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Delineation and evaluation of management zones for site-specific nutrient management using a geostatistical and fuzzy C mean cluster approach

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Expansive soil spatial variability plays a key role in the over- and under-application of fertilizers, contributing to environmental pollution. Assess soil variability and delineate it into management zones to adopt site-specific nutrient management for balanced fertilization and sustainable agriculture. To assess spatial variability by geostatistical methods and delineate and evaluate nutrient management zones for site-specific nutrient management and variable rate fertilizer application using fuzzy c-means clustering. Overall, 200 soil samples (0–15 cm depth) with geographical coordinates were collected with a grid size of 14.2 m × 14.2 m from a 4-ha maize cultivated 4-ha of Mahagoan village of Bhainsa Mandal, Nirmal district, Telangana, India. The collected samples were tested with different reagents to determine the soil reaction and available nutrient status. Soil spatial variability was assessed by the geostatistical method, and delineation of nutrient management zones was carried out by integrating principal component analysis and fuzzy c-means clustering. Geostatistical analysis revealed spherical (pH, electrical conductivity, organic carbon, available sulfur, and available Zn) and Gaussian (available nitrogen, available P_2O_5, available K_2O, available Fe, available Zn, and available Cu) as the best-fit semivariogram model with strong spatial dependence. Five management zones were delineated by principal component analysis and fuzzy c-means clustering based on fuzzy performance index (FPI) and normalized classification entropy (NCE) indices. Variable rates of fertilizer recommendations in different management zones were calculated using a soil test crop response equation. The results show the highest grain yield and fertilizer saving in MZ^{-5}, followed by MZ^{-4}, MZ^{-3}, MZ^{-2}, and MZ^{-1}, compared to farmer fertilizer practices. The study aims to delineate the management zone to reduce fertilizer application, ensure balanced fertilizer application, minimize environmental pollution, and increase crop grain yield and profitability.

Keywords Fuzzy C-means clustering, Fuzzy performance index, Management zone, Normalized classification index, Principal component analysis, Spatial variability, Soil test crop response

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The hot and dry semi-arid climate poses significant challenges to sustainable crop production due to high variability in physical and chemical properties of soil and even in soil fertility by complex interaction among geology, topography, climate, and land use practices[1]. Irregular rainfall pattern in terms of intensity and distribution exacerbates negative plant-nutrient balances in many cropping systems and hinders sustainable crop production in semi-arid climatic regions. Persistent land degradation in the semi-arid areas has compromised the sustainability of many existing cropping systems over the long term[2]. Typically, soil in the semi-arid areas is low in organic matter, highly susceptible to degradation, and subject to mechanical deterioration. Nutrient use efficiency (NUE) in semi-arid areas is generally less than 25%, and the response to the applied fertilizer is poor and inconsistent[3]. A Precise nutrient management approach is essential and crucial to address this limitation. The targeted fertilizer application based on soil need substantially improves nutrient use efficiency, which increases crop grain production[4]. Therefore, effective methods should be developed to assess soil spatial variability to delineate uniform fertility zones for efficient nutrient management[5]. The management zones (MZs) approach emphasizes dividing a field-bounded area into smaller, homogeneous zones. These zones represent portions of land with similar characteristics, such as nutrient levels. However, accurately identifying management zones remains challenging due to the highly complex relationships among the various factors that influence crop productivity. Furthermore, demonstrating the coexistence of multiple influencing variables within a given approach may make subfield-level management assessments particularly difficult[6–8].

The spatial and temporal variability in soil properties limits crop productivity within agricultural areas. Typically, this heterogeneity is neglected in soil sampling time, laboratory analysis, and agronomic management practices. As a result, soil-specific recommendations within the paradigm of precision agriculture can present a valuable opportunity in soil management[9,10]. Recently developed advanced technology can measure and map soil properties precisely at a spatial scale. The introduction of novel spatial technology in precision agriculture allows farmers to gather data from different farm regions to facilitate specific differential management[11,12]. Soil nutrient mapping is adopted to monitor soil fertility status, evaluate fertilizer treatments, and recommend agronomical management practices. Today, site-specific nutrient management (SSNM) approach is needed to recommend fertilizer based on soil demand and need by understanding spatial and temporal variability in soil properties. Geospatial tools and techniques have been adopted to delineate management zones for site-specific nutrient management. Delineation of MZs is possible with geospatial tools, principal component analysis, and fuzzy clustering algorithms. Some conventional methods used to delineate MZs include soil nutrient mapping, slope percent, yield mapping, and nutrient indexing approaches[4,13,14].

Over the last two decades, soil scientists have widely used geostatistical analysis to determine spatial variability in soil properties across both small and large geographical scales[15,16]. Geostatistical analysis is used to model, predict, and interpret the spatial variability of soil properties. The semivariogram is a core concept in geostatistical analysis that measures the degree of spatial dependence between paired observations based on the distance separating them[17,18]. Some clustering techniques have been widely adopted to classify continuous spatial variability into different clusters for delineation of management zones. Among these, the fuzzy C mean (FCM) clustering algorithm is most widely used for delineation of management zones for better understanding and management of spatial variability in soil properties[18–20].

In precision agriculture (PA), land areas are classified into different homogeneous management zones using the fuzzy C-means clustering algorithm. This algorithm assigns a fuzzy membership value to each data point based on a membership function, allowing observations to be classified into multiple clusters with varying degrees of association[1,21,22].

Distinguishing the individual effect of soil properties on soil quality is often difficult, making it challenging to delineate the boundaries between management zones clearly. To address this complexity, advanced analytical techniques such as principal component analysis (PCA) and fuzzy C-means (FCM) clustering analysis have been widely adopted to delineate management zones. PCA reduces data dimensionality by identifying the principal components (PCs) that account for most variance within the dataset, thereby highlighting the most influential soil variable[23,24]. These PCs are further used as input for fuzzy cluster analysis, which is the most effective method for spatial autocorrelation and delineation of management zones. This integrated approach improves the accuracy of delineation of management zones (MZs) by condensing most correlated soil variables into fewer components. Consequently, the accuracy of delineation of management zones using PCA and the FCM clustering approach can be assessed by the difference in grain yield across zones. This study underscores the utility of combining PCA and FCM techniques for identifying MZs in precision agriculture based on spatially correlated soil data[12,13,25].

Spatial heterogeneity typically influences field management decisions regarding soil properties. The high degree of soil variability in soil characteristics at one location spatially changes over time. Therefore, there is a need for reliable recommendations for management-based zones. In light of the foregoing, this current investigation served to (1) assess the temporal variation in soil properties by geostatistics, (2) delineate MZs by principal component analysis (PCA) & fuzzy C mean (FCM) clustering, & (3) evaluate delineated management zones (MZs) for vil in Telangana's Northern area.

Materials and methods
Study area
This study was conducted at a farmer's field located in Mahagoan village, Bhainsa Mandal, Nirmal district, in northern Telangana, India (latitude 19.18424 N to 19.18244 N and Longitude 77.96867 E to 77.96959 E) (Fig. 1). A total area of four hectares under maize cultivation was selected for soil sampling. The site lies within the Deccan Plateau agro-climatic zone and is classified as a hot, moist, semi-arid ecological subregion, characterized by a growing period of 120 to 150 days. The region experiences a predominantly dry climate, with hot summers and cool winters. Average annual rainfall ranges from 867 mm to 1189 mm, of which approximately 86% occurs during the southwest monsoon (June to September), while the remaining is received from the northeast

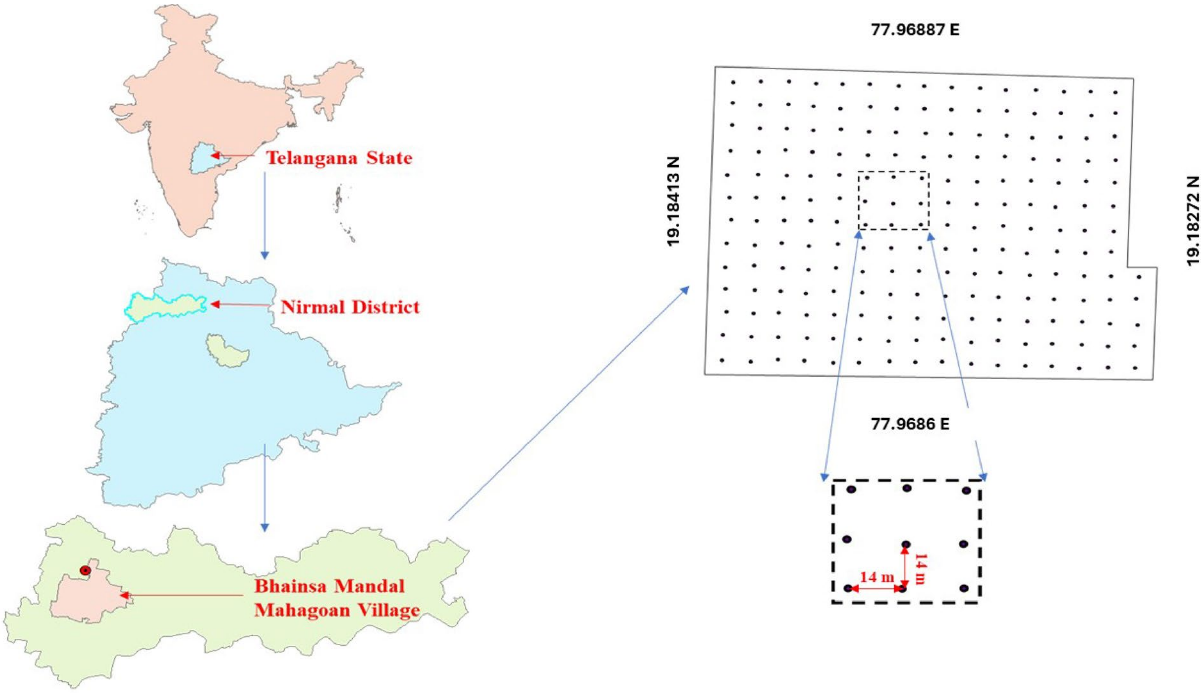

Fig. 1. Study site and soil sampling points in Mahagoan village, *Bhainsa* Mandal, Nirmal district, Northern region of Telangana.

