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Delineation and Evaluation of Management Zones for Site Specific Nutrient Management in Maize Tracts of Northern Telangana using Geostatistical and Fuzzy C Mean Cluster approach.

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Abstract

Identification and demarcation of management zones (MZs) are required to maximize profit, reduce environmental damage, and enhance soil and crop health. The management zone with uniform spatial homogeneity and production potential may solve the problem of sustainable soil nutrient management. Hence, this current investigation was carried out to evaluate variations in soil parameters in order to demarcate the soil fertility zone for site-specific nutrient management. Overall, 200 soil samples (0-15 cm depth) with geographical coordinate were collected with a grid size of 14.2 m × 14.2 m from 4 ha maize cultivated area of Bogumpadu village of Ellanthakuntha mandal, Karimnagar district, Telangana, India. The collected samples were tested with different reagents to know the soil reaction and available nutrients in soil. The geostatistical technique was implemented to assess nutrient variability and preparation of variability map. The spatial variability of soil properties was explained by different models whereas
spherical, exponential, and Gaussian models identified as the best-fitted models. Furthermore, the management zone was delineated by principal component analysis and fuzzy C-means clustering algorithm. Five PCs with eigenvalue > 1, explaining 99.98% of variation in overall variation were selected for the next statistics. Three management zone were identified by using the fuzzy performance index (FPI) and normalized classification entropy (NCE). The management zone significantly differs from each other. MZ-1 covers an area of 45.5%, followed by MZ-2 (29.5%) and MZ-3 (25%). To evaluate the management zone productivity, site-specific nutrient management experiment was conducted in the maize field. The different fertilizer doses were calculated for three management zones by the Soil test crop response model and compared with farmer fertilizer practices. The result showed the highest maize grain yield in MZ-3 (80.18 q ha⁻¹) followed by MZ-2 (79.25 q ha⁻¹) and MZ-1 (77.89 q ha⁻¹) and the lowest grain yield with farmer fertilizer practice (72.69 q ha⁻¹). The highest N, P₂O₅ and K₂O fertilizer saving was observed in MZ-3 followed by MZ-2 and MZ-1 compared to farmer fertilizer practices. This study concluded that the management zone concept reduced the application of fertilizer, reduced environmental pollution and increased the maize grain yield and profit.

**Keywords:** Fuzzy C mean, Management zone, PCA, Spatial variability and STCR

**Graphical Abstract**

**Introduction**

The hot and dry semi-arid climate exhibits numerous challenges to crop management. The soil of semi-arid ecosystems is greatly variable in nature. The variations in fertility status of soil are primarily due to the complex interplay of geology, topography, climate, and soil usage. The most of the semi-arid areas receive irregular rainfall, both in terms of intensity and frequency and exhibit negative plant-nutrient equilibrium for many cropping systems. Due to land degradation, many of the existing cropping systems in semi-arid areas could not be able to work in the long run. Soil with lower organic matter are typically underdeveloped and susceptible to the degradation and mechanical deterioration. Nutrient use efficiency in plants grown in semi-arid area is less than twenty-five per cent, which is much variable (Singh et al., 2007). Farmers also experienced poor and unproductive responses to the applied...
fertilizers. Precise fertilizer management may enhance nutrient use efficiency, resulting in significant increases in crop yield and biomass production. Therefore, effective methods should be devised to precisely assess soil spatial variability in order to demarcation of uniform fertility zone for the judicious nutrient management (Peralta and Costa, 2013). The Management zone approach emphasizes the dividing of area in to small homogenous zone within a field-bounded area. These small homogenous zones comprise a fraction of an area that has identical properties like nutrient levels. Because of the highly complex relationship between the elements that presumably influence crop productivity, and it make difficult to precisely identify management zones. Moreover, to show that the variables coexist in a approach might make it extremely challenging to assess subfield management.

Soil characteristics that limit crop productivity within agricultural areas typically fluctuate significantly over time and space. Typically, this heterogeneity is purposefully neglected in soil sampling systems, laboratory investigations, and crop management agronomic strategies. As a result, it appears that using soil-specific techniques within the paradigm of precision agriculture does have the potential to enhance our existing management of soils. Modern technologies that allow exact measurement of the distribution of soil properties. With introduction of novel spatial technology in precision agriculture allows farmers to gather data from tiny regions inside this farm to manage specific regions differently (Bullock et al., 2007). Soil nutrient mapping would also allow for thorough monitoring and assessment of suggested farming technology at various sites. The application of geospatial tools and methodologies in the definition of MZs contributes to more sustainable site-specific nutrient management. Furthermore, understanding the soil fertility condition may aid in delineating the optimum MZs for specific places for efficient fertilizer management, agricultural production, and environmental protection. Traditional approaches for identifying management zones include soil survey, topography mapping, grain yield and nutrient indices approach.

Soil scientists have employed geostatistical methods during the last two decades to forecast spatial variance in soil parameters using various geostatistical techniques on narrow to broad geographical scales (Chatterjee et al., 2015). Geostatistics is a branch of statistics that is utilized to identify, predict, and describe regionally changing temporal dynamics. It is predicated on the simulation as well as interpretation of semivariograms, which correspond to such a distinction in coupled datasets to the path length among each sample couple (Goovaerts, 1998). Some many cluster approaches like C-means were frequently utilized to categorize management areas. Researchers have been able to explain the continuous variation in soil characteristics by applying the concept of fuzzy sets to clustering
(Guastaferro et al., 2010). In precision agriculture, the fuzzy clustering algorithm is employed to identify capability of each homogenous area. Each data point in the fuzzy cluster method does have the level of fuzzy membership function, which can be utilized to measure very adjacent observed values proximity to a group (Bezdek, 1981).

It may be hard to distinguish effect of any soil characteristic of soil quality, so it challenging to identify the border between management zones. As a result, existing analysis like principal component analysis and Fuzzy cluster analysis become widely utilized for MZ demarcation. The PCA provides detailed information about the proportion of variance as well as factor that have the biggest effect in each component. The PCs results acquired from PCA is utilized as an input variable for FCM technique to consider autocorrelation in spatial data clustering. The idea driving the approach is that including PCA of soil variables into fuzzy classification will result in MZs. As a result, higher difference of average of grain produce between management zone are anticipated for principle component analysis & fuzzy C mean analysis. This work main goal is just to demonstrate the suggested potential strategies for identifying MZs in precision agriculture based on highly correlated soil data.

