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Delineation of Homogeneous Management Zones in Sugarcane-Growing Soils for Site-specific Nutrient Management in Indo-Gangetic Plains of India

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ABSTRACT

Soil, a vital natural resource, requires sustainable management to prevent land degradation, promote healthy plant, animal, and human life, and ensure ecosystem sustainability. A study was conducted at research farm of Indian Institute of Sugarcane Research, Lucknow located in Indo-Gangetic plains of India. The study was conducted to develop various digital soil properties maps and delineation of homogeneous management zones. Geographically, study site was located between 26.794° to 26.809° N latitude, 80.922° to 80.936° E longitude and 111 m altitude. Grid based 240 soil samples were analysed for various soil physico-chemical properties. Texture of soil was loam and silty loam and pH was neutral to alkaline in reaction. Average soil organic carbon (SOC) was 0.52%, and available nitrogen phosphorus and potash (AN, AP and AK) were 240.63, 17.19 and 227.74 kg ha^{-1}, respectively. Sulphur nutrient was found widely deficient in the soils. SOC exhibited significantly positive correlation with clay (0.18), AN (0.32) and copper (0.13) however, pH revealed significantly negative correlation with AS (0.11), zinc (0.15), copper (0.12) and manganese (0.33). The best-fit geo-statistical semivariogram models were hole-effect for sand and silt; Pentaspherical for pH; K-bessel for electrical conductivity; J-bessel for SOC, AK and iron; Exponential for AN; Rational Quadratic for clay, AP and copper, Circular for AS, Hole-effect for zinc, and Gaussian for manganese. The four homogeneous management zones were delineated based on status of soil properties.

Digital soil properties maps were developed to implement site-specific nutrient management for sustainable higher crop production.

Keywords: Soil mapping, site-specific nutrient management, spatial distribution, alluvial soil, *Inceptisol*, Gangetic plains

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1. INRODUCTION

Sustainable soil nutrient management plays a crucial role in ecosystem sustainability (Powlson et al., 2011; Adeniyi et al., 2024). Decline in physical, biological and chemical soil quality leads to soil degradation which diminishes the entire ecosystem (Lal, 2015; Krasilnikov et al. 2016; Behera et al. 2023). Imbalanced application of nutrients in soil affects not only the quality of the crop produce and production but also degrades the soil quality (Bhattacharya, 2019). The present scenario of selective nutrient mining in different regions of developing world owing to large scale adoption of blanket recommendations on nutrient doses have depleted the soil reserve, declined the soil health and have caused wide-spread nutritional deficiency in large sections of human and animal populations (Das, 2022; Bora, 2022). Providing the quantitative information of the soil properties in spatiotemporal scale is therefore pivotal for farm scale site specific nutrient management leading to sustainable intensification. The eco-system sustainability of farm lands is largely governed by the soil organic carbon (SOC) content and the judicious use of chemical and other fertilizers needed to enhance crop productivity and production (Hoffland et al., 2020; Yalin et al., 2023). However, an excessive or selective use of few major nutrients (mostly nitrogen) results in compromised over all nutrient use efficiency, enhanced environmental pollution and a plethora of social and economic problems (Yousaf et al., 2017). A soil test-based site-specific balanced use of

fertilizers holds promise for increasing the crop yield (Singh et al., 2021; Aliyu et al., 2024) without adversely impacting the eco-system under such a scenario.

As a consequence of imbalanced nutrient management in agriculture, rapid urbanization, uncared quarrying, deforestation, and heavy dependence on chemical fertilizers *etc.*, soil degradation and land management has emerged as a global challenge (Srinivasarao et al., 2023; Motavalli et al., 2013). Efforts to gather quantitative soil data on various properties over time and space and deployment of different techniques such as geo-statistical analysis and machine learning has been adopted worldwide to systematically manage soil resource database and address soil security issues (McBratney et al., 2014; Dash et al., 2022). The upper layer of soil is recognised as the most biologically active zone of the soil (Sposito, 2023). Intensive cropping without redressing the soil health through site specific precision nutrient management contributes to soil fertility decline, SOC depletion and multi-nutrient deficiencies. Variation in the soil properties at regional level to farm scale occurs due to soil farming factors and anthropogenic activities to various factors like climate, soil type, topography and drainage, fertilization, practices of cropping system and crop management practices (Agegnehu et al., 2023). Indo-Gangetic plains (IGP) of India recognized as one of the most productive zones of the world (Kumar et al., 2004) gets characterized with alluvial soils of *Inceptisol* order (Bhattacharyya et al., 2013) put to use for intensive cultivation of rice-wheat system while sugarcane is grown in the zone as a cash crop (Rana et al., 2023). Repeated cultivation of these nutrient exhaustive crops year after year combined with field management practices like puddling for rice transplanting leaves the soil nutritionally poor and physically deteriorated. As the IGP contributes about 44% to National granary nutrient management for sustainable crop production is the key to fulfil the food requirements of the population (Powlson et al., 2011) that presently stands about 450 million and half of that depends on agriculture for livelihood. To achieve the higher crop productivity with sustainable soil health management it is essential

to implement the site-specific nutrient management based on the availability status of the nutrients in soil (Jin and Jiang, 2021). To achieve that it is essential to study the spatial variability of the plant nutrients availability particularly at the farm level or at intra-field level to effect site-specific nutrient management in crops at individual field level (Behera et al., 2022; Salem et al., 2024).

With an advancement of geographical information system and its geo-statistical techniques following the semivariogram based ordinary kriging, the spatial mapping of soil properties with limited number of soil samples and predicting the map for the entire study region (Burgess and Webster, 1980; Heuvelink et al., 2022) is possible. This technique reduces the expenditure which occurs on labour for extensive large number of sampling and financial resources involved in processing and laboratory analyses process (Li et al., 2020). The accuracy of the developed maps can be checked by using the standard method like root mean square error and the best-fit models selected for the mapping of soil properties (Tripathi et al., 2015). The small-scale soil properties mapping considering large area as zone, region or country have been attempted in different parts of the world including India (Shukla et al., 2016; Behera et al., 2018; Nagarjuna et al., 2021). However, most of the times it was found that these maps are meagrely used by the end user (farmer) mainly owing to inability to locate their own field on the maps. It is therefore, large scale soil properties mapping up to farm level can be very useful for individual fields and the end user to promote precision farming because, these kinds of maps are easy to understand by locating individual's field on the map (Cambardella et al 1994; Santra et al., 2008; Wani et al., 2013; Bogunovic et al., 2017; Roy et al., 2022; Behera et al., 2022). Further, delineation of management zones, involving several factors is useful for application of site-specific nutrient management (Jena et al., 2024). Hence, farm level soil property mapping and delineation of management zones is needed to enable farmers for implementation of crop specific and site-specific soil nutrient status-based fertilizer application

for higher crop productivity with sustainable soil health management. However, such large-scale farm level soil properties mapping studies in sugarcane growing soils are scanty and lacking particularly in rice-sugarcane-wheat growing systems in the world. Keeping all these in view an attempt has been made in the present study to develop maps of various soil properties at farm level to support implementation of site-specific nutrient management at individual field level. The study was conducted with the objectives i) to characterise the spatial distribution of soil properties at farm level, ii) to study relationship among different physic-chemical properties of the soil and iii) to develop spatial distribution maps for various soil properties and find out the soil properties which contributes more in the soil quality and delineation of soil management zones.