monsoon (December to January)[26]. Maximum temperatures during the pre-monsoon period (March to early June) range from 31 °C to 39 °C, whereas minimum temperatures during winter (December to February) range from 14 °C to 25 °C. The dominant soil type is deep black soil, which is calcareous, fine-textured, and neutral to strongly alkaline. It has a medium to strong subangular blocky structure with irregular aggregates. According to Soil Taxonomy, these soils are classified as *hyperthermic*, *udic Chromusterts*, characterized by very fine montmorillonitic clay[27]. The prevailing cropping system in the region is cotton–maize. The recommended fertilizer application rates are 150 kg N ha^{-1}, 60 kg P_2O_5 ha^{-1}, and 60 kg K_2O ha^{-1} for *kharif* cotton, and 250 kg N ha^{-1}, 40 kg P_2O_5 ha^{-1}, and 40 kg K_2O ha^{-1} for *rabi* maize. Groundwater serves as the primary source of irrigation for this cropping system.

Collection and analysis of soil

A total of 200 composite topsoil samples (0–15 cm) were collected in 2020 on a 14.2 m × 14.2 m sampling grid using a handheld GPS unit (Garmin eTrex) **(**Fig. 2**)**. The samples were air-dried, thoroughly mixed, and gently crushed with a wooden mallet before passing through a 2 mm sieve. The < 2 mm fraction was stored in polyethylene bags for laboratory analysis; a sub-sample was further ground to < 0.2 mm for organic-carbon determinations. Soil pH and electrical conductivity (EC) were measured potentiometrically and conductometrically, respectively[28]. Soil organic carbon (SOC) was determined by the Walkley–Black wet-digestion method[29]. Available nitrogen (N) was estimated with the alkaline $KMnO_4$ method[30]. Available phosphorus (P_2O_5) was extracted with 0.5 M $NaHCO_3$ at pH 8.5[31]; available potassium (K_2O) with 1 N NH_4OAc[32]. Available sulphur (S) was measured turbidimetrically[33]. Micronutrients (Fe, Mn, Zn, Cu) were extracted with 0.005 M DTPA[34].

Statistical analysis

The studied soil properties were subjected to a descriptive statistical analysis, which included minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV), skewness, and kurtosis. Pearson's correlation coefficient was used to evaluate the relationships among the soil parameters. All statistical analyses were performed using XLSTAT software (version 2020).

Geostatistical analysis

Geostatistical analyses were performed using ArcGIS 10.8 software, developed by Environmental Systems Research Institute (ESRI), to assess soil spatiotemporal variability[35]. Prior to geostatistical analysis, a normality test was conducted to verify whether the soil data followed a normal distribution. The quantile–quantile (Q-Q) plot technique was employed for this purpose. In geostatistics, the spatial distribution of soil variables is represented by the semivariogram, which measures the degree of similarity between data points separated by distance h (Fig. 3). The semivariogram $\widehat{\gamma}\ (h)$ for soil properties was calculated using Eq. 3[17]:

$$\widehat{\gamma}\ (h) = \frac{1}{2N\,(h)} \sum{}_{i=1}^{N(h)} \lfloor Z\left(\mathrm{x}_{(\mathrm{i})}\right) - Z(x_{(i)} + h)^2 \rfloor \tag{1}$$

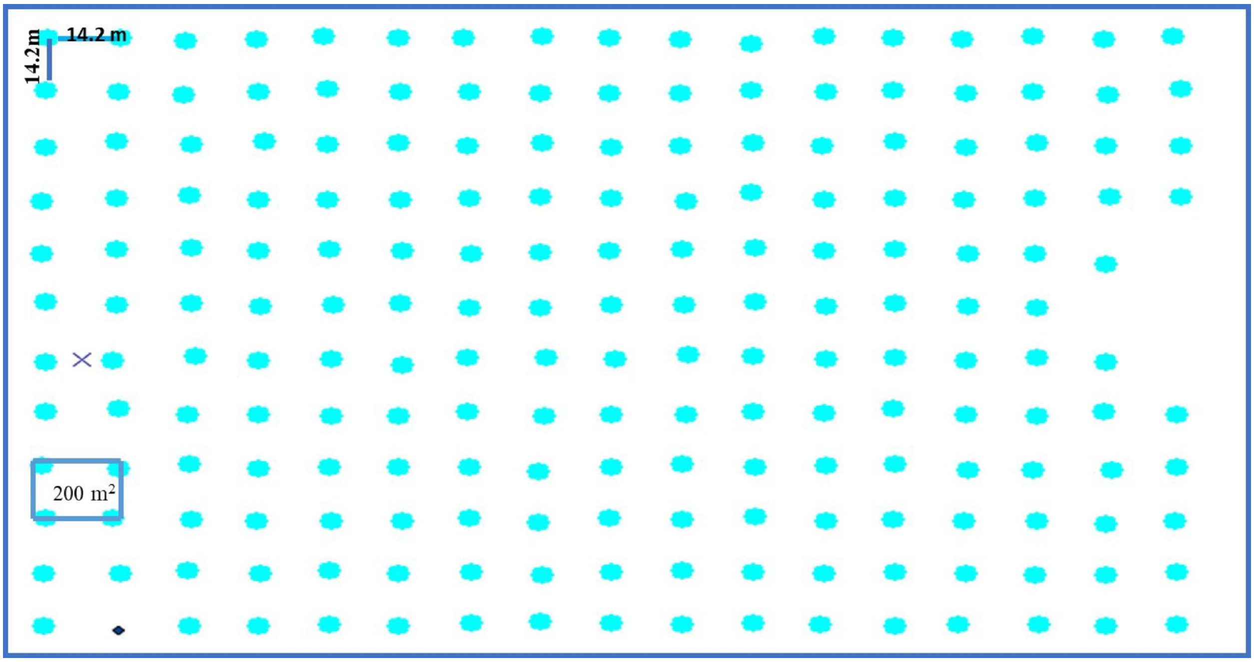

Fig. 2. The sampling scheme has a 14.2 m intermodal in the horizontal direction and 14.2 m in the vertical direction.

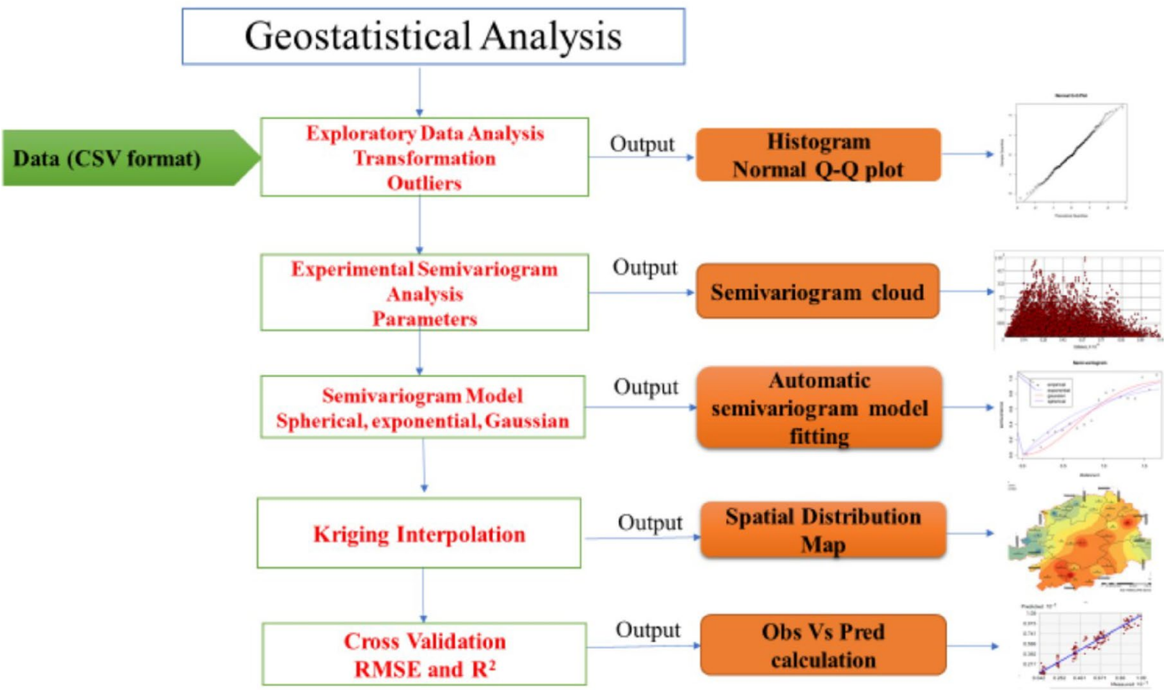

Fig. 3. Flowchart This figure methodology of geostatistical analysis.

where N(h) represents the number of data pairs at a specified distance and direction, $Z\left(\mathrm{x}_{(\mathrm{i})}\right)$ denotes the value of the variable at position $\mathrm{x}_{(\mathrm{i})}$, $Z(x_{(i)}+h)$ denotes the value of the variable at a distance of h from a position $\mathrm{x}_{(\mathrm{i})}$. The above semivariogram equation fits the standard model and calculates the spatial variation parameters: nugget, sill, and range. Semivariogram models, such as spherical, exponential, and Gaussian, were selected based on cross-validation indices like root mean square error (RMSE) to explain the spatial correlation of soil parameters. A preferred model was then applied using an ordinary kriging (OK) technique for interpolation and spatial mapping of predicted soil properties data (Fig. 3).

