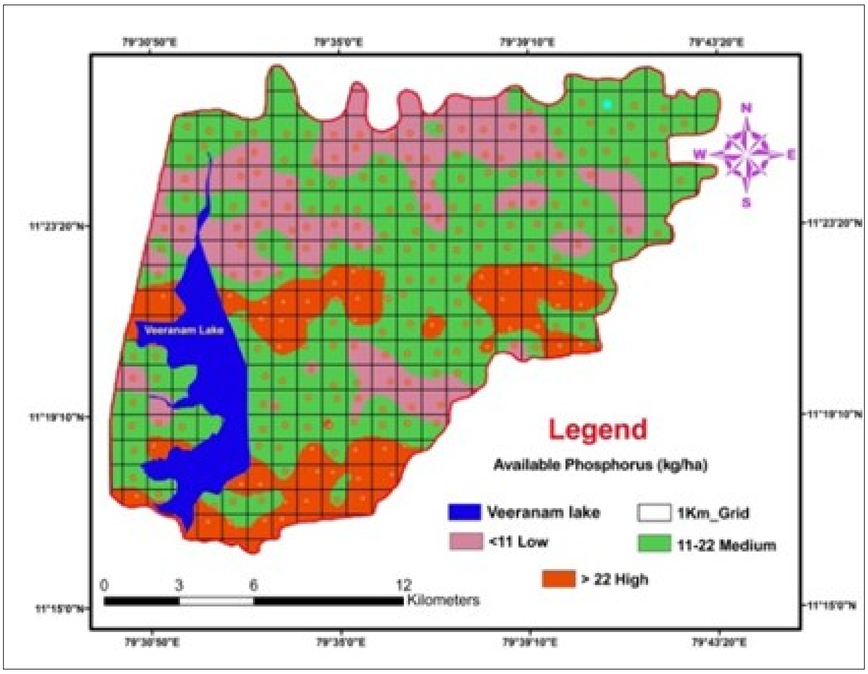
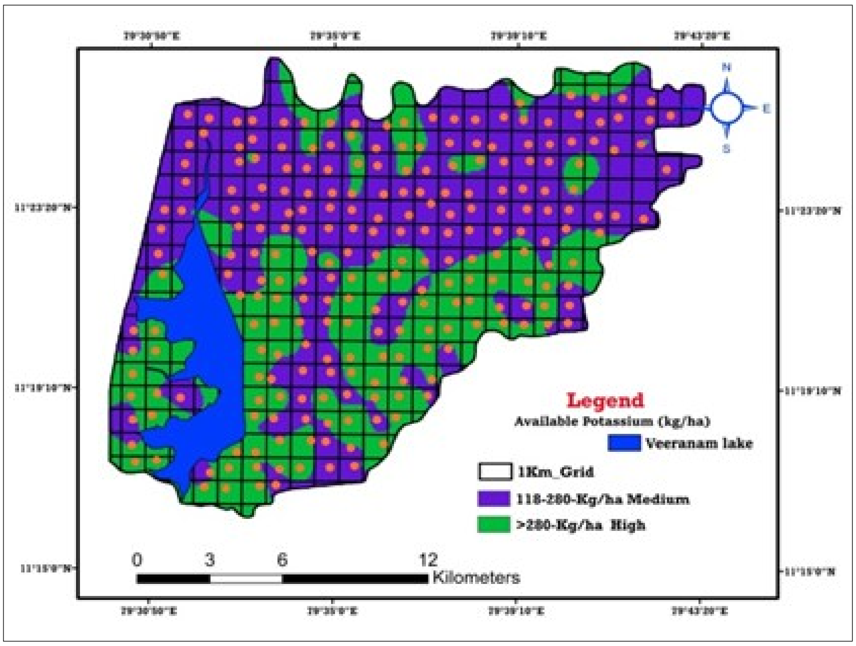
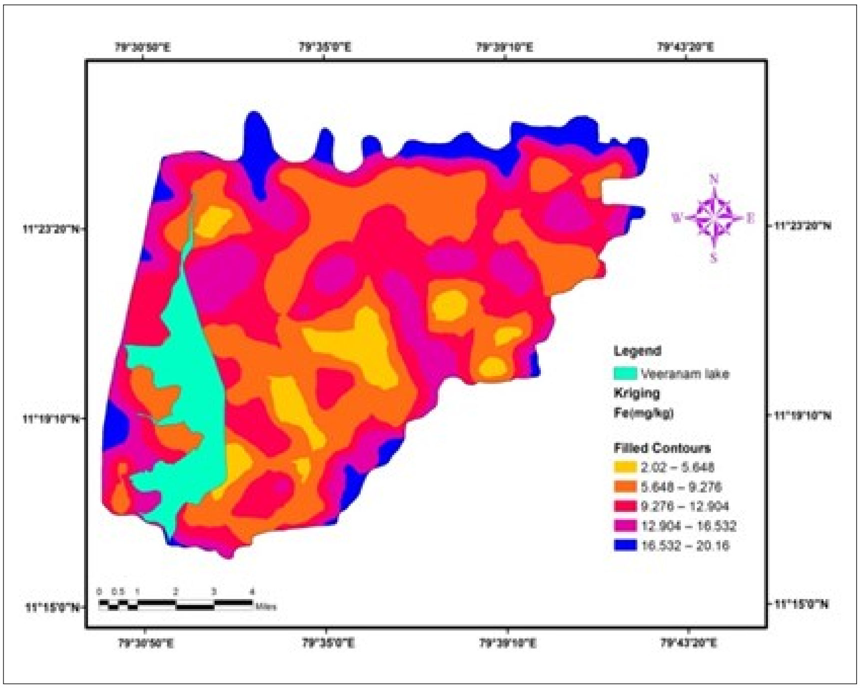
E
Legend
Available Nitrogen (kg/ha)
Veeranam lake
1Km_Grid
Location
<280-Kg/ha Low
0
3
6
12
Kilometers