2. MATERIAL AND METHODS

2.1. Description of the study area

The present study was conducted at research farm of Indian Council of Agricultural Research (ICAR)-Indian Institute of Sugarcane Research (IISR), Lucknow located in the Indo-Gangetic plains of India (Fig 1). Geographically, the study site exists between 26.794° to 26.809° N latitude, 80.922° to 80.936° E longitude and at 111 meter elevation from mean sea level, having an area of 107.62 ha. The soils of the area are developed by the alluvium derived parent material and belongs to the major soil order of *Inceptisol* with plain topography, well managed drainage and non-calcareous mixed *hyperthermic* and *udic ustochrept*. The experiment site as classified by ICAR falls under the agro-ecological zone four named as North plain and central highlands (Gajbhiye and Mandal, 2000). Climate of the region is characterised as semi-arid subtropics where summer season is very hot however winters are very cold. The average monthly maximum temperature (39.2 ^{o}C) was recorded in the month of May whereas; average monthly minimum temperature (7.3 ^{o}C) was recorded in the month of January (Verma et al., 2019). Precipitation is received in the form of rainfall through South-West monsoon mainly during

the rainy season which prevails in the region from the month of June to September. The long-term average annual rainfall of the area is 949 mm and it has been witnessing a declining trend (Srivastava et al., 2022) for the last two decades. Study area is under protected irrigation mainly depending on the ground water lifted for irrigation through tube wells. Major study area is under cultivation of sugarcane (*Saccharum officinarum*) plant and ratoon crops, rice (*Oryza sativa*), wheat (*Triticum aestivum*), chickpea (*Cicer arietinum*), and mustard (*Brassica spp.*) etc. Sugar beet and few short durations crops suitable for intercropping with sugarcane are also grown either in experiment or in demonstrations plots. *Sesbania aculeta* (dhaincha) is grown as green manuring crop in few fields of research farm every year in cyclic manner for enriching the soil fertility. However, about 2.5 ha area is under mixed forest and about 3 ha area is under poplar (*Populus ciliata*) and mixed tree plantation. The entire research farm has been divided in four blocks *viz.* B, C, D, E and F blocks. Further, blocks are subdivided in the fields of about 1 ha area except few fields either corner or boundary sides of the research farm. The farm area is under cultivation of above-mentioned crops in well-defined crop rotations since establishment of the Institute in the year 1952. General schedule of nutrient management is followed based on dose of N, P and K as recommended for the region for various crops.

2.2. Soil sampling and laboratory analysis

Grid based soil samples were collected from the research farm of ICAR- Indian Institute of Sugarcane Research, Lucknow. Soil samples from the fallow fields were collected either during the spring season before the planting of spring sugarcane (Feb/March) or after harvest of the sugarcane crop or during the summer season following harvest of the winter crops in the year 2021. The entire farm area was divided into 70×70 meter size grids and the soil samples were collected from the central point of the each grid. In this way every collected soil sample represented an area of 4900 m^2 (0.49 ha). In such a way 240 soil samples were collected from 0-15 cm soil depth. The latitude and longitude coordinates were recorded with the help of hand-

held Garmin made eTrex 20x model of global positioning system (GPS). The collected soil samples were air dried in shades in protected environment. All the foreign materials were removed like stone and debris etc. Further, the soil samples were ground with wooden made mortar and pastel and passed through 2-mm mesh sieve. Sieved soil samples were stored in a well levelled polythene bags until they were used for analysis of the soil properties. The well processed soil samples stored in air tight polythene bags were measured for soil pH and electrical conductivity (EC) in 1:2.5 weight by volume soil and water suspension with the help of digital pH and conductivity meter (Jackson, 1973). Soil organic carbon (SOC) was determined by titration method (Walkley and Black, 1934). The available nitrogen (AN) was estimated by following the method as suggested by Subbiah and Asija (1956). The colorimetric method was used for determination of available phosphorus (AP) extracted by using 0.5 *M* $NAHCO_3$ (pH 8.5) and measured the colour intensity on spectrophotometer at 660 nm wavelength (Olsen et al., 1954). Available potassium (AK) in the soil was extracted by 1 N ammonium acetate adjusted at pH 7.0 and measured the concentration using the flame photometer (Hanway and Heidel, 1952). Available sulphur (AS) was extracted by 0.15 per cent calcium chloride dehydrates measuring the concentration through UV visible spectrophotometer at 340 nm wavelengths (Williams and Steinberg, 1959). The diethylene triamine penta acetic acid (DTPA) extractable zinc (Zn), Copper (Cu), Iron (Fe) and manganese (Mn) micronutrients were measured by methods as outlined by Lindsay and Norvell (1978) with atomic absorption spectrophotometer (AAS).

2.3 Statistical, geo-statistical, principal component and fuzzy cluster analysis

Descriptive statistical analysis of the data obtained from laboratory analysis on different soil properties was done for parameters including the minimum, maximum, mean, standard deviation (SD), skewness and kurtosis by using the statistical package for social science (SPSS) software, version 20 (Gomez and Gomez, 1984). Coefficient of variation (CV) was worked out

with aim to study the magnitude of variation in data about a soil property. Pearson's correlation analysis was performed to study the relationship among studied soil properties by using the same SPSS software and the significant relationship among them was confirmed at $P<0.05$. The geostatistical analysis was performed with Environmental Systems Research Institute (ESRI) developed geo-graphical information system (GIS) software Arc Map version 10.2 for development of spatial distribution maps of the soil properties at the farm level. The data analysis for outliers (exploratory analysis) and test for normality were carried out. Data on each soil property were checked for normal distribution through visualization of the data by histogram and normal QQ plot (Cooksey, 2020) and if the data were not found normalized then data transformation through log/box-cox option were used (Webster and Oliver, 2007) for further development of semivariogram models for spatial prediction of soil properties at unsampled places. The spatial structure of soil parameters was estimated by experimental semivariogram analysis (Nielsen and Wendroth, 2003). Derivation of the semivariogram for soil properties data has been done with the following mathematical equation-

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(xi) - Z(xi + h)]^2$$

Where $\gamma(h)$ explained as semivariogram at h distance interval; Z(xi) is the value of variable z at the xi location and $N(h)$ is the number of pairs of the sample.