Field management decisions are typically influenced by the finding of spatial heterogeneity in soils parameters. With the high degree of soil variability, it was anticipated that soil characteristics studied at one place would change in their location in space over time, making it more challenging to provide management recommendations based on the MZs. In light to foregoing, this current investigation served to (1) assess the temporal variation in soils properties by geostatistics, (2) delineate MZs by PCA & FCM, & (3) evaluate demarcated MZs for SSNM in Telangana's Northern area.

Materials and Methods

Study area

This investigation was done at farmer field of Bogumpadu village, Ellanthakuntha Mandal, Karimnagar district located in Northern Telangana, India (18.3043154 N to 18.30286507 N, 79.54903058 E to 79.55113991 E) (Fig.1 and 2). A total four ha area of maize crop was selected for soil sampling. It falls in the Deccan plateau region of the agro-climatic region of India and a hot moist semi-arid ecological subregion with 120 – 150 lengths of growing periods. The study area under investigation exhibit dry climatic conditions, hot summers and cool winters with an average annual rainfall between 867 mm to 1189 mm, received 86 % of rainfall is from the southwest monsoon rainfall
during June – September month and the remaining rainfall is received from northeast monsoon rainfall during December – January month. The maximum temperatures range between 31 and 39°C during March–early June and the minimum temperature ranges between 14 and 25°C during December – February (https://www.pjtsau.edu.in/ 2021-22). The dominant black soil is very deep, calcareous, fine textured, neutral to strongly alkaline with medium strong subangular irregular soil aggregate shape. The nomenclature of black soil having very fine montmorillonites clay was *hyperthermic*, udic chromusterts (Vijaykumar et al., 1994). Cotton–maize serves as the most dominant cropping system. The recommended dose of *kharif* cotton and *rabi* maize were 150 N kg ha$^{-1}$ : 60 P$_2$O$_5$ kg ha$^{-1}$ : 60 K$_2$O kg ha$^{-1}$ and 250 N kg ha$^{-1}$ : 40 P$_2$O$_5$ kg ha$^{-1}$ : 40 K$_2$O kg ha$^{-1}$, respectively. Groundwater is used to irrigate the cotton-maize system.

Figure 1: Map of India and Telangana
Figure 2: Study site and soil-sampling points in Bogumpadu village, Ellanthakunta Mandal, Karimnagar district, Northern region of Telangana.

**Collection and analysis of soil**

200 composite topsoil samples (0–15 cm) were taken using 14.2 m × 14.2 m matrix and pocket GPS device (Garmin eTrex handheld GPS navigator) during 2020 (Fig. 3). The collected samples were air-dried, blended & roughly pulverized by hardwood hammer before transferred through 2-mm filter then packed in a polythene bag to laboratory test. 2 mm processed soil utilized for soil parameter analysis except for organic carbon determination. 0.2 mm processed soil utilized for organic carbon determination. Soil pH and EC were determined by potentiometric and conductometric method respectively (Jackson, 1973). SOC had been measured with wet digestion of sample by potassium dichromate solution as outlined by Walkley and Black (1934). Available N content estimated with alkaline KMnO$_4$ (Subbiah and Asija, 1956). 0.5 M sodium bicarbonate (pH 8.5) extractant used to determine available P$_2$O$_5$ as outlined by Olsen et al. (1954). 1N ammonium acetate extractant used to estimate available K$_2$O as per procedure of Hanway and Heidel (1952). Turbidity method was used to determine available S (Chesnin and Yien, 1951). The
available micronutrients were extracted with 0.005 M DTPA as per the procedure described by Lindsay and Norvell (1978).

![Figure 3. Sampling scheme with 14.2 m intermodal in the horizontal direction and 14.2 m in a vertical direction.](image)

**Statistical analysis**

The studied soil properties were subjected to a descriptive statistical analysis, which included minimum, maximum, mean, kurtosis, skewness, standard deviation (SD), and coefficient of variation (CV). Pearson’s correlation coefficient analysis was used to examine the relationships between soil parameters. The soil data was analyzed using XLstat 2020 software.

**Geostatistical analysis**

To know soils spatiotemporal variability, geostatistical elements has been determined by ArcGIS 10.8 software developed by ESRI (Webster and Oliver, 2007). Prior to geostatistical analysis, a normality test was carried out to know whether soil data followed normal distribution or not. Q-Q plot technique was used for the normality test. The spatial distribution of different soil variables is expressed in geostatistics by the semivariogram, that assesses overall degree of similarity among dataset separated with distance h (Fig. 4). The semivariograms of soil properties \( \gamma(h) \) was derived from below formula (Goovaerts, 1998):
\[
\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_{(i)}) - Z(x_{(i)} + h)]^2
\]

where, \(N(h)\) represent the number of data pairs into a specified distance and direction, \(Z(x_{(i)})\) represent the value of the variable at position \(x_{(i)}\), \(Z(x_{(i)} + h)\) represent the value of the variable at a distance of \(h\) from position \(x_{(i)}\). The above semivariogram equation fitted with standard model calculated spatial variation parameter: nugget, sill and range. Several semivariogram models such as spherical, exponential and gaussian were selected based on cross-validation indice (RMSE) for the explanation of spatial correlation of soil parameters. A selected model is adopted to OK technique with interpolation for spatial mapping of predicted data of soil properties (Fig. 4).

The root mean square error was used as a comparison criterion to predict the accuracy of the semivariogram model as calculated by given formula:

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [Z(x_{(i)}) - \bar{Z}(x_{(i)})]^2}
\]

Where, \(Z(X_i)\) represent the observed value at position \(x_{(i)}\), \(\bar{Z}(x_{(i)})\) represent the predicted value at position \(x_{(i)}\) and \(N\) is the total number of data.