The root mean square error was used as a comparison criterion to evaluate the predictive accuracy of semivariogram model, as calculated using Eq. 4:

$$RMSE = \sqrt{\frac{1}{N} \sum {}_{i=1}^{N} [Z\left(x_{(i)}\right) - \bar{Z}\left(x_{(i)}\right)]^2} \tag{2}$$

Where, Z(Xi) represents the observed value at position $x_{(i)}$, $\bar{Z}\left(x_{(i)}\right)$ denotes the predicted value at position $x_{(i)}$ and N is the total number of data points.

Principal component analysis

PCA is a multidimensional technique that extracts the underlying structure of a dataset by identifying components that explain the most variance (Fig. 4**).** The data were transformed by rotating the coordinate system along its principal axes to allocate the variance into distinct components. This analytical method emphasizes capturing the highest variation in the first principal component, with decreasing variance in subsequent components. In place of a correlation matrix, a covariance matrix was used for PCA better to reflect the relationships among the selected soil parameters. All soil variables were considered as inputs for PCA. Principal components with eigenvalues greater than or equal to one were retained for further analysis in delineating MZs. The loading values of each soil property on the principal components were analyzed to interpret the contribution and variability of each variable across components.

Fuzzy cluster algorithm analysis

There are many unsupervised machine learning methods used to group similar data points, such as Fuzzy C-Means (FCM), K-Means Clustering, Gaussian Mixture Models (GMM), and DBSCAN (Density-Based Spatial Clustering of Applications with Noise). In this study, the FCM clustering algorithm was selected for delineating management zones due to its ability to handle the inherent uncertainty and gradual transition in soil characteristics, which is a typical feature of agricultural fields. Unlike hard clustering algorithms such as K-means, which assign each data point to a single cluster, FCM allows each data point to belong to multiple clusters with varying degrees of membership. This soft partitioning is particularly suitable for spatial data in soil science, where boundaries between soil zones are rarely distinct. Moreover, FCM is computationally efficient and integrates seamlessly with PCA to reduce dimensionality and multicollinearity, which is essential when dealing with multiple soil attributes. While Gaussian Mixture Models (GMMs) are probabilistic and flexible, they assume normal distribution and are sensitive to initialization, which may lead to convergence issues in heterogeneous soil datasets. Similarly, DBSCAN is effective for detecting clusters of arbitrary shape but struggles with datasets of varying density and is highly sensitive to parameter selection. Therefore, the FCM algorithm was preferred as it balances robustness and interpretability for delineating management zones, especially when combined with PCA to enhance spatial classification accuracy in precision agriculture.

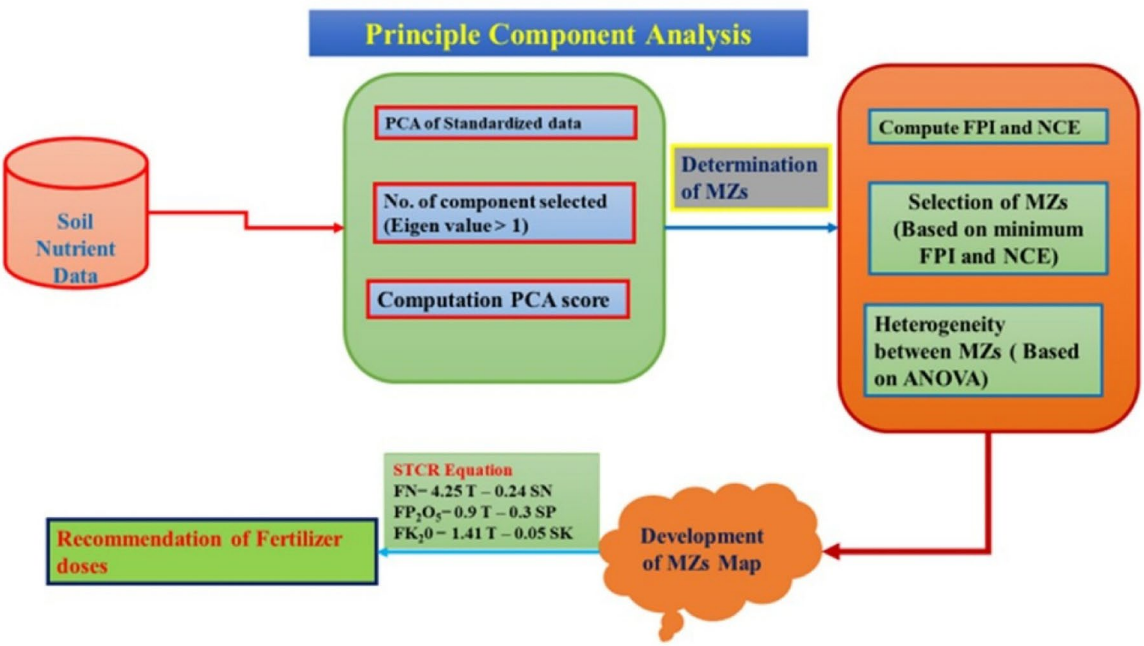

Fig. 4. Schematic representation of the methodology of PCA and Management zone for fertilizer recommendation in the study area.

The FCM clustering approach is applied to develop distinct homogeneous management zones. It's a modified form of cluster analysis. This algorithm assigns a fuzzy membership value to each data point based on a membership function, classifying observations into multiple clusters with varying degrees of association. This approach mitigates the impact of outliers and captures the inherent fuzziness in the dataset. In this study, the number of clusters varied from a minimum of three to a maximum of eight to identify the optimal number of MZs. The algorithm was initialized with randomly assigned cluster centers. Each data point was then assigned a membership grade based on its proximity to the cluster centers. These centers were subsequently updated iteratively using weighted means, recalculated from the membership grades. The Euclidean distance metric assessed the similarity between data points and cluster centers, assuming equal variance and statistical independence across variables. MZA software was used for the task, with the following parameters set: maximum number of iterations = 300, halting criteria = 0.0001, minimum and maximum number of clusters 3 & 8, respectively, and fuzziness component = 1.5. The optimal number of clusters was determined based on the FPI and NCE, calculated using Eqs. 3 and 4, respectively.

$$\mathrm{FPI} = 1 - \frac{\mathrm{C}}{\mathrm{C}-1}\,[1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{c}} \sum_{\mathrm{k}=1}^{\mathrm{n}} (\mu\,\mathrm{ik})^2}{\mathrm{n}}] \tag{3}$$

$$\mathrm{NCE} = \frac{\mathrm{n}}{\mathrm{n}-\mathrm{c}}\left[\frac{\sum_{\mathrm{k}=1}^{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{c}} \mu\,\mathrm{ik}\,\log_a\,(\mu\,\mathrm{ik})}{\mathrm{n}}\right] \tag{4}$$

.

where c is the number of clusters, n is the number of observations, μik is the fuzzy membership degree of point i in cluster k, and $\log_a$ is the natural logarithm.

The FPI evaluates the degree of fuzziness a given number of clusters introduces. Its values range from 0 to 1, where values close to 0 indicate well-defined clusters with minimal membership overlap, while values approaching 1 imply indistinct clustering with significant membership sharing among clusters. The NCE quantifies the level of disorder or uncertainty associated with a specific number of clusters. The optimal number of MZs is indicated by the lowest values of both FPI and NCE (Fig. 5). A one-way analysis of variance (ANOVA) was conducted on soil parameters across the different MZs using SPSS software to evaluate statistical differences. Finally, a management zone delineation map was generated using ArcGIS 10.8 software.

Results and discussion

Descriptive statistics of soil parameters

The descriptive statistics of the soil parameters are presented in Table 1. The study site exhibits moderate to strongly alkaline conditions, as indicated by the pH range of 8.26–8.79, and a low coefficient of variation (CV) of 1.57%. Previous studies have also reported minimal variation in soil pH compared to other soil parameters[36–43]. The alkaline nature of the soil is attributed to its development from basic parent material[27,44]. The low variability in soil pH can be explained by the logarithmic nature of the pH scale, which reflects hydrogen ion concentration; direct measurement of proton concentration would show greater variability. Moreover, the buffering capacity of soils generally resists abrupt changes in pH, even under diverse agricultural systems and management practices in the region Electrical conductivity (EC) also exhibited low variability, as reflected by a CV of 16.33%, and low skewness (−0.14) and kurtosis (−0.95). This low variation is likely due to using non-saline groundwater for