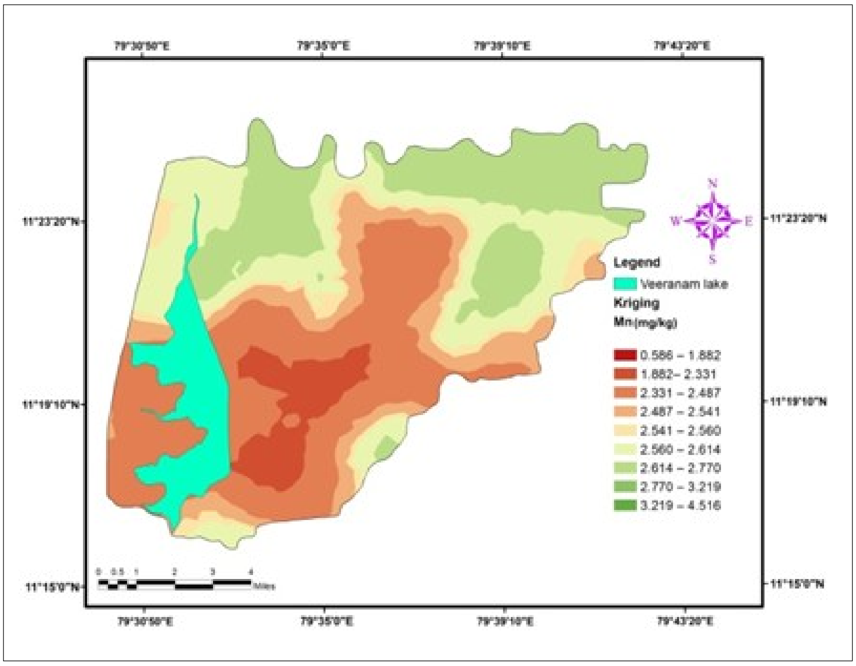

79°30'50"E
79°35'0"E
79°39'10"E
79°43'20"E
11°23'20"N
11°19'10"N
11°15'0"N
N
S
E
W
Veeranam Lake
Legend
Available Phosphorus (kg/ha)
Veeranam lake
1Km_Grid
<11 Low
11-22 Medium
> 22 High
0
3
6
12
Kilometers