Figure 4: Flowchart methodology of geostatistical analysis.
**Principal component analysis**

It's a multidimensional technique used to extract elements within datasets (Fig. 5). The data were transformed by pivoting its diagonal coordinates to assign variance into distinct components. This analytical approach works by loading a greater degree of variation in initial group & a smaller degree of variation in succeeding group. In place of correlation analysis of selected soil parameters, a covariance analysis was employed to the principal component analysis. All soil parameters representing principal component in the analysis. To develop a management zones - MZs, principal components with eigenvalues one or more was considered for further analysis. A PCs loading of studied soil properties was undertaken to better understand the variability of properties under different PCs.

![Figure 5: Schematic representation of the methodology of PCA and Management zone for fertilizer recommendation in study area.](image)

**Fuzzy cluster algorithm analysis**

C mean fuzzy cluster approach is applied to develop distinct homogeneous subregions. It's a modified form of cluster analysis whereby a dataset is sorted into specified range of groups using a particular method. The clustered approach allows data of several variables to concurrently pertain to many groups and potentially allocate enrollment to specific clusters in order to reduce the imperfection produced by outliers. We used the three clusters as minimum
and eight clusters as maximum number for delineation of management zone. The involvement of data for each cluster were established iteratively, initially by an arbitrary collection of groups average results. Each data was classified according to the average that was closest to it. The new mean was produced for each cluster based on the distance between the cluster mean and each observation. The Euclidean distance was utilized to compute the distance between data points based on equal variance and statistical independence. 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 cluster 3 & 8, respectively and fuzziness component = 1.5.

The optimal number of clusters was determined using the fuzzy performance index (FPI) and normalized classification entropy (NCE).

\[
FPI = 1 - \frac{c}{C - 1} \left[ 1 - \frac{\sum_{k=1}^{C} \sum_{i=1}^{n} (u_{ik})^2}{n} \right]
\]

\[
NCE = \frac{n}{n-c} \left[ \frac{\sum_{k=1}^{C} \sum_{i=1}^{n} (u_{ik} \log u_{ik})}{n} \right]
\]

where \(c\) is the number of clusters; \(n\) is the number of observations; \(u_{ij}\) is the element \(ij\) of the fuzzy membership and \(\log\) is the natural logarithm.

FPI assesses the degree of fuzziness produced by a given number of classes. Its values might vary from 0 to 1. FPI values around 0 suggest strong clustering with low membership sharing. Values near to one, on the other hand, suggest that the data has no discrete classes and a high degree of membership sharing. NCE calculates the amount of disorganization caused by a given number of courses. The lowest FPI and NCE values specify the number of MZs (Fig.6). A one-way ANOVA test was performed on soil parameters of different management zones using SPSS software. A MZs delineation map developed by ArcGIS 10.8 software.
Results and Discussion

Descriptive Statistics of soils parameters

The descriptive statistics of the soil’s parameter shown in Table 1. This site is neutral to slightly alkaline, as shown by the pH range of 7.07 to 8.50 in addition to least coefficient of variance. Prior investigation found a least variation in soil pH compared to another soil’s parameter (Aliyu et al., 2020; Amer et al., 2021; Davatgar et al., 2012; Gorai et al., 2015; Jena et al., 2022; Moharana et al., 2020; Reza et al., 2017; Verma et al., 2021). The alkaline nature of soil is result of development of soil from basic parent material (vijaykumar et al., 1994). The lower variance in soils pH can related to the assumption that pH is logarithmic scales of hydrogen contents in soils solution; if soil response is stated directly in terms of proton concentration, the variability would be much higher. Soil buffering capacity, in general, resists sudden changes in soils pH or its considerable variation under diversified agricultural systems and practices under studied region. The EC value showed low CV, skewness and kurtosis (19.05 %, 0.51 and -0.52, respectively). Low variability in EC is attributed due to the non-saline groundwater used for irrigation purposes Narsaiah et al. (2018), Ramulu and Kamalakar (2022), Vilakar et al. (2021), Mahesh et al. (2018) and Shalini et al. (2022) were reported non-saline soil i.e. < 2 dS m$^{-1}$ in a different part of Telangana state. The average content of SOC in the study area (i.e., 3.7 g kg$^{-1}$) is rated low, despite the SOC content varying from 2.3 to 5.6 g kg$^{-1}$. This is in line
with the findings of Narsaiah et al. (2018), Vilakar et al. (2021), and Shalini et al. (2022) who reported the low content of soil organic carbon (5 g kg$^{-1}$) in different district of Telangana state. The lower soil organic carbon in the area may be attributed to lower organic manure application and the farmers in that area barely retain crop residues on the field. The CV value of SOC, available nitrogen, available P$_2$O$_5$ and available K$_2$O were low (CV of < 25 %), ranging from 12.74 % to 19.55 %. Tagore et al. (2014) and Qinghuo et al. (2019) were reported less than 25 % of CV. It indicated the less heterogeneity in soil organic carbon. Available nitrogen varied from 70 – 154 kg N ha$^{-1}$ with mean value of 111 kg N ha$^{-1}$. The low variability and nitrogen content are accounted for by leaching of dissolved organic nutrient and inorganic nitrogen (Verma et al., 2021). Moharana et al. (2020) recorded low available nitrogen in soil of western plain of Rajasthan, India. This is in line with the findings of Moharana et al. (2020); Reza et al. (2017); Tagore et al. (2014) who reported less than < 25% of CV, which indicated the fewer heterogeneity in available nitrogen of soil. The available P$_2$O$_5$ and K$_2$O content were high, varied from 81 – 145 kg ha$^{-1}$ and 327 kg ha$^{-1}$ – 524 kg ha$^{-1}$ with a mean of 108 kg ha$^{-1}$ and 420 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 results regarding to phosphorus obtained by Ramulu and Kamalakar (2022); Himabindhu et al. (2022); Vilakar et al. (2021). The high level of phosphorus in soil might be caused by the prolonged consumption of P fertilizer without testing of soil. (Satish et al., 2018). Another reason for the increase of phosphorus content in rhizosphere was the fixation of P with Ca (Rajeshwar and Mani, 2014). Ravi et al. (2017) found the high available K$_2$O range from 406 – 572 kg ha$^{-1}$ in the Karimnagar district of Telangana state. Similar result also found by Ramulu and Reddy (2018). It is possible to attribute the high level of available potassium may be ascribed by the mineralization of potassium from organic residues, the release of potassium from the non-exchangeable site of 2:1 type of clay mineral, release of potassium during weathering of primary mineral, dumping of potassic fertilizers, and the upstream movement of potassium from deeper depths along with capillary groundwater rise. The variability of available Sulphur was moderate with an CV value of 29.42 %. This is in line with the findings of Tagore et al. (2014); Behera et al. (2018); Aliyu et al. (2020) who reported the moderate coefficient of variability i.e. between 25 -75 %, which represented moderate heterogeneity in available Sulphur content in soil. The available Sulphur content was high, varied from 10 mg kg$^{-1}$ - 31 mg kg$^{-1}$ with a mean value of 19.0 mg kg$^{-1}$. Distribution of micronutrients Fe, Mn, Zn, Cu, and B exhibits moderate variability in the area based on CV > 25 – 75 % according to Wilding classification. The mean values of Fe, Mn, Zn and Cu in this region were 11.1, 7.1, 3.4 and 4.7 mg kg$^{-1}$, respectively. Ramulu and Reddy (2018) found the high micronutrients status (Fe, Mn, Zn and Cu) in Warangal soil of
Telangana state. Soil management activities, such as fertilizer application and other crop management techniques, may be responsible for the observed differences in soil properties across study regions (Shukla et al., 2017). 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 regard to their quantity at different locations within the studied region.