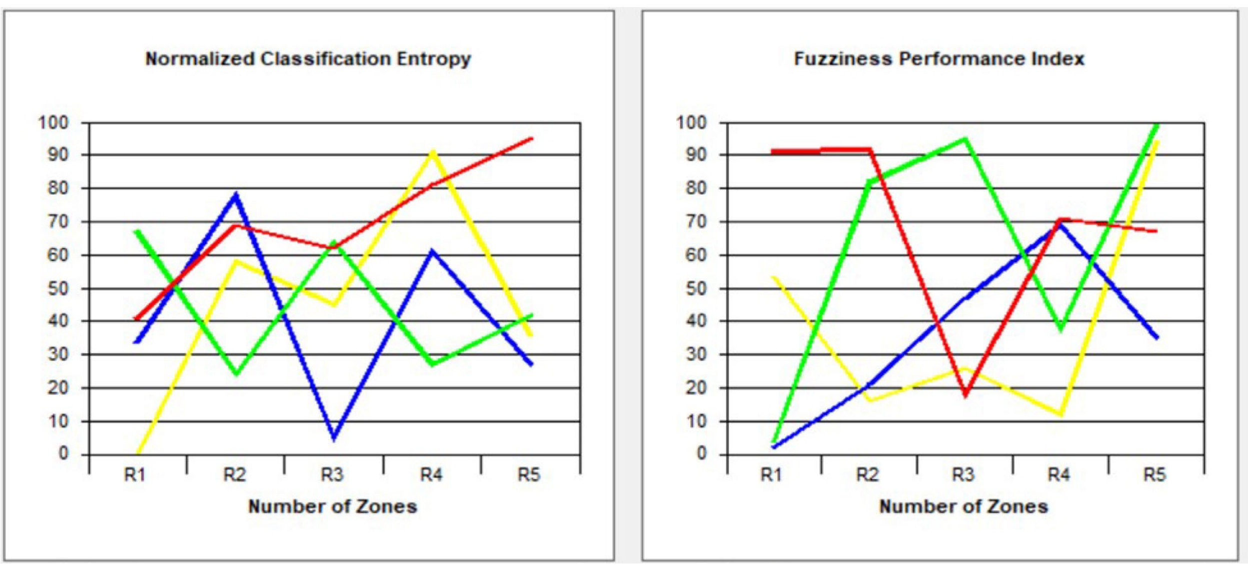

Fig. 5. FPI and NCE for identifying the optimum management zone.

Parameters	Min	Max	Range	Skewness	Kurtosis	SD	Mean	CV (%)
pH	8.26	8.79	0.53	0.00	−0.90	0.13	8.54	1.57
EC (dS m^{-1})	0.229	0.423	0.194	−0.14	−0.95	0.05	0.331	16.33
Organic carbon (g kg^{-1})	2.3	4.2	1.9	0.02	−0.88	0.5	3.3	15.08
Available N (kg N ha^{-1})	81	161	80	−0.15	−0.51	18.95	127	14.96
Available P_2O_5 (kg P_2O_5 ha^{-1})	98	159	61	0.26	−0.91	16.46	128	12.90
Available K_2O (kg K_2O ha^{-1})	292	647	355	0.45	0.06	74.62	426	17.52
Available S (mg kg^{-1})	4	27	23	0.24	−1.14	6.47	14	45.20
Available Fe (mg kg^{-1})	15.7	41.4	25.7	−0.23	−1.01	7.55	29.2	25.86
Available Mn (mg kg^{-1})	8.6	36.5	27.9	0.01	−0.79	7.45	21.0	35.56
Available Zn (mg kg^{-1})	3.1	12.9	9.8	−0.04	−0.91	2.78	7.8	35.61
Available Cu (mg kg^{-1})	3.8	22.0	18.2	1.52	6.21	2.39	7.6	31.56

Table 1. Descriptive statistics of soil parameter (N= 200 samples) of Mahagoan village, Bhainsa mandal, nirmal district.

irrigation. Soils with EC values below 2 dS m^{-1} are classified as non-saline and have been similarly reported in various parts of Telangana[45–49].

The average soil organic carbon (SOC) content in the study area was found to be 3.3 g kg^{-1}, which is considered low, with a range from 2.3 to 4.2 g kg^{-1}. These findings are consistent with those reported in various districts of Telangana and other parts of India, where SOC levels have also been found to be low, with average values around 5 g kg^{-1}[49].

The soil organic carbon in the area may be attributed to lower organic manure application, and the farmers in that area barely retain crop residues[1,50,51]. The CV values of SOC, available nitrogen, available P_2O_5, and available K_2O were low (CV of <25%), anging from 12.90% to17.52%. Tis indicates minimum heterogeneity and uniform distribution of these soil properties across the study area[15,52–54]. Available nitrogen varied from 81 to 161 kg N ha^{-1} with a mean value of 127 kg N ha^{-1}. The low variability and nitrogen content are accounted for by the leaching of dissolved organic nutrients and inorganic nitrogen[43]. Similar patterns have been found in different parts of India with low available nitrogen content in soil, particularly in areas with minimal organic matter and poor nutrient management practices[41,42,54]. The available P_2O_5 and K_2O content were high, varying from 98 to 159 kg ha^{-1} and 292 kg ha^{-1}– 647 kg ha^{-1} with a mean of 128 kg ha^{-1} and 426 kg ha^{-1}, respectively, which was mainly because of the production of recalcitrant Ca–P compounds and fixing of potassium in a soil environment. Similar trends in the increase of phosphorus and potassium content in soil have been found in other studies[47,49,55].The prolonged consumption of P fertilizer might cause a high level of phosphorus in the soil without testing the soil[56]. Another reason for the increase of phosphorus content in the rhizosphere was the fixation of P with Ca[57].

Previous studies have reported high levels of available K_2O ranging from 406 to 572 kg ha^{-1} in various districts of Telangana State[58]. The elevated potassium levels may be attributed to several factors, including the mineralization of potassium from organic residues, the release of potassium from non-exchangeable sites in 2:1 type clay minerals, the weathering of primary minerals, excessive application of potassic fertilizers, and the upward movement of potassium from deeper soil layers due to capillary rise of groundwater.

The variability of available Sulphur was moderate, with a CV value of 45.20%. Previous studies have reported a moderate coefficient of variability, i.e., between 25 and 75%, which represented moderate heterogeneity in available Sulphur content in the soil[59]. The available sulfur content was low to high, varying from 4 mg kg^{-1} – 27 mg kg^{-1}, with a mean value of 14.0 mg kg^{-1}. According to Wilding's classification, the distribution of micronutrients Fe, Mn, Zn, Cu, and B exhibits moderate variability in the area based on CV >25–75%. Ths region's mean values of Fe, Mn, Zn, and Cu were 29.2, 21.0, 7.8, and 7.6 mg kg^{-1}, respectively, indicating high micronutrient status (Fe, Mn, Zn, and Cu) in the Warangal soil of Telangana state[58]. Soil management activities, such as fertilizer application and other crop management techniques, may be to responsible for the observed differences in soil properties across study regions[60]. The spatial heterogeneity of crop production may be attributed to the fact that the uniform application of nutrients led to a variable amount of nutrients in terms of quantity at different locations within the studied region.

Geostatistical analysis

Table 2 presents the parameters of the best-fitting semivariogram models for soil characteristics. Three models, i.e., Spherical, Exponential, and Gaussian, were observed as strongly fitted to the analyzed soil parameters based on minimum RMSE value. Other researchers employed similar procedures to identify the best model for interpolation using kriging[42,61,62]. Figure 6 **(a-k)** illustrate the spatial distribution maps of various soil parameters. The best-fitted model for soil pH, EC, SOC, available sulfur, and Zn was the spherical semivariogram model (Fig. 7. (**a**, **b**, **c**, **g and j**). In contrast, the Gaussian semivariogram model was the best-fitting model for available nitrogen, P_2O_5, available K_2O, Fe, Mn, and Cu (Figs. 7. (**d**, **e**, **f**, **h**, **I and k**)). The best-fit semivariogram models for different soil parameters represent whether human activities and local factors affect the spatiotemporal variation of soil attributes[41,63,64]. The nugget value denotes the microvariability and variance measurement resulting from sampling errors[43]. The nugget value denotes micro-variability and potential measurement errors or sampling inaccuracies. In this study, the nugget values for all soil parameters were nearly zero, suggesting

Variable	Transformation	Model	Nugget	Partial sill	Sill	Nugget/sill (%)	Range (m)	Spatial dependence	RMSE
pH	Log	Spherical	0.0	0.0000732	0.0000732	0.0	39.32	Strong	0.044
EC (dS m^{-1})	None	Spherical	0.0	0.0002906	0.0002906	0.0	42.01	Strong	0.010
OC (g kg^{-1})	None	Spherical	0.0	0.000419	0.000419	0.0	39.70	Strong	0.014
Available N (kg N ha^{-1})	Log	Gaussian	0.0	0.003468	0.003468	0.0	28.26	Strong	4.43
Available P_2O_5 (kg P_2O_5 ha^{-1})	Log	Gaussian	0.000044	0.00223	0.002274	1.93	28.80	Strong	3.76
Available K_2O (kg K_2O ha^{-1})	Log	Gaussian	0.0	0.00125	0.00125	0.0	30.48	Strong	6.96
Available S (mg kg^{-1})	Log	Spherical	0.00364	0.0309	0.03454	10.5	51.22	Strong	1.64
Available Fe (mg kg^{-1})	None	Gaussian	0.0094	9.4042	9.4136	0.09	29.63	Strong	1.64
Available Mn (mg kg^{-1})	Log	Gaussian	0.0078	0.0299	0.0378	20.63	43.63	Strong	2.12
Available Zn (mg kg^{-1})	Log	Spherical	0.0	0.03786	0.03786	0.0	60.13	Strong	0.74
Available Cu (mg kg^{-1})	Log	Gaussian	0.00115	0.00529	0.00644	17.86	33.81	Strong	0.41

Table 2. Semivariogram analysis of soil samples (N = 200) collected from Mahagoan village of *Bhainsa* mandal, nirmal district.

minimal measurement error and strong spatial continuity. The sill represents the semivariance level at which the semivariogram flattens, theoretically equating to the total variance of the dataset at large lag distances[65,66]. The lowest sill value was observed for pH (0.0000732), while the highest was recorded for iron (Fe) (9.4136). Spatial dependence was assessed using the nugget-to-sill ratio, classified into three categories: strong (< 0.25), moderate (0.25–0.75), and weak (> 0.75)[35,67]. These classifications provide insight into the degree of spatial structure in the observed soil properties.