The spatial variability in different soil properties was mapped by interpolation through kriging/ Cokriging option of geo-statistical method. The ordinary kriging (OK) with interpolation was used to decide the best suitable semivariogram models for spatial mapping of predicted data of soil properties. The Circular, Spherical, Tetraspherical, Pentaspherical, Exponential, Gaussian, Rational Quadratic, Hole Effect, K-bessel, J-bessel and Stable models were tested. The mean standard error (MSE) criterion was used to decide the best-fit semivariogram model. Semivariogram with the lowest MSE was considered as the superior semivariogram model.

196 Semivariogram models developed for each soil properties were compared to each other and the
197 model which was found with the lowest MSE was considered the best-fit semivarigram for that
198 soil property. The MSE of the semivariogram was calculated by using the following formula-

199 $$MSE = \frac{\sum_{i=1}^{n}(\theta i - \theta m)^2}{n}$$

200 Where θi denotes the prediction value, θm represent the mean values and n represents the total
201 number of predictions in each validation. Spatial dependence of the soil properties was assessed
202 by nugget/sill ratio. Cambardella et al. (1994) described the nugget sill ratio as if ratio <0.25 it
203 represents strong dependence, 0.25 to 0.75 moderate dependence and >0.75 represents week
204 spatial dependence.

205 The principal component analysis (PCA) was conducted to find out the most important
206 variables for management from the large data set. The PCA analysis was conducted with the
207 help of SPSS software version 20. Transformation of the data on soil properties was done by
208 rotating the orthogonal coordinates in order to apportion variance to the different components.
209 Higher magnitudes of the variance of variable were loaded on the first component and
210 subsequently lower magnitudes of variance of the following components. Pearson's correlation
211 matrix of selected soil properties was used as input for analysis resulting in normalized PCA.
212 The soil properties were included as variables in analysis and PCs receiving higher eigenvalues
213 were assumed to best represent soil properties. A bi-plot was developed to represent differential
214 loading for soil properties in PC1 and PC2 graphically for facilitating interpretation of
215 differences in variability of these properties.
216 Fuzzy cluster algorithm was used to find out the optimum number of clusters. A FuzMe
217 software version 3.0 developed by the Australian Centre for Precision Agriculture (Minasny
218 and McBratney, 2002) was used for this purpose. The software settings were used as:
219 Euclidean metric distance, fuzziness exponent 1.30, maximum iterations 300, stopping

criterion 0.0001, minimum number of classes 2 and the maximum number of classes 8. The FuzMe software was run with these settings to estimate fuzzy performance index (FPI) and normalized classification entropy (NCI) in the procedure outlined below-

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

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

Where, c indicates number of clusters, n number of observations, $\boldsymbol{\mu}$ik fuzzy membership and $\log_a$ natural logarithm. FPI estimates the degree of fuzziness created by specific number of classes. It ranges from 0 to 1.0. Its values approaching towards 0 indicates distinct classes with little membership sharing while value near 1.0 indicates no distinct classes with large degree of membership sharing. NCE measures amount of disorganization created by specific classes. Optimum number of clusters was obtained with lowest FPI and NCE values representing least membership sharing and greatest amount of organization (Fridgen et al., 2004). Differences among the MZs were tested by variance analysis.

3. RESULTS AND DISCUSSION

3.1. Soil properties variability

The soil properties *viz.* sand, silt, clay, pH, electrical conductivity (EC), soil organic carbon (SOC), available nitrogen (AN), available phosphorus (AP), available potash (AK), available sulphur (AS) and micronutrients zinc (Zn), iron (Fe) copper (Cu) and manganese (Mn) showed wide variability in study area located in Indo-Gangetic plains of India (Table 1). Soil texture is an important characteristic of soil which influences the physical, chemical and biological properties of the soil (Taghizadeh-Mehrjardi et al., 2021). The descriptive analysis of the soil separates i.e. sand, silt and clay revealed that silt content was predominant in the study area, with an average of 52.85%, whereas sand and clay contents were 29.12% and 17.83%, respectively. The highest coefficient of variation (CV) was found in sand (37.19%) which

exhibited the comparatively highest variation among the soil separates. The silt and clay had CV vales 20.52% and 18.56%, respectively. Based on the presence of primary soil separates, the soils were categorized as silt loam and loam soil textures according to the USDA soil texture classification system (Figure 2). The spatial distribution of soil textures in the study area have been depicted in Figure 3. Soil pH is one of the dominant factors which affect the activities of the microbial organisms and affects the availability of the many plant nutrients (Zheng et al., 2019). It varied from 7.10 to 8.80 with mean of 8.01±0.32 with coefficient (CV) of 3.97% and skewness and kurtosis values of -0.41 and -0.22, respectively. Soil pH varied from neutral to alkaline in reaction. It is well established fact that most of the trace elements are more available in slightly acidic to slightly alkaline condition whereas, there solubility decreases in the soil solution with increase of the soil pH which leads to lower concentration in soil solution (Kabata-Pendias, 2011). Electrical conductivity of soil represents the concentration of salt present in it. It varied from 0.06 to 0.61 dSm^{-1} with mean of 0.16±0.07 dSm^{-1} with CV, skewness and kurtosis of 43.75, 1.89 and 6.41, respectively. The similar findings were also reported by the several researchers for soil pH and electrical conductivity in Gangetic plains of India (Shukla et al., 2016; Verma et al., 2016). SOC content is an important soil property and integral part of soil organic matter. It influences the physical, biological and chemical properties of soil and act as a major factor to determine the crop yield (Das et al., 2022). SOC varied from 0.27 to 0.86% with mean of 0.52±0.09% having CV, skewness and kurtosis of 17.31%, 1.89 and 6.41, respectively. The highest 44 % soil samples were categorized under medium availability status followed by 27.4% in low category and 28.0% in higher category status. Our findings were corroborated by Singh et al. (2015) and Shukla et al. (2020) in northern Gangetic plains of India; they predicted the spatial distribution of organic carbon content in surface soil in the range of 0.10 to 1.99%. The higher area under low and medium category indicates loss in soil fertility. The low SOC in Gangetic plains can be mainly attributed