Table 1. Descriptive statistics of soil samples (N = 200) collected from Bogumpadu village of Ellanthakuntha mandal of Karimnagar district.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Min</th>
<th>Max</th>
<th>Range</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>SD</th>
<th>Mean</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>pH</td>
<td>7.07</td>
<td>8.52</td>
<td>1.45</td>
<td>0.19</td>
<td>0.33</td>
<td>0.23</td>
<td>7.99</td>
<td>2.88</td>
</tr>
<tr>
<td>EC (dS m⁻¹)</td>
<td>0.091</td>
<td>0.199</td>
<td>0.108</td>
<td>0.51</td>
<td>-0.52</td>
<td>0.03</td>
<td>0.14</td>
<td>19.05</td>
</tr>
<tr>
<td>OC (g kg⁻¹)</td>
<td>2.3</td>
<td>5.6</td>
<td>3.3</td>
<td>-0.28</td>
<td>-0.94</td>
<td>0.07</td>
<td>3.7</td>
<td>18.92</td>
</tr>
<tr>
<td>Available N (kg ha⁻¹)</td>
<td>70</td>
<td>154</td>
<td>84</td>
<td>-0.20</td>
<td>-0.67</td>
<td>22</td>
<td>111</td>
<td>19.55</td>
</tr>
<tr>
<td>Available P₂O₅ (kg P₂O₅ ha⁻¹)</td>
<td>81</td>
<td>145</td>
<td>64</td>
<td>0.14</td>
<td>-0.52</td>
<td>16</td>
<td>108</td>
<td>14.51</td>
</tr>
<tr>
<td>Available K₂O (kg K₂O ha⁻¹)</td>
<td>327</td>
<td>524</td>
<td>197</td>
<td>0.31</td>
<td>-1.15</td>
<td>54</td>
<td>420</td>
<td>12.74</td>
</tr>
<tr>
<td>Available S (mg kg⁻¹)</td>
<td>10</td>
<td>31</td>
<td>21</td>
<td>0.26</td>
<td>-0.87</td>
<td>6</td>
<td>19</td>
<td>29.42</td>
</tr>
<tr>
<td>Fe (mg kg⁻¹)</td>
<td>3.2</td>
<td>20.6</td>
<td>17</td>
<td>0.09</td>
<td>-1.04</td>
<td>4.9</td>
<td>11.1</td>
<td>44.14</td>
</tr>
<tr>
<td>Mn (mg kg⁻¹)</td>
<td>1.9</td>
<td>12.8</td>
<td>11</td>
<td>0.19</td>
<td>-1.09</td>
<td>3.3</td>
<td>7.1</td>
<td>46.48</td>
</tr>
<tr>
<td>Zn (mg kg⁻¹)</td>
<td>1.4</td>
<td>6.3</td>
<td>4.9</td>
<td>0.42</td>
<td>-0.92</td>
<td>1.5</td>
<td>3.4</td>
<td>44.12</td>
</tr>
<tr>
<td>Cu (mg kg⁻¹)</td>
<td>2.2</td>
<td>8.9</td>
<td>6.7</td>
<td>0.55</td>
<td>-0.85</td>
<td>1.9</td>
<td>4.7</td>
<td>40.43</td>
</tr>
</tbody>
</table>