The observed variability in soil nutrient concentrations may be attributed to farmers' improper or inconsistent fertilizer application in the study area[41]. In geostatistical analysis, the range parameter defines the distance the semivariance reaches the sill, indicating the extent of spatial dependence for a particular soil property[42]. This range reflects the **maximum distance** over which two samples are spatially correlated. A shorter distance between sampling points generally corresponds to more similar soil characteristics[41]. In this study, the range of spatial dependence for soil parameters varied between **28 and 61 m**. According to Moharana et al.[41]the range also represents the radius of influence or area of impact for a given soil property, providing insights into the scale at which management practices might be effectively applied. Maps depicting the spatial distribution of all soil parameters are shown in Figs. 6 **(a-k).** Heterogeneous management and fertilizer application mostly led to high levels of all soil nutrients except Zn in the southeast, east, and south, and low levels in the north and northwest direction. The concentration of pH, EC, available nitrogen, available P_2O_5, available K_2O, available sulfur, Fe, Mn, and Cu increased from northeast to southeast, north to south, and west to east. Zn had the opposite distribution pattern. Its contents decrease from northeast to southeast, north to south, and west to east. This was most likely brought by the parent material, irrigation, fertilizer use, and crop planting. The quantitative data derived from such mappings are sometimes utilized to alter site-specific nutrient management (SSNM) and introduce variable rate technology (VRT) for long-term sustainability. The soil fertility location maps could serve as a tool to develop an SSNM plan for maximizing agricultural production while reducing adverse effects on the ecosystem and cost of cultivation.

Principal components analysis

A correlation analysis of the soil variables revealed significant relationships among the measured parameters, as shown in Table 3. To reduce data complexity and identify the underlying structure of variability, Principal Component Analysis (PCA) was employed. PCA helps in transforming a large set of correlated variables into a smaller number of uncorrelated variables known as Principal Components (PCs). This study generated eleven PCs, corresponding to the number of independent variables analyzed (Table 4). Of these, the first five PCs, each having an eigenvalue greater than 1, were retained for further interpretation based on Kaiser's criterion, as they collectively accounted for 100% of the total variance in the data set. A principal component with an eigenvalue > 1 explains more variation than any original variable. Tables 4 and 5 illustrate the results of the component. PC1 accounted for 96.9% of total variability, whereas available K_2O, N, EC, available P_2O_5, available S, Mn, OC, Cu, Fe, Zn and pH dominated it. available P_2O_5, available S and available K_2O were the dominant factors for PC2 and accounted 1.8% of the variability. PC3 contributed 0.8% of the variance, whereas it was dominated by pH, available N, and EC. The PC4 accounted for 0.3% of the variance and was mostly influenced by the Fe, cu, and available S. The PC5 accounted for 0.2% of the variance and was dominated by Mn. The PC6 accounted for 0.09% of the variance and was mostly influenced by the available S. PC7 accounted for 0.01% of the variance and was mostly influenced by the available Zn.

Several studies have found three PCs from PCA by aggregating and summarizing the variability of soil properties in different regions of India[38,59,64]. Other studies have reported the four PCs from PCA by aggregating

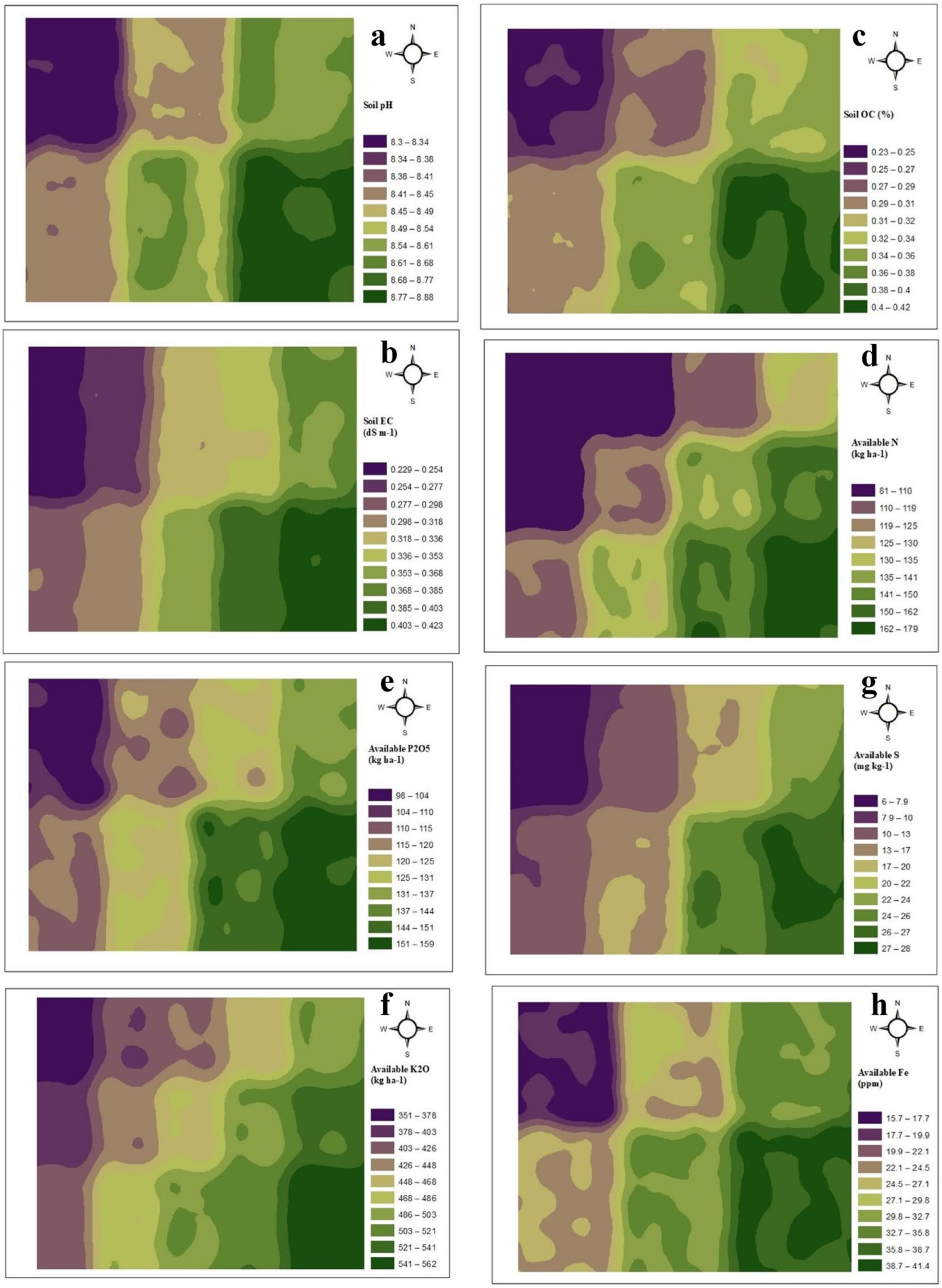

Fig. 6. **(a)** Spatial distribution map of pH, **(b)** Spatial distribution map of EC, **(c)** Spatial distribution map of organic carbon, **(d)** Spatial distribution map of available N, **(e)** Spatial distribution map of available P_2O_5, **(f)** Spatial distribution map of available K_2O, **(g)** Spatial distribution map of available S, **(h)** Spatial distribution map of available Fe, **(i)** Spatial distribution map of available Mn, **(j)** Spatial distribution map of available Zn, **(k)** Spatial distribution map of available Cu.

and summarizing the variability of soil properties in different regions such as Nigeria, north Iran, and east India[36,43,68]. Additionally some research found 12 PCs, whereas five PCs explained 78.66% of the vaiability that occurred in the study area[69].

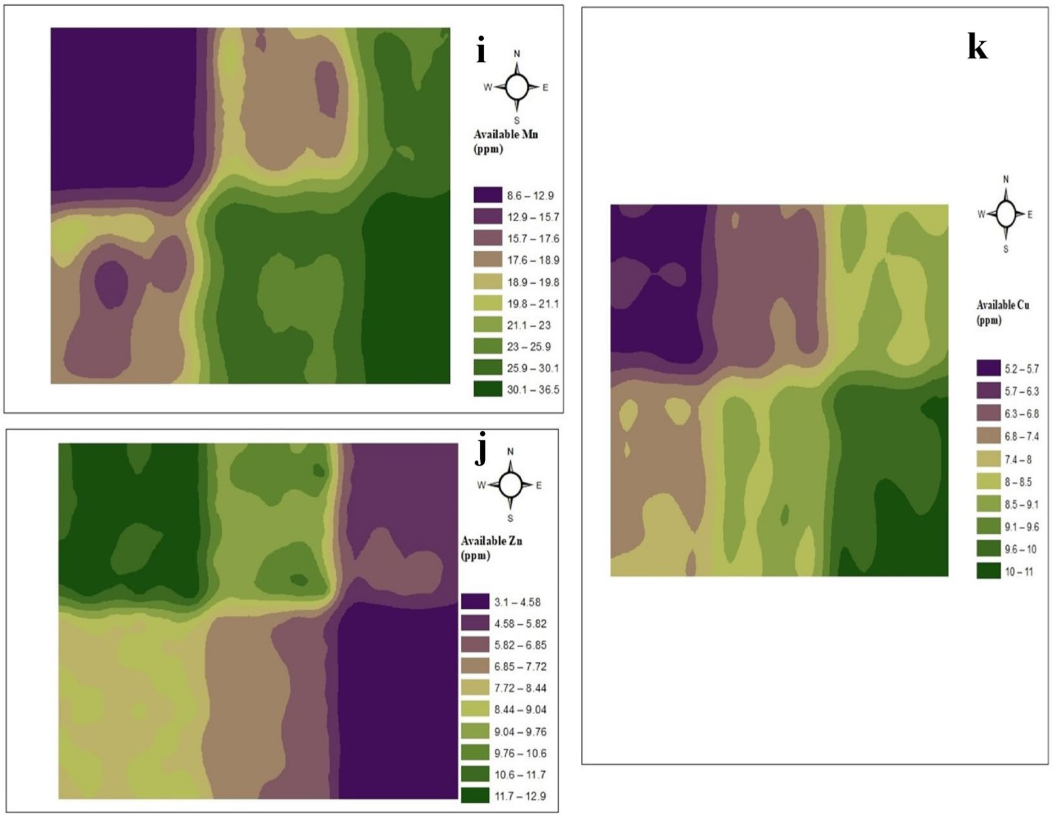

Fig. 6. (continued)