to imbalance fertilizer application, less crop residue addition in soil and adoption of extensive tillage practices. Nitrogen nutrient is removed by the crop plants in large quantity from the soil, AN in the soils of study area ranged from 194.43 to 301.05 kg ha^{-1} with mean availability of 240.63±20.28 kg ha^{-1} that indicates that the research farm has a low N availability status (<280 kg ha^{-1}). Its CV, skewness and kurtosis were 8.43%, 0.23 and -0.41, respectively. The low availability status of nitrogen in soil might be attributed by the several factors like its losses through leaching, runoff and volatilization, denitrification, higher uptake by the crop plants, low status of soil organic matter and imbalanced fertilization (Mahmud et al., 2021; Yadav et al., 2023). AP ranged between 7.68 -32.75 kg ha^{-1} with mean of 17.19±4.71, CV of 27.40%, skewness 0.37 and kurtosis -0.23. The high availability of AP might be attributed to neutral to slightly alkaline soil pH and adequate application of phosphate fertilizers and vice versa low AP might have attributed due to high soil pH, less phosphate fertilizer uses and low soil organic carbon content (Zheng et al., 2019). AK varied from 106.77 to 1345.76 kg ha^{-1}, mean of 227.74±120.51 kg ha^{-1}. It showed very high CV (52.91%) and the highest skewness (6.34) and kurtosis (54.04) among the studied soil properties. The higher potassium status was mainly restricted in the mixed forest area of research farm. The higher concentration of potassium in the soil might be due to original soil farming parent material especially clay content, restricted uptake by trees from top layer of soil and continuous addition of tree leaves on the surface soil and their decomposition leads to release of potassium mineral in soil (Taiwo et al., 2018; Bader et al., 2021). However, the lower availability of potassium in the cultivated area might be due to the continuous mining of potassium by intensive cultivation of exhaustive crops like sugarcane in crop rotation with less or no application of potassium fertilizer in soil (Singh et al., 2015; Das et al., 2022). Since the studied research farm is under sugarcane cultivation from the last 73 years, therefore, it could be the reason of low availability of the potassium in certain areas of the farm owing to heavy removal of potassium from the soil by the sugarcane crop.

Among the secondary plant nutrients AS varied from 3.53 to 69.82 kg ha^{-1} with mean of 10.16±6.03 kg ha^{-1}, CV of 59.35%, skewness 5.08 and kurtosis of 42.50. Although, the average status of available sulphur was found in medium category however, many areas were found deficient. This could be attributed to unbalanced fertilizer use and negligible use of sulfur containing fertilizers. Our finding was corroborated by Singh et al. (2015) who reported sulphur deficiency in soils under rice-wheat cropping system in Indio-Gangetic Plains of India. Results of studied micronutrients i.e. Zn, Cu, Fe and Mn in the study revealed that Mn had recorded the highest CV 73.66% and it varied from 2.04 to 50.52 mg kg^{-1} with mean of 11.96±8.81 mg kg^{-1}. Fe varied from 2.32 to 60.64 mg kg^{-1} with mean of 17.02±9.62 mg kg^{-1} and CV 56.52%. Zn varied from 0.24 mg kg^{-1} that is below the critical limit (0.6 mg kg^{-1}) to 3.16 mg kg^{-1}. Similarly, Cu spatial variation ranged from 0.58 to 6.04 mg ha^{-1} with mean 2.13±0.94 mg kg^{-1}. It was inferred from the micronutrient presence in the soil that zinc, iron and manganese were found deficient in the certain fields of the research farm that might be attributed to organic matter depletion, little or no use of micronutrient enriched fertilizers, intensive agriculture and unfavourable soil pH (Das et al., 2022). However, Cu availability was found adequate.

3.2. **Relationship among the soil properties**

The relationship through correlation coefficients among the soil separates (sand, silt and clay) pH, EC, SOC, primary plant nutrients (AN, AP and AK), secondary plant nutrient (AS) and micronutrients (Zn, Cu, Fe and Mn) have been depicted in Figure 3. Result of the Pearson's correlation coefficient among the soil properties revealed that sand exhibited significantly negative correlation with silt (0.956), clay (0.195), EC (0.185) and copper (0.151). Clay showed significantly positive correlation with EC (0.186) and soil organic carbon (0.176). The positive correlation between clay and organic matter was also reported by Malepfane et al. (2022) in South Africa and cited the reason that it could be the greater soil aggregation and

organic carbon protection by the clay particles. Soil pH showed significantly negative correlation with AS (0.110), Zn (0.153), Cu (0.117) and Mn (0.333). Shukla et al. (2021) also reported significantly negative correlation of soil pH with available sulphur in cultivated Indian coastal soil. Strong negative correlation between soil sulphur and pH was reported by Ma et al. (2020) at abundant coal gangues, Guizhou, China. Singh et al. (2023) reported a strong negative correlation of Zn solubilising bacteria with rhizosphere soil pH in rage of 7.6 to 9.3 in Indo-Gangetic plains. Li et al. (2019) also reported negative correlation between Cu and soil pH in turnip growing soils of China. The significantly negative correlation between soil pH and Fe was reported in soils of central Serbia (Dragović et al., 2023). A significantly positive correlation of SOC was found with AN (0.320), and Cu (0.130). Our finding of positive correlation between SOC and AN was corroborated by Jing et al. (2020) in rice growing soils of China and Sanad et al. (2024) in Mnasra region, Moracco. Filipović et al. (2023) also reported significantly positive correlation between Cu and dissolved organic carbon in foot slope of Corosia. EC showed significantly positive correlation with SOC (0.237), AK (0.218), AS (0.465), and Cu (0.150) however, negatively correlated with Fe (0.126) and Mn (0.222). The findings of positive correlation of EC with AK, AS and SOC were supported by Bogunovic et al. (2017) and Behera et al. (2022).

3.3 Interpolation for spatial variability and distribution of soil parameters

Geo-statistical analysis was performed with soil data on pH, EC, SOC, AN, AP, AK, AS, Zn, Cu, Fe and Mn. Best-fit semivariogram models were selected based on the least mean standard error. The parameters of best-fit semivariograms models like nugget, partial sill, sill, nugget/ sill ratio, nugget/ sill (%), range, Moran's test value p-value, spatial auto correlation and spatial dependence of various soil properties have been presented in Table 3. Box-cox transformation was done for soil pH, AN, AP, AK, AS, Zn, Cu and Mn before development of ordinary kriging based semivariogram models. Similarly, log transformation was used for electrical

conductivity and iron content. Whereas, sand, silt clay and soil organic carbon data were normally distributed, hence, the transformation was not applied. Results of the geo-statistical analysis reveals that Hole-effect semivariogram model was found best-fit for sand and silt per cent, Pentaspherical for pH, K-bessel for EC, Circular for S, Hole-effect for Zn, Gaussian for Mn and Exponential for AN. Rational Quadratic semivariogram model was found best-fit for clay, AP and Cu. However, semivariogram model J-bessel was found best-fit for SOC, AK, and Fe. These findings were supported by several researchers for AN in lateritic soil of West Bengal (Bhunia et al., 2018), in humid sub-tropical North-Eastern India (Reza et al., 2019) in farm scale variability mapping in central India (Behera et al., 2022), and in Jawali area of North-West region of Himalayas (Kumar et al., 2023). Similarly, Mn in Kashmir agricultural landscape of India (Wani et al., 2013), in Himalayan region (Kumar et al., 2023) and northern China (Sheng et al., 2023). Nugget is the value on y-axis on which semivariogram intercepts. Its overall measurement of errors might be contributed by sampling method, adequacy in sample size, assessing process and other contributing variance sources (Clark, 2010). Nugget values of best-fit semivariogram models for soil properties vary widely from 0.01 to 89874014.08. The higher nugget values were found for soil pH (89874014.08), AN (354.46), AK (128.96), silt (114.60), sand (110.67) and AP (2.68). Whereas, soil properties like EC, AS, Zn, Cu, Fe and Mn nugget values were close to zero. Sill is the maximum value where variograms flatten off at increasing distance. It is considered theoretically equal to the variance of the data used for semivariogram calculation. The sill values of the best-fit semivariograms varied from 0.01 to 121201776.1. Nugget sill ratio was used to classify the spatial dependence of the soil properties. The spatial dependence classified as strong, moderate and weak with nugget sill ratio of ≤25%, between 25 to 75% and >75%, respectively (Cambardella et al., 1994). Sand, silt, SOC, AN and Zn availability in soil showed a week spatial dependence. Similarly, clay content, pH, EC, AP, AK, Cu, Fe and Mn availability in soil showed moderate