Geostatistical analysis

Table 2 presents the parameters of the best-fitting semivariogram models for soil characteristics. Three models, i.e. Spherical, Exponential and Gaussians model observed as a strongly fitted model to the analyzed soils parameters based on minimum RMSE value. Similar procedures were employed by other researchers to identify the best model for interpolation using kriging (Verma et al., 2018; Reza et al., 2017; Pal et al. 2010). Figure 7.1 – 7.11 depicts the spatial distribution maps for various soil parameters. The best fitted model for soil pH, available nitrogen, available P₂O₅, available K₂O, available sulphur, Fe, and Mn was found to be the spherical semivariogram model (Fig.
The best-fitting model for soil EC and SOC was found to be the exponential semivariogram model (Fig. 8.2 and 8.3). However, the best-fitting models for Zn and Cu semivariograms were found to be Gaussian models. (Fig. 8.10 and 8.11). The best-fit semivariogram models for different soil parameters represent whether human activities and local factors affect the spatiotemporal variation of soils attributes (Behera et al., 2015; Tripathi et al., 2019; Moharana et al., 2020). The nugget value denotes the microvariability and variance measurement resulting from sampling errors (Verma et al., 2021). The nugget value represents the microvariability and variance measurement arising from sampling inaccuracy. Best-fit semivariogram nugget values ranged from 0 to 0.0025. With the exception of Zn, all soil properties showed the zero-nugget effect. If the data are trendless, the sill is theoretically equal to the variance of the sampled population at a high separation distance. Moreover, it is the semi-variance value at which the curve stabilizes consistently (Mulla, 2012; Brito, 2018). The lowest reported sill figure for pH was 0.00068, while the highest sill value was for available nitrogen (54.53). For spatial dependency, the nugget: sill ratio was categorized as mild (>0.75), moderate (0.25 to 0.75) and strong (0.25) (Cambardella et al., 1994; Oliver and Webster, 2014). This variance in soil nutrients may be caused due to the inappropriate application of fertilizer to crops in the study area by the farmer (Moharana et al., 2020). A range parameter in geostatistical analysis is a length where the semi-variance curve reached at highest sill point. The sill roughly corresponds to spatial variation (Reza et al., 2017). A range was considered radius of the area of impact which represents an mean largest length along where an soils attribute is linked between two samples (Moharana et al., 2020). As the distance between two sample sites within the soil spatial range decreased, the measured characteristic of the soil became similar. Other than organic carbon and available sulphur, the range of soil characteristics is between 30 and 55 meters. Maps depicting the spatial distribution of all soil parameters are shown in Figs. 7.1–7.11. 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 P₂O₅, available K₂O, available sulphur, Fe, Mn, and Cu increased from northeast to southeast, north to south, and west to east direction. Zn had the opposite distribution pattern. Its contents decrease from northeast to southeast, north to south, and west to east direction. 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 SSNM as well as to introduced VRTs for long-term sustainability. The soil fertility location maps could serve as a tool in order to develop SSNM plan for maximizing agricultural production while reduction of adverse effect on ecosystem and cost of cultivation.
Table 2. Semivariogram analysis of soil samples (N = 200) collected from Bogumpadu village of Ellanthakuntha mandal of Karimnagar district.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Transformation</th>
<th>Model</th>
<th>Nugget</th>
<th>Partial Sill</th>
<th>Sill</th>
<th>Nugget / sill (%)</th>
<th>Range (m)</th>
<th>Spatial dependence</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>pH</td>
<td>Log</td>
<td>Spherical</td>
<td>0</td>
<td>0.00068</td>
<td>0.00068</td>
<td>0</td>
<td>49.79</td>
<td>Strong</td>
<td>0.11</td>
</tr>
<tr>
<td>EC (dS m$^{-1}$)</td>
<td>Log</td>
<td>Exponential</td>
<td>0</td>
<td>0.00488</td>
<td>0.00488</td>
<td>0</td>
<td>32.25</td>
<td>Strong</td>
<td>0.008</td>
</tr>
<tr>
<td>Organic carbon (g kg$^{-1}$)</td>
<td>Log</td>
<td>Exponential</td>
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<td>0.0122</td>
<td>0.0122</td>
<td>0</td>
<td>70.59</td>
<td>Strong</td>
<td>0.025</td>
</tr>
<tr>
<td>Available N (kg N ha$^{-1}$)</td>
<td>None</td>
<td>Spherical</td>
<td>0</td>
<td>54.53</td>
<td>54.53</td>
<td>0</td>
<td>38.95</td>
<td>Strong</td>
<td>8.09</td>
</tr>
<tr>
<td>Available P$_2$O$_5$ (kg P$_2$O$_5$ ha$^{-1}$)</td>
<td>Log</td>
<td>Spherical</td>
<td>0</td>
<td>0.003</td>
<td>0.003</td>
<td>0</td>
<td>42.01</td>
<td>Strong</td>
<td>3.47</td>
</tr>
<tr>
<td>Available K$_2$O (kg K$_2$O ha$^{-1}$)</td>
<td>Log</td>
<td>Spherical</td>
<td>0</td>
<td>0.0019</td>
<td>0.0019</td>
<td>0</td>
<td>40.07</td>
<td>Strong</td>
<td>12.53</td>
</tr>
<tr>
<td>Available S (mg kg$^{-1}$)</td>
<td>Log</td>
<td>Spherical</td>
<td>0</td>
<td>0.084</td>
<td>0.084</td>
<td>0</td>
<td>113.16</td>
<td>Strong</td>
<td>1.79</td>
</tr>
<tr>
<td>Available Fe (mg kg$^{-1}$)</td>
<td>None</td>
<td>Spherical</td>
<td>0</td>
<td>4.86</td>
<td>4.86</td>
<td>0</td>
<td>44.04</td>
<td>Strong</td>
<td>1.27</td>
</tr>
<tr>
<td>Available Mn (mg kg$^{-1}$)</td>
<td>Log</td>
<td>Spherical</td>
<td>0</td>
<td>0.045</td>
<td>0.045</td>
<td>0</td>
<td>55.23</td>
<td>Strong</td>
<td>0.75</td>
</tr>
<tr>
<td>Available Zn (mg kg$^{-1}$)</td>
<td>Log</td>
<td>Gaussian</td>
<td>0.0025</td>
<td>0.0353</td>
<td>0.0378</td>
<td>6.61</td>
<td>40.45</td>
<td>Strong</td>
<td>0.29</td>
</tr>
<tr>
<td>Available Cu (mg kg$^{-1}$)</td>
<td>Log</td>
<td>Gaussian</td>
<td>0</td>
<td>0.027</td>
<td>0.027</td>
<td>0</td>
<td>31.35</td>
<td>Strong</td>
<td>0.46</td>
</tr>
</tbody>
</table>
Fig. 7.1. Spatial distribution map of pH

Fig. 7.2. Spatial distribution map of EC

Fig. 7.3. Spatial distribution map of organic carbon

Fig. 7.4. Spatial distribution map of available N
Fig. 7.5. Spatial distribution map of available $\text{P}_2\text{O}_5$

Fig. 7.6. Spatial distribution map of available $\text{K}_2\text{O}$

Fig. 7.7. Spatial distribution map of available $\text{S}$

Fig. 7.8. Spatial distribution map of available $\text{Fe}$
Fig. 7.9. Spatial distribution map of Mn

Fig. 7.10. Spatial distribution map of Zn

Fig. 7.11. Spatial distribution map of Cu
Fig. 8.1. Best fitted semivariogram model of pH

Fig. 8.2. Best fitted semivariogram model of EC

Fig. 8.3. Best fitted semivariogram model of OC

Fig. 8.4. Best fitted semivariogram model of available N
Fig. 8.5. Best-fitted semivariogram model of available P₂O₅

Fig. 8.6. Best fitted semivariogram model of available K₂O

Fig. 8.7. Best fitted semivariogram model of available S

Fig. 8.8. Best fitted semivariogram model of available Fe
Fig. 8.9. Best fitted semivariogram model of available Mn