Legend
Available Potassium (kg/ha)
Veeranam lake
1Km_Grid
118-280-Kg/ha Medium
>280-Kg/ha High
0 3 6 12
Kilometers



Legend
Veeranam lake
Kriging
Fe(mg/kg)
Filled Contours
2.02 – 5.648
5.648 – 9.276
9.276 – 12.904
12.904 – 16.532
16.532 – 20.16



Legend
Veeranam lake
Kriging
Mn(mg/kg)
0.586 – 1.882
1.882– 2.331
2.331 – 2.487
2.487 – 2.541
2.541 – 2.560
2.560 – 2.614
2.614 – 2.770
2.770 – 3.219
3.219 – 4.516

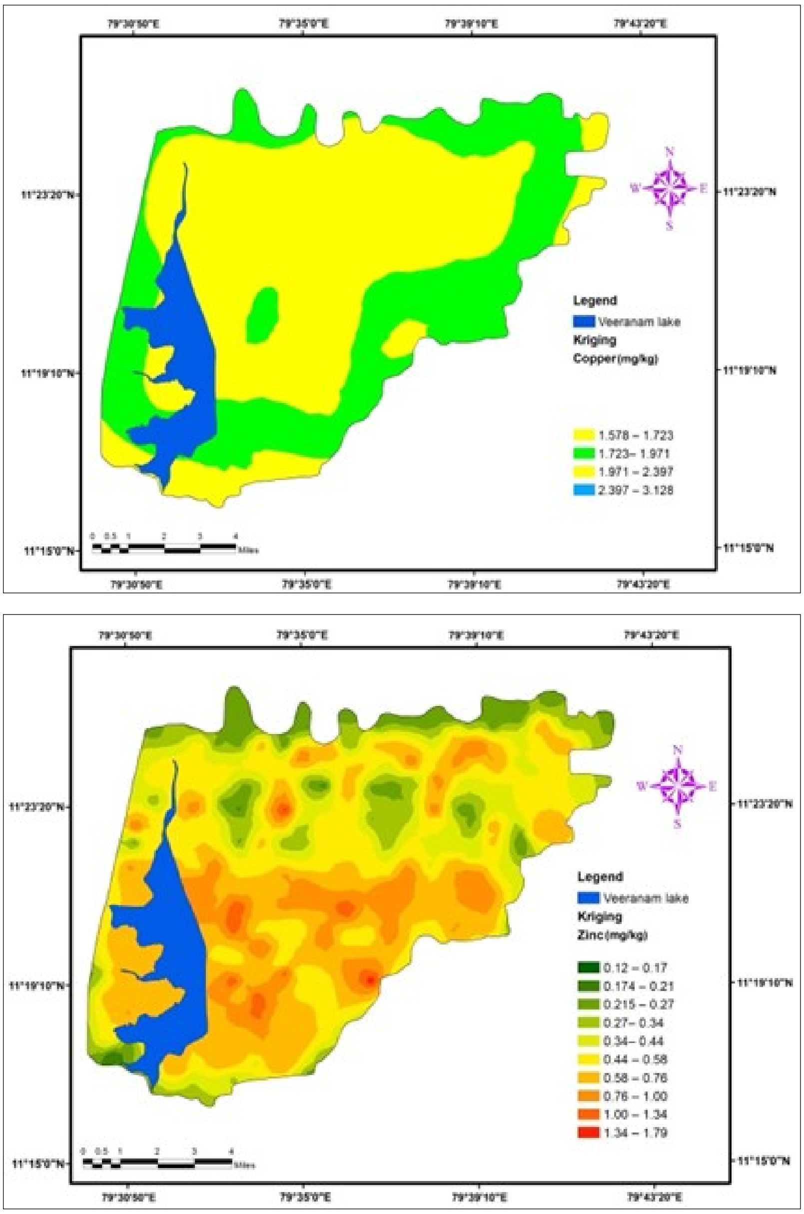


Fig. 4. Map of spatial distribution for ten soil properties in the study area. OC, N, P, K, Fe, Mn, Cu and Zn.