spatial dependence. However, AS reflected the strong spatial dependence among all the soil properties. The strong spatial dependence for soil parameters might be due to intrinsic variations in the soil characteristics like soil texture and mineralogy. Similarly, the weak spatial dependence may be due to extrinsic variations like fertilizer application and tillage practices (Muhaimeed et al., 2013). The majority of the studied soil properties exhibited moderate spatial dependence. Soil pH, AN and Zn have not exhibited spatial auto correlation. It indicates that these properties are distributed evenly across the study area (Meik and Lawing, 2017). The weak spatial dependence of SOC, AN and Zn was also reported in soils of temperate Himalayas, lower Brahmaputra and in Southern Ethiopia (Reza et al., 2016; Ramzan et al., 2017; Abdu et al., 2023). Similarly, the moderate spatial dependence for pH, EC, AP, AK, Cu, Fe and Mn was reported from India and USA (Behera et al., 2023; Salem et al., 2024) and strong spatial dependence for AS was reported from China (Sheng et al., 2023). The range parameter of semivariogram models varied widely among the soil properties. It varied from 188.88 meters (AS) to 840.00 meters (AN). The higher range values were exhibited for AN and pH in best-fit semivariogram models as compared to other soil properties. The attributes of the best-fit semivariograms were used for interpolation to generate spatial distribution maps of soil properties. The predicted soil property maps of sand, silt and clay have been depicted in Figure 4 whereas, soil texture, pH, EC, SOC, AN, AP, AK, AS and micronutrients Zn, Cu Fe and Mn maps have been depicted in Figure 5. These maps have been developed on the basis of best-fit semivariogram models which showed MSE close to zero indicating that these semivariogram model predictions are unbiased. The accuracy these kind of maps mainly affected by number of samples, distance between the sampling points and interpolation method (Kravchenko, 2003). These developed spatial distribution maps are useful to facilitate the implementation of site-specific nutrient management for enhanced crop productivity and sustainable soil health management.

3.4. Management Zones

Considering the relationship among different soil properties principal component analysis was conducted for the studied soil properties and the result of the analysis has been presented in table 4. The result exhibited five principal components considering the eigenvalues 1.0 or more. The cumulative variability of the six PCs was 67.90%. The PC 1, 2, 3, 4, 5 and 6 showed the eigenvalues of 2.36, 2.02, 1.52, 1.30, 1.21 and 1.10 and variance of 16.84, 14.42, 10.83, 9.30, 8.66 and 7.84%, respectively. The highest eigenvalue and variance was found for PC1 and followed by successive PCs. PC1 was dominated by PC loadings of the AS, Zn, Cu, and EC. The PC2 was dominated by PC loadings of Mn, EC and Fe. PC3 was dominated by PC loading of AP. PC4 was dominated by the PC loadings of SOC and AN. The last PC5 was dominated by PC loading of AK. PC analysis results enable researcher for prioritisation of the studied variables for their management. The present study of PC analysis results and expert opinion suggested the nutrient management priorities in the order of SOC, AN, AP, AK, AS, Zn.

The scores of first six principal components were imported in FuzMe software to optimize the number of clusters on the basis of fuzzy cluster algorithm. The values of fuzziness performance index (FPI) and normalized classification entropy (NCE) were computed to optimize the number of clusters. These values of FPI and NCE were plotted against the number of classes (Figure 6). The optimum number of clusters were obtained when both FPI & NCE value were lower representing the least membership sharing. The clustering process optimized with six PCs finalizes to four number of clusters. Based on this result, the four soil management zones (MZs) were delineating in the study area (Figure 7). Similar approach was also adopted by several other researchers to develop the soil management zones. Verma et al. (2018), Kumar et al. (2023) and Salem et al. (2024) also reported 2 soil management zones in Western Ghats of coastal India, Himachal Himalaya, India and Southern Idaho, USA, respectively. Tripathi et al. (2015) and Behera et al. (2018) reported 3 soil management zones in Eastern and Southern

India. Four nutrient management zones were reported in Shiwalik, North-Eastern Himalayan region of India and in Khorasan Razvi province of Iran, (Shukla et al., 2017; Jena et al., 2022 and Maleki et al., 2023). The mean values of soil properties under different developed soil MZs have been presented in Table 5. Analysis of variance was performed to check the significant heterogeneity status of soil properties among the developed soil MZs. Significantly higher available phosphors (25.06 kg ha^{-1}) and EC (0.27 dSm^{-1}) were recorded in MZ2 however other MZs for the same properties were statistically at par. Available potassium (1312.40 kg ha^{-1}) was found significantly higher in MZ2, followed by MZ1 (364.41 kg ha^{-1}), MZ3 (240.00 kg ha^{-1}) and MZ4 (172.52 kg ha^{-1}). The medium status of potassium represented by MZ3 and MZ4 of the study area has been reported from areas under similar intensive cultivation growing high potassium exhaustive crops like sugarcane and cereal crops like rice and wheat in the cropping system (Das et al., 2022). Significantly higher Cu (2.58 mg kg^{-1}) and Mn (13.01 mg kg^{-1}) were found in MZ1. Whereas, significantly higher Fe (17.38 mg kg^{-1}) content was found in MZ4. Since the soils of the MZ2 is under mixed forest hence, the high availability of potassium in these soils can be explained due to addition of potassium in soil through biogeochemical weathering of cyclic forest litter in soil (Huang et al., 2023). Zinc and copper content were found below their critical limits in MZ2. Sand, silt, clay, pH, organic carbon, available nitrogen and zinc did not show any significant difference among the developed MZs that may be attributed to the similar parent material, cropping system, uniform plain land topography and adoption of long-term same fertilizers application approach in the cropping system.