Fig. 8.10. Best fitted semivariogram model of available Zn

Fig. 8.11. Best fitted semivariogram model of Available Cu
**Principal components analysis**

A correlation study of the soil variables revealed significant relation, as shown in Table 3. Therefore, principal component analysis has been utilized to decrease complexity in dataset while reveal its underlying primary components (PCs). When analyzing a set of data, the number of PCs generated (Table 4) is always equal to the number of independent variables. Eleven PCs were generated, and the first five that had an eigenvalue greater than 1 were selected for further study since they accounted for 99.98% of the variance. According to Sharma (1996), a principal component (PC) with an eigenvalue greater than 1 explains more variation than a single attribute. Tables 4 and 5 illustrate the results of the component. PC1 accounted for 95.92% of total variability, whereas available K, Mn, available P, Cu, Zn, Fe, available N, EC, and OC dominated it. pH was the dominant factor for PC2. PC3 contributed 0.99% of the variance, whereas it was dominated by available sulphur. The PC4 accounted for 0.4% of the variance and was mostly influenced by the available sulphur. The PC5 accounted for 0.06% of variance and was predominated by Fe. Behera et al. (2018); Tripathi et al. (2019); Devatgar et al. (2012) found three PCs from PCA by aggregating and summarizing the variability of soil properties in south India, eastern India and north Iran respectively. Some researcher such as Aliyu et al. (2020); Khaledian et al. (2017); Verma et al. (2021) reported the four PCs from PCA by aggregating and summarizing the variability of soil properties in Nigeria, north Iran and east India respectively.

**Table 3. Pearson’s correlation matrix between soil properties (N = 200)**

<table>
<thead>
<tr>
<th></th>
<th>pH</th>
<th>EC</th>
<th>OC</th>
<th>N</th>
<th>P</th>
<th>K</th>
<th>S</th>
<th>Fe</th>
<th>Mn</th>
<th>Zn</th>
<th>Cu</th>
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<tr>
<td>pH</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EC</td>
<td>0.25**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OC</td>
<td>0.18*</td>
<td>0.81**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>0.24**</td>
<td>0.95**</td>
<td>0.85**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P</td>
<td>0.14*</td>
<td>0.89**</td>
<td>0.90**</td>
<td>0.90**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>K</td>
<td>0.10</td>
<td>0.88**</td>
<td>0.86**</td>
<td>0.88**</td>
<td>0.93**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S</td>
<td>0.07</td>
<td>0.26**</td>
<td>0.48**</td>
<td>0.35**</td>
<td>0.42**</td>
<td>0.26**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fe</td>
<td>0.17*</td>
<td>0.83**</td>
<td>0.92**</td>
<td>0.86**</td>
<td>0.94**</td>
<td>0.90**</td>
<td>0.51**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mn</td>
<td>0.16*</td>
<td>0.87**</td>
<td>0.92**</td>
<td>0.90**</td>
<td>0.95**</td>
<td>0.94**</td>
<td>0.45**</td>
<td>0.96**</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zn</td>
<td>-0.15*</td>
<td>-0.84**</td>
<td>-0.95**</td>
<td>-0.88**</td>
<td>-0.96**</td>
<td>-0.91**</td>
<td>-0.52**</td>
<td>-0.96**</td>
<td>-0.96**</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Cu</td>
<td>0.12</td>
<td>0.88**</td>
<td>0.85**</td>
<td>0.89**</td>
<td>0.95**</td>
<td>0.92**</td>
<td>0.42**</td>
<td>0.92**</td>
<td>0.94**</td>
<td>-0.90**</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 4. Principle component analysis of soil properties and loading coefficient for the first five principal components (N = 200)

<table>
<thead>
<tr>
<th>Principal Components</th>
<th>Eigen Values</th>
<th>Proportion of the total variance (PTV) (%)</th>
<th>Cumulative PTV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC1</td>
<td>3.434.84</td>
<td>95.92</td>
<td>95.92</td>
</tr>
<tr>
<td>PC2</td>
<td>93.04</td>
<td>2.59</td>
<td>98.52</td>
</tr>
<tr>
<td>PC3</td>
<td>35.481</td>
<td>0.99</td>
<td>99.50</td>
</tr>
<tr>
<td>PC4</td>
<td>14.362</td>
<td>0.4</td>
<td>99.92</td>
</tr>
<tr>
<td>PC5</td>
<td>2.09</td>
<td>0.058</td>
<td>99.98</td>
</tr>
<tr>
<td>PC6</td>
<td>0.399</td>
<td>0.011</td>
<td>99.99</td>
</tr>
<tr>
<td>PC7</td>
<td>0.341</td>
<td>0.01</td>
<td>99.99</td>
</tr>
<tr>
<td>PC8</td>
<td>0.066</td>
<td>0.02</td>
<td>99.99</td>
</tr>
<tr>
<td>PC9</td>
<td>0.042</td>
<td>0.01</td>
<td>100.00</td>
</tr>
<tr>
<td>PC10</td>
<td>0.001</td>
<td>0.00001</td>
<td>100.00</td>
</tr>
<tr>
<td>PC11</td>
<td>0.0</td>
<td>0.000001</td>
<td>100.00</td>
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Table 5. PC loading for each variable