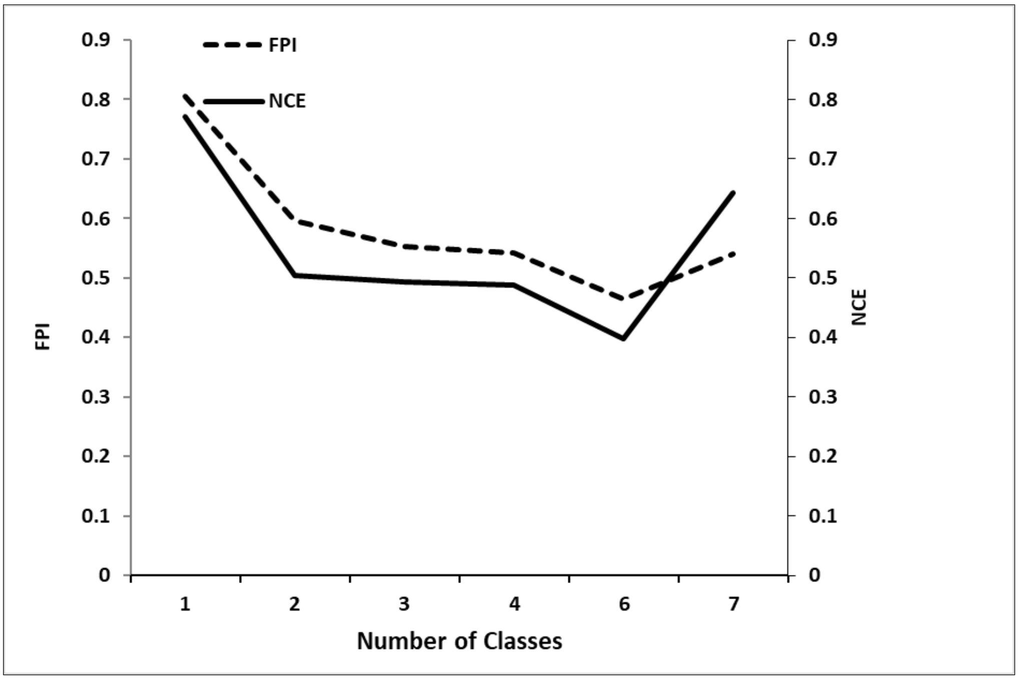


Fig. 5. Fuzzy performance index (FPI) and normalized classification entropy (NCE) calculated for identifying the optimum clusters for the study area.