4. CONCLUSIONS

Development of spatial maps of soil properties in large scale category are highly suitable for study of soil nutrient status at research farm level and their use for implementation for nutrient management for sustainable crops production and soil health. The Geo-statistical analysis is the key for studying the spatial variability of soil properties and phyto-available nutrients in

444 soils. The present study was conducted at research farm of ICAR-Indian Institute of Sugarcane
445 research, Lucknow located in the fertile Indo-Gangetic plain zone of India. The soils of the
446 study area were found silty loam and loam in soil texture, neutral to alkaline in reaction and
447 neutral in soil salinity. The average availability of nitrogen was categorised low however,
448 phosphorus and potassium were found in the medium availability status. A large number of the
449 samples were found low in availability of sulphur however, its average status was found in
450 medium status. Under the micronutrient category zinc was found deficient in several places.
451 The CV values varied from 3.97% (pH) to 73.66% (Mn) of studied soil properties. Soil pH
452 exhibited significantly negative correlation with AS, Cu, Zn and Mn however, soil organic
453 carbon showed significantly positive correlation with available nitrogen and copper content in
454 soil. Based on the principal component analysis five principal components were identified with
455 eigenvalues of one or more and based on the study and expert opinion the soil organic carbon,
456 available nitrogen, phosphorus, potassium, sulphur and zinc were deciphered for nutrient
457 management prioritisation in that order. The spatial distribution maps for sand, silt, clay, SOC,
458 EC, AN, AP, AK, AS, Zn, Cu, Fe and Mn were developed through ordinary kriging
459 interpolation technique based on best-fit semivariogram models like Hole-effect for sand and
460 silt, Pentaspherical for soil pH, K- Bessel for EC, J-Bessel for SOC AK and Fe, Exponential
461 for AN, Rational Quadratic for clay, AP and Cu, Circular for S, Hole-effect for Zn, and
462 Gaussian for Mn. Further, based on principal component and cluster analysis techniques four
463 management zones were delineated in the study area. The spatial distribution maps developed
464 in the present study for various soil properties using the geo-statistics approach ordinary kriging
465 through interpolation will be highly useful for locating the research experiments at various sites
466 based on the requirement of soil properties and site-specific nutrient management. The study
467 also shows the road map to conduct the similar studies at different research farms in India or
468 elsewhere in the world. Based on the present study similar approach can be followed for

delineation of nutrient management zones in various sugar mill command areas to facilitate sugarcane farmers for site specific nutrient management in sugarcane based cropping system. The sugar mills can also take advantage of the present study to ensure precision nutrient management in sugarcane crop in their mill command area for sustainable higher sugarcane production and soil health management for their long-term economic sustainability.

Authors Contribution

RRV contributed in conceptualization of the study, execution of research work and writing first draft of the manuscript. TKS contributed in data curation statistical analysis and review of the first draft of the manuscript. PS carried out figures design and presentation and reviewed the first draft of manuscript. RKS contributed in soil sampling, laboratory analysis and data tabulation. All authors further jointly reviewed the manuscript and finalized for its publication.

Competing Interest

Authors declares that they do not have any competing interest

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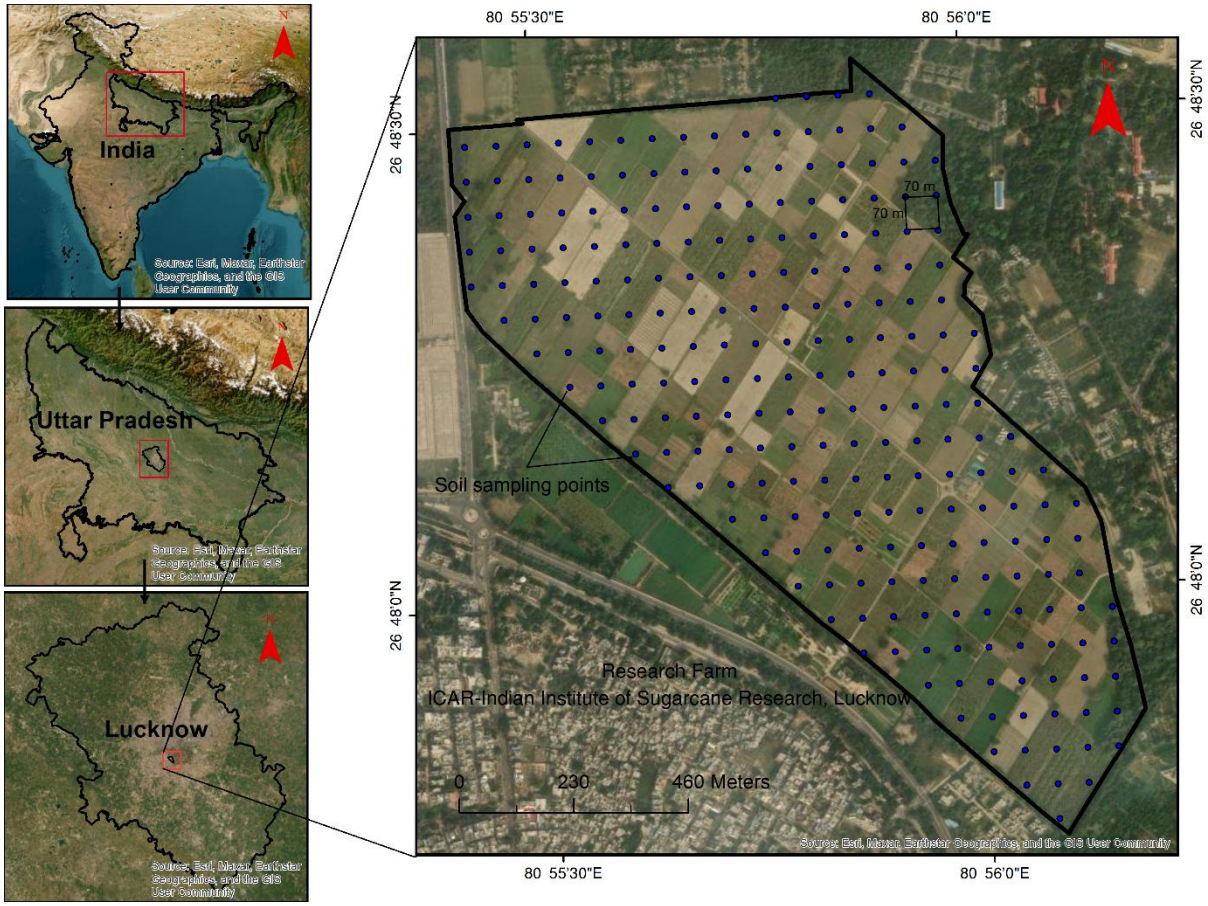
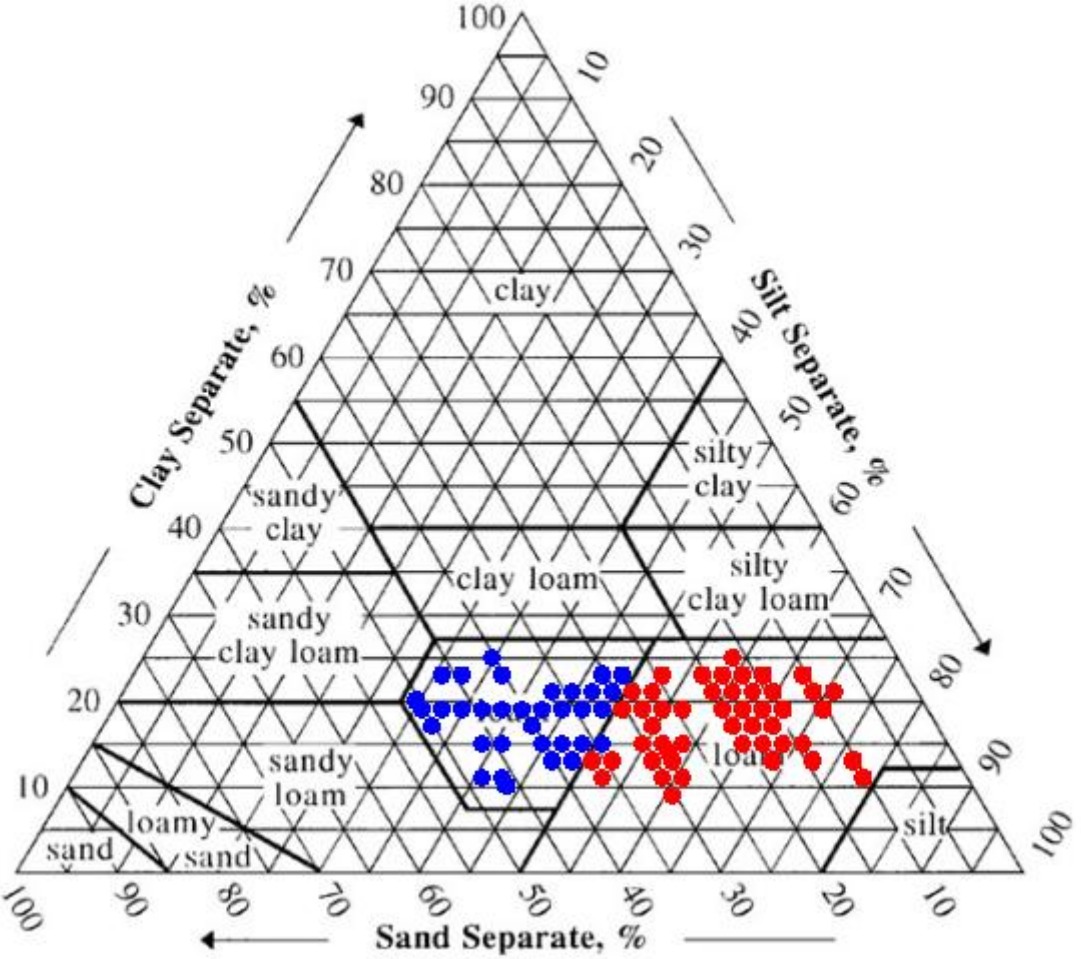