Clustering analysis for delineating management zones

The seven principal components (PCs) were used to delineate MZs through cluster analysis. To determine the optimal number of MZs, the FCM clustering algorithm was applied to the PC scores using MZA software. This approach facilitates classifying areas with similar soil characteristics and distinct variability. The FPI and NCE were calculated and plotted against varying cluster numbers (Fig. 8**).** The optimal number of MZs was determined based on the lowest values of both FPI and NCE, indicating the most suitable clustering solution.

As can be seen in Fig. 8, the optimal number of management zones for this study was determined to be six, but six management zones were statistically insignificant. Therefore, five management zones (MZs) were selected for evaluation. Previous studies have reported four management zones, indicating the heterogeneity of soil properties in MZs due to soil types, soil, and nutrient management practices[37,38,40,41,64,70]. The management zone map (Fig. 9) was developed using ArcGIS 10.3.1 software. Several studies have shown that the analysis of variance is a useful tool for determining the differences between zones. Therefore, a one-way ANOVA was conducted to assess the efficiency of PCA and fuzzy c-means cluster method in defining MZs and their spatial variability.

The variability in soil parameters between management zones was clarified via findings (Table 6). Means of pH, EC, organic carbon, and available nutrients between MZs exist statistically distinct at $P < 0.01$ (Table 6). Management zone 4 occupied the largest sampling site region (30%), then MZ^{-3} (28%). MZ^{-5} (24%), MZ-2 (12%) and MZ^{-1} (6%). The highest value of soil variables except Zn was recorded in MZ- 5, and the lowest value except Zn was recorded in Management $Zone^{-1}$. The maximum value of Zn was in MZ $^{-1}$, whereas the lowest value was in MZ-5. A significant variation in soil parameters between the five management zones is due to the soil type, soil & nutrient management practices[59]. The zonation approach may benefit the scientific management of nutrients efficiently and effectively. The geospatial assessment revealed spatial variability in the fertility status of sampling sites. Therefore, farmers and other stakeholders might utilize knowledge about MZs for site-specific nutrient management.

Fertilizer recommendation strategies

The wide spatial variability in soil properties, resulting from diverse production techniques, underscores the importance of SSNM practices. SSNM enables the recommendation of precise fertilizer quantities tailored to the nutrient status of specific land parcels, thereby enhancing nutrient use efficiency. In India, where small and fragmented farm holdings dominate agricultural landscapes, implementing field-specific fertilizer schedules poses significant challenges. One viable solution is to cluster farms with similar soil fertility characteristics into uniform MZs, which can then be treated as single units for nutrient management purposes.

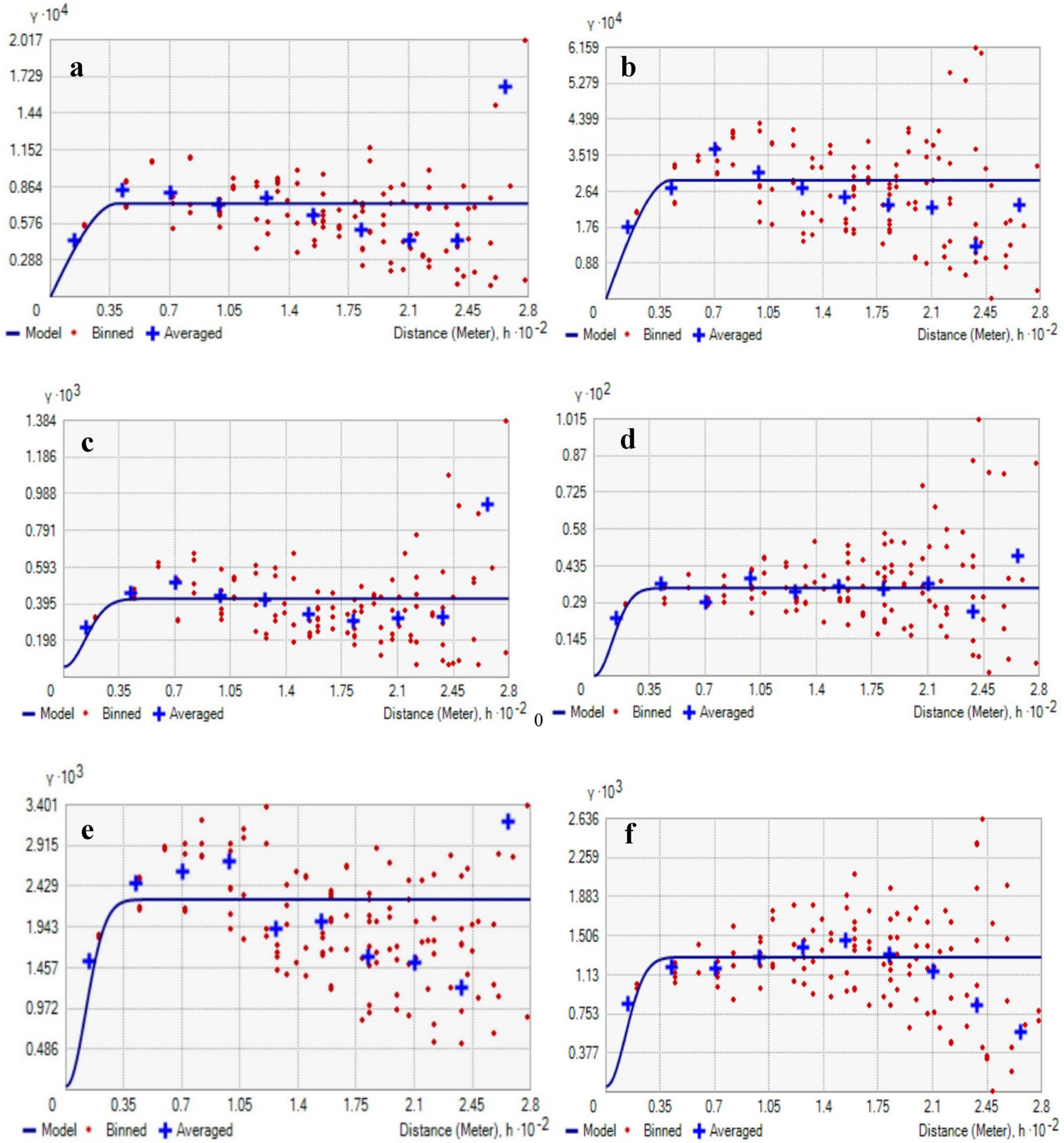

Fig. 7. **(a)** Best fitted semivariogram model of pH, **(b)** Best fitted semivariogram model of EC, **(c)** Best fitted semivariogram model of organic carbon, **(d)** Best fitted semivariogram model of available N, **(e)** Best fitted semivariogram model of available P_2O_5, **(f)** Best fitted semivariogram model of available K_2O, **(g)** Best fitted semivariogram model of available S, **(h)** Best fitted semivariogram model of available Fe, **(i)** Spatial distribution ma Best fitted semivariogram model of available Mn, **(j)** Best fitted semivariogram model of available Zn, **(k)** Best fitted semivariogram model of available Cu.