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<th>Attributes</th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
<th>PC5</th>
<th>Communality k=1</th>
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<tr>
<td>PH</td>
<td>0.122</td>
<td>0.294</td>
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<td>0.002</td>
<td>0.139</td>
<td>0.015</td>
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<tr>
<td>EC</td>
<td>0.898</td>
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<td>-0.126</td>
<td>-0.063</td>
<td>-0.006</td>
<td>0.807</td>
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<tr>
<td>OC</td>
<td>0.880</td>
<td>0.196</td>
<td>0.187</td>
<td>0.031</td>
<td>0.127</td>
<td>0.775</td>
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<tr>
<td>N</td>
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<td>-0.128</td>
<td>0.025</td>
<td>-0.001</td>
<td>0.817</td>
</tr>
<tr>
<td>P</td>
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<td>0.195</td>
<td>-0.180</td>
<td>-0.017</td>
<td>0.900</td>
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<tr>
<td>K</td>
<td>0.998</td>
<td>-0.069</td>
<td>-0.005</td>
<td>0.010</td>
<td>-0.001</td>
<td>0.995</td>
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<tr>
<td>S</td>
<td>0.291</td>
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<td>0.743</td>
<td>0.430</td>
<td>-0.052</td>
<td>0.084</td>
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<tr>
<td>Fe</td>
<td>0.913</td>
<td>0.161</td>
<td>0.260</td>
<td>-0.003</td>
<td>0.266</td>
<td>0.834</td>
</tr>
<tr>
<td>Mn</td>
<td>0.949</td>
<td>0.143</td>
<td>0.157</td>
<td>0.018</td>
<td>0.145</td>
<td>0.902</td>
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<td>Zn</td>
<td>-0.922</td>
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<td>-0.252</td>
<td>0.021</td>
<td>-0.097</td>
<td>0.851</td>
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<tr>
<td>Cu</td>
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<td>0.156</td>
<td>0.137</td>
<td>-0.046</td>
<td>0.046</td>
<td>0.869</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Eigen Value</th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
<th>PC5</th>
<th>Total variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of variance</td>
<td>95.92</td>
<td>2.59</td>
<td>0.99</td>
<td>0.4</td>
<td>0.058</td>
<td>99.98%</td>
</tr>
</tbody>
</table>
Clustering analysis for delineating management zones

The four PCs were categorized into MZs using cluster analysis. In order to determine the optimal number of MZs, the MZA software was used to perform the fuzzy c-means cluster algorithm on the scores of the four PCs. By using this method, we are able to separate areas with mostly similar values and significant variances between them. The NCE and FPI parameters were computed and plotted against the number of clusters (shown in Figure 9) to determine the optimal number of MZs (or MZs). Therefore, the optimum number of MZs may be determined when the FPI and NCE values are minimum. As can be seen in Figure 9, the optimal number of management zones for this study was determined to be three. This is in line with findings of other researchers (Xin-Zhang et al., 2009; Davatgar et al., 2012; Tripathi et al., 2019; Shukla et al., 2017). ArcGIS 10.3.1 software was used to develop the management zone map (Fig 10.). Several researches have shown that the analysis of variance is a useful tool for determining the differences between the zones. Therefore, a one-way ANOVA was conducted to assess the efficiency of PCA and fuzzy c-means cluster method in defining MZs, as well as their spatial variability.

The variability in soils parameters between management zones were cleared via findings (Table 6). A mean of EC and available nutrients between MZs exist statistically distinct at P < 0.01(Table 6). There were no statistical differences in pH, OC & available sulphur between management zones. management zone - 1 was occupied the largest sampling site region (45.5%) then MZ - 2 (29.5 %) and MZ - 3 (25 %). The highest value of soil variables except Zn were recorded in MZ- 3 and the lowest value of soil variables except Zn were recorded in Management zone - 1. The maximum value of Zn had in Management zone -1 whereas lowest value in MZ-3. A significant variation in soils parameter between three management zones because of the soil type, soil & nutrient management practices (Behera et al. (2018). The approach of zonation may benefit the scientific management of nutrients in an efficient and effective manner. Geospatial assessment revealed spatial variability in fertility status of sampling sites. Therefore, farmers and other stakeholders might utilize the knowledge about MZs for site-specific nutrient management.
Figure 9. Fuzzy performance index (FPI) and normalized classification entropy (NCE) for management zone optimization in Bogompadu village of Ellanthakuntha mandal, Karimnagar district of Telangana state.
Figure 10: Management zone map of Bogumpadu village of *Ellanthakuntha* mandal of Karimnagar district.
Table 6. Mean value and one-way ANOVA analysis of available soil properties of management zones in Bogumpadu village of Ellanthakuntha mandal, Karimnagar district of Telangana state (N = 200)

<table>
<thead>
<tr>
<th>MZs</th>
<th>pH</th>
<th>EC</th>
<th>OC</th>
<th>N</th>
<th>P₂O₅</th>
<th>K₂O</th>
<th>S</th>
<th>Fe</th>
<th>Mn</th>
<th>Zn</th>
<th>Cu</th>
</tr>
</thead>
<tbody>
<tr>
<td>MZ -1</td>
<td>7.95</td>
<td>0.116</td>
<td>3.0</td>
<td>99</td>
<td>94</td>
<td>370</td>
<td>17</td>
<td>6.6</td>
<td>4.0</td>
<td>4.8</td>
<td>3.1</td>
</tr>
<tr>
<td>MZ - 2</td>
<td>8.06</td>
<td>0.144</td>
<td>4.2</td>
<td>120</td>
<td>113</td>
<td>434</td>
<td>21</td>
<td>12.8</td>
<td>8.1</td>
<td>2.7</td>
<td>4.9</td>
</tr>
<tr>
<td>MZ - 3</td>
<td>7.98</td>
<td>0.171</td>
<td>4.5</td>
<td>140</td>
<td>129</td>
<td>495</td>
<td>21</td>
<td>17.3</td>
<td>11.4</td>
<td>1.7</td>
<td>7.6</td>
</tr>
</tbody>
</table>

*tₜₐₜ = 2.30, tₐₜₐ = 1.81 Horizontal group*

*Units: EC - dS m⁻¹, OC - organic carbon (g kg⁻¹), N - available N (kg N ha⁻¹), P₂O₅ -available P₂O₅ (kg P₂O₅ ha⁻¹), K₂O - available K₂O (kg K₂O ha⁻¹), S, Fe, Mn, Zn, and Cu – mg kg⁻¹*

Fertilizer recommendation strategies

Wide spatial variability in soil properties due to a variety of production techniques highlighted the advantage of SSNM practices for recommending precise quantities of fertilizer to the soil & plant in the particular land allocation area. In India, intensive agriculture with a small size of several farm holdings making difficult to implement a field-specific fertilizer application schedule unless one could group farms having identical nutrient-providing potential into distinct MZs & designate these like a single unit. The Professor Jayashankar Telangana State Agricultural University (PJTSAU) developed a targeted yield equation for crop-wise and soil-wise fertilizer recommendations. A targeted yield equation to maize crop is

\[ FN = 4.25T-0.24 SN, \quad FP₂O₅ = 0.9T- 0.3 SP, \quad FK₂O = 1.41 T-0.05 SK. \]

NPK fertilizer was applied to obtain 65 q ha⁻¹ targeted yield in maize.