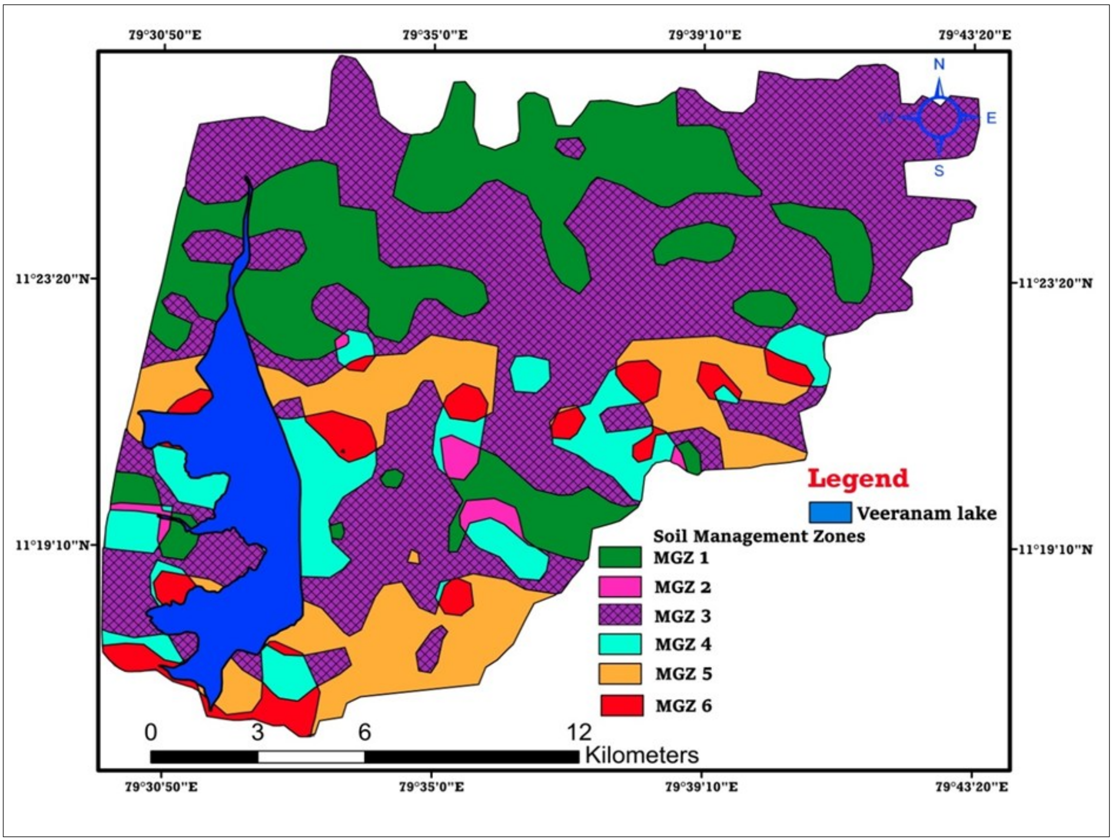


Fig. 6. Management zones map for the study area.

The best-fit semivariogram model was spherical. Additionally, researchers observed that spherical models are well suited to represent major soil parameters (40). The spatial variability map of soil properties pH, EC, OC and Cu were highly accurate as compared to other soil properties. The finding demonstrated that there is spatial autocorrelation in the soil parameters. It is attributed to environmental factors such as closeness to the Veeranam lake, farming systems, fertilization and management practices implemented for farming (41). EC, OC, N, P, K, Fe, Zn, Cu and Mn had modest geographical dependence, but pH recorded large geographical dependence. Strong spatial dependency for pH is attributed to closeness to the Veeranam lake and prevailing climatic conditions, whereas moderate spatial dependence of the soil properties is ascribed to the intrinsic soil characteristics, differences in farming techniques and soil fertilization. The spatial distribution maps showed high variations of soil nutrients, which are ascribed to land use and management. The PCA aggregated ten variables into four PCs to account for gross spatial variability in these properties. The technique used to delineate management zones solely considered the available nutrients and spatial information in the PCA.

The management zone map indicates six fertility management zones, as shown in Fig. 6. ANOVA was performed to evaluate the combined effect of PCA and the fuzzy cluster algorithm in delineating management zones. The six MZs that were produced were distinct from one another. A similar approach was adopted by other researchers (46, 47). The low status of N may be ascribed to the nutrient mining due to continuous cultivation of paddy without replenishing it with organic matter. The western study area is surrounded by Veeranam lake and may supplement the soil with K. Except MZ1, K deficiency was less widespread in the research area (16).

Poor SOC in all six zones can be attributed to the fact that extremely little or nearly no organic residues get incorporated into soils. The primary macronutrients-N, P and K are crucial factors limiting crop development in the soil (48, 49). The delineation results revealed that the north and northwestern region of the study area (MZ1) exhibited the lowest average values for the N, P and K, underscoring the need for appropriate fertilizer input in this zone. To achieve an ideal crop yield, the amount of fertilizer should be increased proportionally in formula fertilization. Assessing the mean soil properties of the MZs, the central part of the study area (MZ3) generally exhibited higher soil fertility, prominently reflected in its elevated soil OM, P, K and other values.