Fig. 1. Location of study site and soil sampling points in Indo-Gangetic plain zone



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732 Fig. 2. Soil samples textural classification in USDA soil textural triangle

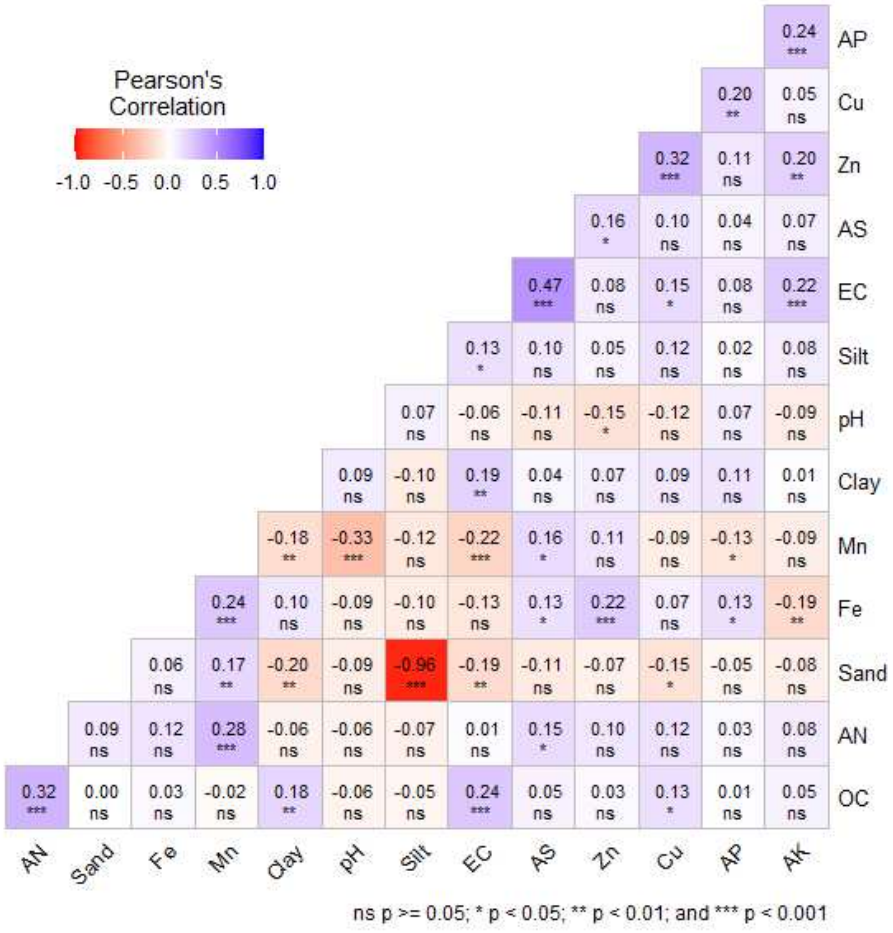


Fig. 3. Pearson's correlation matrix among the soil properties of study area. * Correlation is significant at P< 0.05; **Correlation is significant at P< 0.0 and ***Correlation is significant at P<0.001. Where, red and violet colour indicates represents respective negative and positive correlation. EC= electrical conductivity; OC=organic carbon; AN= available carbon, AP=available phosphorus; AK= available potassium; AS= available sulphur; Zn=zinc, Cu=copper, Fe =iron and Mn = manganese. The values are based on 240 geo-referenced soil samples (N=240).