It is possible to connect these equations with the MZs map by using the results of the soil tests to determine the fertilizer doses. It was determined the amount of fertilizer could be saved in each of the three MZ in maize production (Table 7). Among the three management zone, the highest quantity of fertilizer was saved in MZ -3 (up to 36 kg N ha⁻¹, 39 kg P₂O₅ ha⁻¹ and 31 kg K₂O ha⁻¹) compared to farmer fertilizer practices, followed by MZ -2 (up to 21 kg N ha⁻¹, 33 kg P₂O₅ ha⁻¹ and 21 kg K₂O ha⁻¹) and MZ -1 (up to 12 kg N ha⁻¹, 27 kg P₂O₅ ha⁻¹ and 15 kg K₂O ha⁻¹). This is in line with the findings of Moharan et al. (2020) who have saved the 40 – 46 kg ha⁻¹ nitrogenous fertilizer, 13 – 15 kg ha⁻¹ phosphorus fertilizer and 6-12 kg ha⁻¹ potassic fertilizer in rice crop after the adoption of management zone approach. The amounts of fertilizer needed to produce the targeted yield of maize @ 65 q ha⁻¹ in
MZ-1, MZ-2, and MZ-3 were 228:53:65, 219:47:59 and 204:41:49 NPK kg ha\(^{-1}\), respectively. The variation of fertilizer doses between management zones was based on relative fertility of each management zone. Owing to soil fertility differences amongst the three management zones, MZ-1 received the largest fertilizer dosage due to its low fertility status, while MZ-3 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 -3 had the highest grain yield and B:C ratio, whereas MZ -1 had the lowest. Since more fertilizer was applied to MZ-3, its grain yield and B:C ratio were higher than those of MZ-2, MZ-1, and farmer fertilization practices (Table 8). This is in line with the findings of Madhavi et al. (2020); Rajamani et al. (2020); Giri et al. (2015); Suresh and Santhi (2018); Shreenivas et al. (2017) who reported the highest grain yield in maize with the STCR based fertilizer recommendation compared to farmer fertilizer practices due to the proper allocation of fertilizer. Based on the results of this research, it seems that SSNM greatly decreases nutrient quantity in similar environment & production system. As a result, MZs approach could decrease the need of fertilizer in agriculture, reduce the damage caused to the environment, and boost farmer earnings. Aggregation of dataset into number of clusters, as is done by clustering method, which decrease level of variability within each cluster and offer certain facts to do location-wise fertilizer application, with the ultimate goal of optimizing grain yield over a whole area (Moharana et al., 2020).

Table 7. Fertilizer application in different management zones.

<table>
<thead>
<tr>
<th>Management zone</th>
<th>Fertilizer dose</th>
<th>Fertilizer Saving</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N (kg ha(^{-1}))</td>
<td>P(_2)O(_5) (kg ha(^{-1}))</td>
</tr>
<tr>
<td>MZ - 1</td>
<td>228</td>
<td>53</td>
</tr>
<tr>
<td>MZ - 2</td>
<td>219</td>
<td>47</td>
</tr>
<tr>
<td>MZ - 3</td>
<td>204</td>
<td>41</td>
</tr>
<tr>
<td>Farmer fertilizer practices</td>
<td>240</td>
<td>80</td>
</tr>
</tbody>
</table>
Table 8. Grain yield, cost of cultivation, gross return, net return and B:C ratio in different management zones

<table>
<thead>
<tr>
<th>Management zone</th>
<th>Grain Yield (q ha⁻¹)</th>
<th>Cost of cultivation (₹. ha⁻¹)</th>
<th>Gross Return (₹. ha⁻¹)</th>
<th>Net Return (₹. ha⁻¹)</th>
<th>B:C ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>MZ - 1</td>
<td>77.89</td>
<td>57349</td>
<td>145654</td>
<td>88305</td>
<td>2.54</td>
</tr>
<tr>
<td>MZ - 2</td>
<td>79.25</td>
<td>57035</td>
<td>148198</td>
<td>91163</td>
<td>2.60</td>
</tr>
<tr>
<td>MZ - 3</td>
<td>80.18</td>
<td>56598</td>
<td>149937</td>
<td>93339</td>
<td>2.65</td>
</tr>
<tr>
<td>Farmer fertilizer practices</td>
<td>72.69</td>
<td>58392</td>
<td>135930</td>
<td>77539</td>
<td>2.33</td>
</tr>
</tbody>
</table>

Conclusion

Many studies on site-specific fertilization have shown that partitioning crop land to the finite amount of uniformity zones is most efficient, cost-effective, and ecologically friendly way to deal with soil variability. In this study, geostatistical techniques were assessed soil spatial heterogeneity of eleven parameters, which were then aggregated into management zones by PCA and FCM algorithms. Geostatistical analysis found spherical, exponentials & gaussians model as best suited models for several parameters and suggested strong spatial correlation between different variables. The results indicated soil heterogeneity that clustered in the three homogenous management zones. A management zones depend STCR prescription significantly decreases NPK fertilizer amount to be needs. Recommended amount of NPK fertilizer depend upon management zone maps may be used as a major guidance to farming community for implementing SSNM practices and meets basic standards of MZs in being concise, realistic, effective to apply and financially viable. The management zones consider coherence as well as consistency into account & assist agricultural activities. In addition, the adoption of MZs can save fertilizer. These studies provided clarification for site-specific soil fertilizer management that minimizes negative environmental impacts while increasing overall output.

Author Contributions Statement

The authors confirm the contribution to the paper as follow: Preparation of Manuscript text - Pandit, V.B., Preparation of Tables and Figures - T. Anjaiah, Calculation of fertilizer doses using soil test crop response equation - M. Uma Devi, Geostatistical analysis of soil data - T.L. Neelima, Descriptive statistics of data, Principle component analysis of data, Fuzzy C Mean Cluster analysis of data, Delineation of management zones - D. Srinivasa Chary and all authors reviewed the manuscript.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.
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Declarations
All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

Competing interests
The authors declare no competing interests.

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