MZ3 had the highest soil pH value. K, P and N were extremely deficient in MZ1. The P was medium in MZ2, MZ3, MZ4, MZ5 and MZ6. The K was high in MZ2, MZ3 and MZ4. The SOC was very low in MZ1, MZ5 and MZ6. Furthermore, soil OM is a critical source of various nutrients and serves as a key indicator for evaluating soil quality (50). The SOC content has to be enhanced by various management techniques, including crop rotation with leguminous crops, organic manuring and conservation tillage. Available Fe, Zn, Mn and Cu were lower than the critical limit required for cultivation in MZ1. The Fe, Zn, Cu and Mn values were moderate to support the crop production in the management zones (MZ2, MZ3, MZ4, MZ5 and MZ6), despite the high variability of these micronutrients. However, MZ2, MZ3 and MZ4 have the better innate soil fertility owing to greater nutrient reserves and high buffering capacity. Since the soil pH in the four MZs ranged from 6.72 to 8.21, the availability of P and other micronutrients is moderate. The homogeneous management zone based on nutrient availability will result in competent and better scientific management of nutrients. This spatial variability study depicts the variation in soil properties. Farmers will be able to make decisions about nutrient management as per site conditions with the use of soil information in different management zones. The nutrient recommendations for rice crop to get the maximum yield for MZ1 is to apply 12.5 t/ha of organic manures, 170 kg N/ha, 76 kg of P/ha and 75 kg of K/ha. The dose of fertilizer nutrients for MZ2, MZ3, MZ4, MZ5 and MZ6 were 134 : 58 : 66 NPK kg/ha, 138 : 60 : 63 NPK kg/ha, 124 : 53 : 63 NPK kg/ha, 133 : 68 : 58 NPK kg/ha and 105 : 64 : 75 NPK kg/ha respectively.

Upon examining the ordinary kriging interpolation results of the 10 soil properties within the study area, it becomes evident that the reason for this outcome lies in the substantial variations in soil properties in the Veeranam Command area. The physical and chemical properties of the soil contribute to spatial similarities among different soil properties. This is further confirmed by the property distribution maps and significant correlations between soil properties. Farmers will be able to make decisions about nutrient management as per site conditions with the use of soil information in different management zones. This will help the farmers to reduce the input cost thereby increasing the profit.

Conclusion

The geographical heterogeneity in soil characteristics and accessible nutrients is demonstrated by the current study as a potential strategy to delineate management zones in the Veeranam Command area. In this study, geostatistical analysis tools were employed to scrutinize the spatial variation characteristics of soil properties of Veeranam Command area. The spatial variation is influenced by extrinsic factors or a combination of intrinsic and extrinsic factors. The soil properties of the six MZs, as demarcated by the PCA and the fuzzy c-means clustering method, exhibit significant disparities. The input cost of every farmer has to be reduced to increase the profits in agriculture, thereby optimising the fertilizer use. Utilizing the average soil properties of each management zone as a benchmark for quantitative fertilization can be valuable and adopting an agricultural management approach proves effective in enhancing agricultural productivity. The study's findings will assist the farmer in selecting the best fertilizer combination for maximizing the yield and optimizing profits while simultaneously decreasing the fertilizer requirement.

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Authors' contributions

VA contributed to the conceptualization and analysis of the study including writing the original draft manuscript. KM and PSG carried out data analysis. SB, DD, NS, TB, MV and KA advised on data processing and interpretation of the results. Each author examined the manuscript and participated in the data analysis. All authors have read and agreed to the published version of the manuscript.

Compliance with ethical standards

Conflict of interest: The authors declare that they have no competing interests related to this research.

Ethical issues: None

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