To address this, Professor Jayashankar Telangana State Agricultural University (PJTSAU) has developed targeted yield equations for crop- and soil-specific fertilizer recommendations. For maize cultivation, the required NPK doses to achieve a target yield of 70 quintals per hectare are calculated using the Soil Test Crop Response (STCR) equations, as presented in Eq. 5.:

$$FN = 4.25T - 0.24\,SN,\ FP_2O_5 = 0.9T - 0.3\,SP,\ FK_2O = 1.41\,T - 0.05\,SK \tag{5}$$

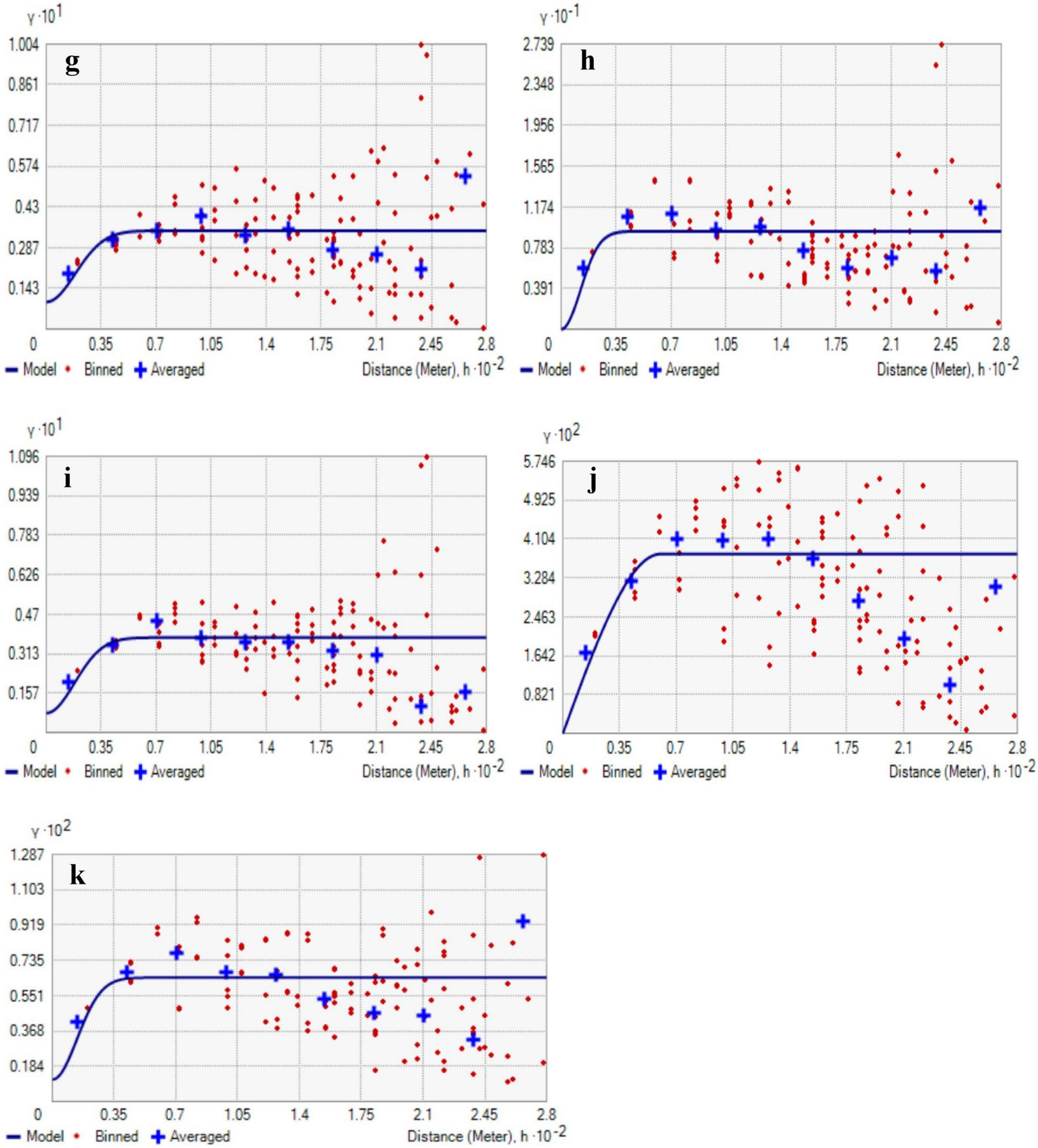

Fig. 7. (continued)

It is possible to connect these equations with the MZs map by utilizing the soil tests results to determine precise fertilizer doses. The amount of fertilizer saved within each of the five MZs in maize production was quantified (Table 7). Among the five management zones, the highest quantity of fertilizer was saved in MZ $^{-5}$ (up to 42 kg N ha^{-1}, 85 kg P_2O_5 ha^{-1} and 28 kg K_2O ha^{-1}) compared to farmer fertilizer practices, followed by MZ −4 (up to 36 kg N ha^{-1}, 79 kg P_2O_5 ha^{-1} and 25 kg K_2O ha^{-1}), MZ −3 (up to 32 kg N ha^{-1}, 74 kg P_2O_5 ha^{-1} and 23 kg K_2O ha^{-1}), MZ^{-2} (up to 28 kg N ha^{-1}, 71 kg P_2O_5 ha^{-1} and 21 kg K_2O ha^{-1}) and MZ $^{-1}$ (up to 21 kg N ha^{-1}, 66 kg P_2O_5 ha^{-1} and 18 kg K_2O ha^{-1}). Previous studies have saved 40–46 kg ha^{-1} nitrogenous fertilizer, 13–15 kg ha^{-1} phosphorus fertilizer, and 6–12 kg ha^{-1} potassic fertilizer in rice crops after adopting management zone approach[41]. The amounts of fertilizer needed to produce the targeted yield of maize @ 70 q ha^{-1} in MZ^{-1}, MZ^{-2}, MZ^{-3}, MZ^{-4}, and MZ-5 were 280:34:82, 272:29:79, 268:26:77, 264:21:75, and 258:15:72 NPK kg ha^{-1}, respectively. The variation of fertilizer doses between management zones was based on the relative fertility of

Parameters	pH	EC	OC	N	P_2O_5	K_2O	S	Fe	Mn	Zn	Cu
pH	1.00										
EC	0.86**	1.00									
OC	0.95**	0.88**	1.00								
N	0.81**	0.88**	0.86**	1.00							
P_2O_5	0.86**	0.90**	0.88**	0.92**	1.00						
K_2O	0.84**	0.93**	0.88**	0.95**	0.89**	1.00					
S	0.85**	0.90**	0.88**	0.90**	0.97**	0.90**	1.00				
Fe	0.95**	0.89**	0.95**	0.83**	0.88**	0.87**	0.89**	1.00			
Mn	0.83**	0.91**	0.83**	0.87**	0.90**	0.89**	0.88**	0.88**	1.00		
Zn	−0.16**	−0.27**	−0.08**	−0.13**	−0.11**	−0.45**	−0.56**	−0.65**	−0.61**	1.00	
Cu	0.94**	0.87**	0.96**	0.87**	0.90**	0.87**	0.89**	0.95**	0.89**	0.60**	1.00

Table 3. Pearson correlation matrix for soil properties (N = 200).

Principle Components	Eigenvalues	Proportion of the total variance (PTV) (%)	Cumulative PTV (%)
PC1	3,948.42	96.9	96.9
PC2	72.432	1.8	98.7
PC3	33.078	0.8	99.5
PC4	10.248	0.3	99.8
PC5	6.378	0.2	99.9
PC6	2.388	0.1	100
PC7	1.09	0	100
PC8	0.122	0	100
PC9	0.002	0	100
PC10	0	0	100
PC11	0	0	100

Table 4. Pearson correlation matrix for soil properties (N = 200).

Parameters	PC1	PC2	PC3	PC4	PC5	PC6	PC7	Communality k = 1
pH	0.853	0.168	0.227	0.212	−0.225	−0.091	−0.079	0.727
EC (dS m^{-1})	0.939	0.051	0.19	0.05	0.013	0.012	0.012	0.881
OC (g kg^{-1})	0.891	0.158	0.169	0.237	−0.155	−0.044	−0.047	0.794
Available N (kg N ha^{-1})	0.962	0.184	−0.201	0.029	−0.004	0.001	0.001	0.925
Available P_2O_5 (kg P_2O_5 ha^{-1})	0.919	0.356	0.145	−0.083	0.009	−0.031	−0.003	0.844
Available K_2O (kg K_2O ha^{-1})	0.998	−0.066	0.01	−0.005	0	0	0	0.995
Available S (mg kg^{-1})	0.919	0.291	0.15	−0.058	−0.065	0.203	0.017	0.844
Available Fe (mg kg^{-1})	0.877	0.164	0.266	0.284	−0.225	−0.035	0.018	0.77
Available Mn (mg kg^{-1})	0.903	0.168	0.193	0.235	0.25	0.019	0.032	0.815
Available Zn (mg kg^{-1})	−0.866	−0.17	−0.179	−0.229	−0.073	−0.074	0.355	0.749
Available Cu (mg kg^{-1})	0.884	0.228	0.162	0.251	−0.123	−0.029	−0.099	0.781
Eigenvalues	**3948.42**	**72.432**	**33.078**	**10.248**	**6.378**	**2.388**	**1.09**	**Total variance**
% of variance	**96.9**	**98.7**	**99.5**	**99.8**	**99.9**	**100**	**100**	**100**

Table 5. Loading coefficient for the first seven principle components.

each management zone. Owing to soil fertility differences amongst the five management zones, MZ^{-1} received the largest fertilizer dosage due to its low fertility status, while MZ^{-5} received the lowest dose due to its high fertility status (Table 7**)**. Table 8 shows the effects of fertilizer application in various management zones on maize grain production, cultivation costs, gross return, net return, and the B: C ratio. Overall, MZ −5 had the highest grain yield and B: C ratio, whereas MZ −1 had the lowest. Since less fertilizer was applied to MZ-5, its grain yield and B: C ratio were higher than those of MZ-2, MZ-1, and farmer fertilization practices (Table 8**)**. Previous studies have reported the highest grain yield in maize with the soil test crop response (STCR) based fertilizer recommendation compared to farmer fertilizer practices due to the proper allocation of fertilizer[71–75]. Based on the results of this research, it seems that SSNM greatly decreases nutrient quantity in similar environments &

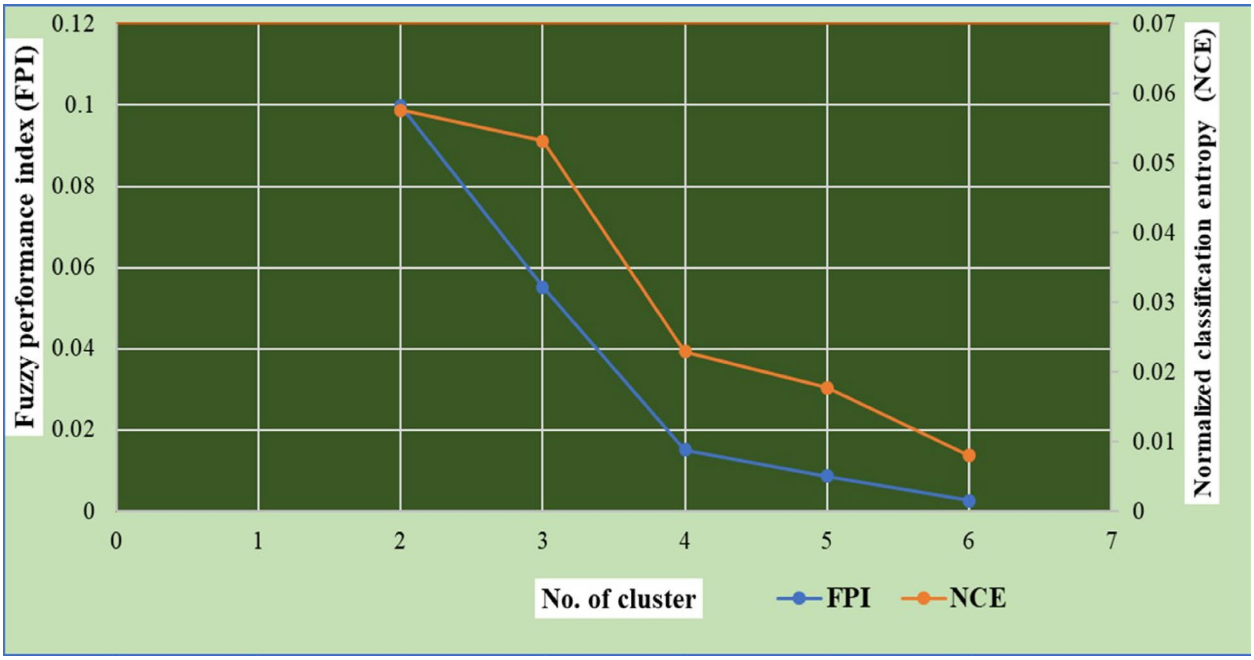

Fig. 8. FPI and NCE for management zone optimization in Mahagoan village of *Bhainsa* Mandal, Nirmal district of Telangana state.

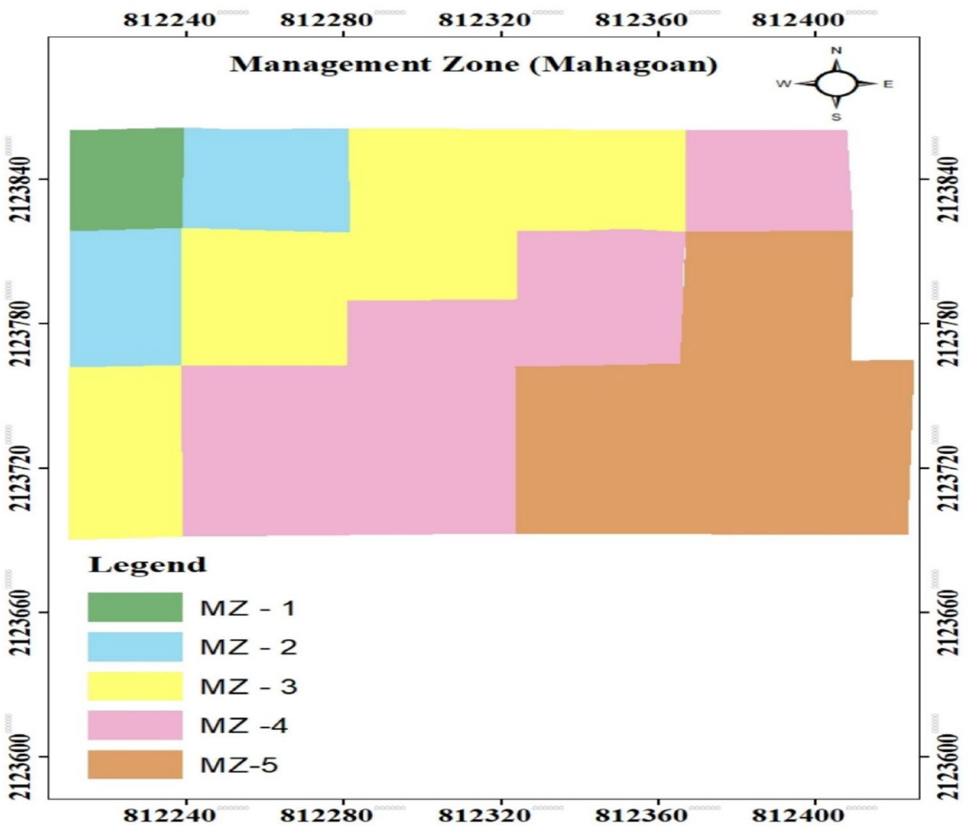

Fig. 9. Management zone map of Mahagoan village of *Bhainsa* mandal, Nirmal district.

MZs	pH	EC	OC	*N*	P_2O_5	K_2O	S	Fe	Mn	Zn	Cu
MZ 1	8.33	0.236	2.5	85	102	354	7	17.7	9.1	11.9	5.7
MZ 2	8.37	0.259	2.7	100	110	397	9	20.8	12	11.1	6.2
MZ 3	8.47	0.310	3.0	115	119	436	13	26.0	17.5	9.1	7.2
MZ 4	8.51	0.344	3.4	133	130	489	19	31.3	23.1	7.2	8.4
MZ 5	8.74	0.398	3.8	157	150	536	26	37.4	29.9	4.4	9.7

Table 6. Mean value and One-way ANOVA analysis for soil properties of management zone in Mahagoan village of *Bhainsa* mandal, nirmal district of Telangana state (N= 200). t_{Cal} = 2.05, t_{tab} = 1.81 Horizontal group. *Units: EC - dS m^{-1}, OC - organic carbon (g kg^{-1}), N - available N (kg N ha^{-1}), P_2O_5 -available P_2O_5 (kg P_2O_5 ha^{-1}), K_2O - available K_2O (kg K_2O ha^{-1}), S, Fe, Mn, Zn, and Cu – mg kg^{-1}.

Management Zones	Fertilizer doses			Fertilizer saving		
	N (kg ha^{-1})	P_2O_5 (kg ha^{-1})	K_2O (kg ha^{-1})	*N* (kg ha^{-1})	P_2O_5 (kg ha^{-1})	K_2O (kg ha^{-1})
MZ-1	280	34	82	21	66	18
MZ-2	272	29	79	28	71	21
MZ-3	268	26	77	32	74	23
MZ-4	264	21	75	36	79	25
MZ-5	258	15	72	42	85	28
Farmer fertilizer practices	300	100	100	-	-	-

Table 7. Fertilizer application in different management zones.

Management zone	Grain Yield (q ha^{-1})	Cost of cultivation (₹. ha^{-1})	Gross Return (₹. ha^{-1})	Net Return (₹. ha^{-1})	B: C ratio
MZ-1	79.66	59,565	148,964	89,399	2.50
MZ-2	82.36	59,153	154,013	94,860	2.60
MZ-3	85.36	58,895	159,623	100,729	2.71
MZ-4	90.51	58,531	169,254	110,723	2.89
MZ-5	94.36	58,057	176,453	118,396	3.04
Farmer fertilizer practices	76.36	63,637	142,793	79,156	2.24

Table 8. Grain yield, cost of cultivation, gross return, net return, and B: C ratio in different management zones.

production systems. As a result, the MZ approach could decrease the need for fertilizer in agriculture, reduce the damage caused to the environment, and boost farmer earnings. Aggregation of the dataset into a number of clusters, as is done by clustering method, which decreases the level of variability within each cluster and offers certain facts to make location-wise fertilizer application, with the ultimate goal of optimizing grain yield over a whole area[41].

Conclusion

This study demonstrates that delineating agricultural land into homogeneous MZs using geostatistical analysis, PCA, and FCM clustering is an effective strategy to address spatial variability in soil properties. The spatial heterogeneity of eleven soil parameters was successfully modeled using spherical, exponential, and Gaussian semivariogram models, indicating strong spatial dependence across the study area. Based on these models, five distinct management zones were identified. Integrating Soil Test Crop Response (STCR) equations with MZ maps enabled more precise fertilizer recommendations. Compared to conventional farmer fertilizer practices, this approach significantly reduced the need for NPK fertilizer requirements, enhanced maize grain yield, and enhanced overall profitability. Implementing site-specific SSNM through management zones also offers environmental advantages by reducing nutrient losses and lowering the risk of pollution.

While this study focused on a single crop (maize), the approach demonstrates a scalable framework that can be adapted to other regions and cropping systems with appropriate calibration. Although temporal variability was not the primary focus, the strong spatial correlations identified provide a solid foundation for future research incorporating seasonal dynamics. Moreover, applying advanced geostatistical and clustering techniques has shown high potential for delineating meaningful management zones. Building on this, future studies can expand the validation through long-term trials to further reinforce the robustness and applicability of the methodology across diverse agro-ecological conditions. In conclusion, this study enhances the utility of precision agriculture tools for sustainable nutrient management. Future work should validate these management zones across different crops, years, and broader agroecological zones to fully harness their agronomic and environmental benefits.

Data availability
Data available upon request to the first author (vaibhavsoil39@gmail.com).

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Declarations

Competing interests
The authors declare no competing interests.

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