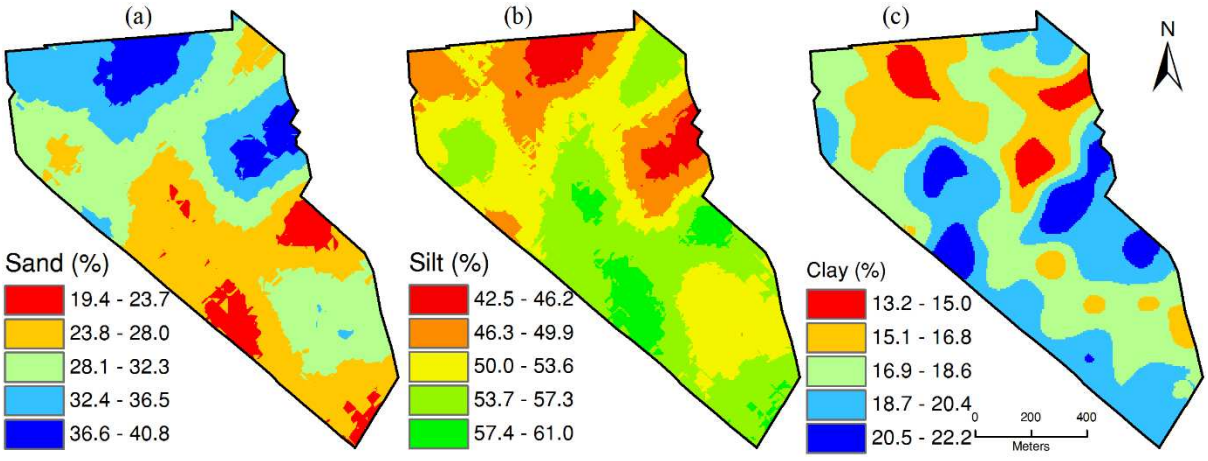
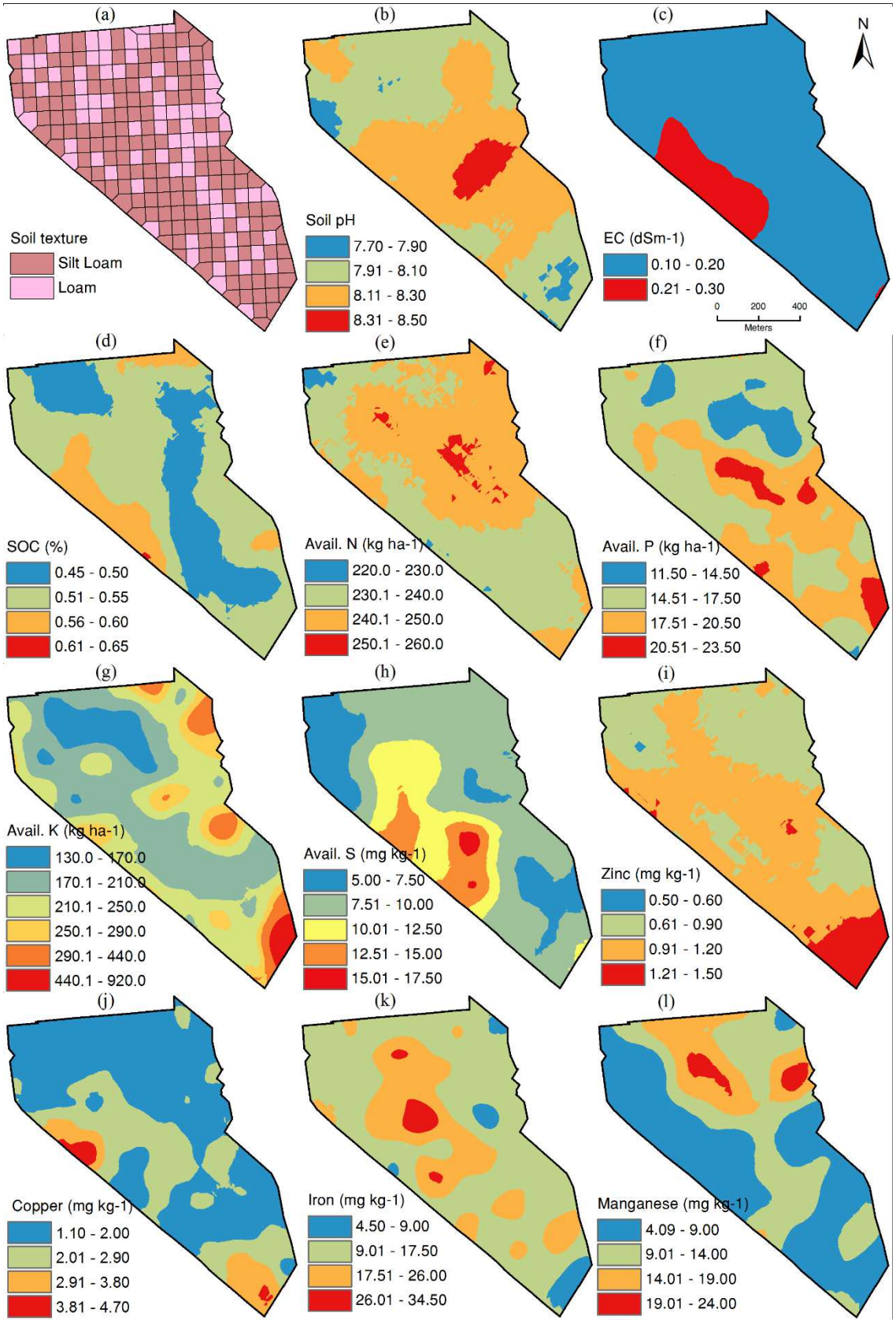
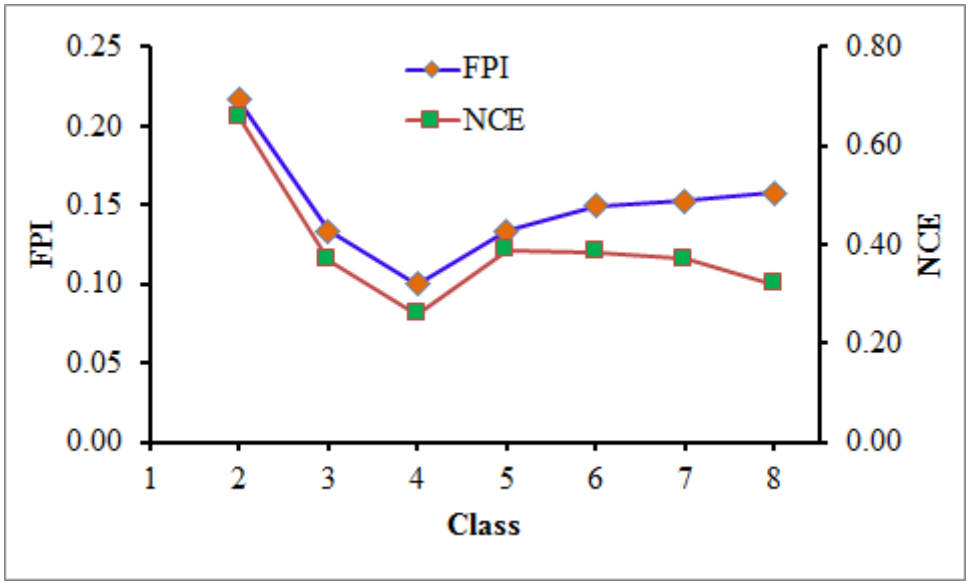


Fig.4. Predicted spatial distribution map of soil sand silt and clay in Indo-Gangetic plain Zone



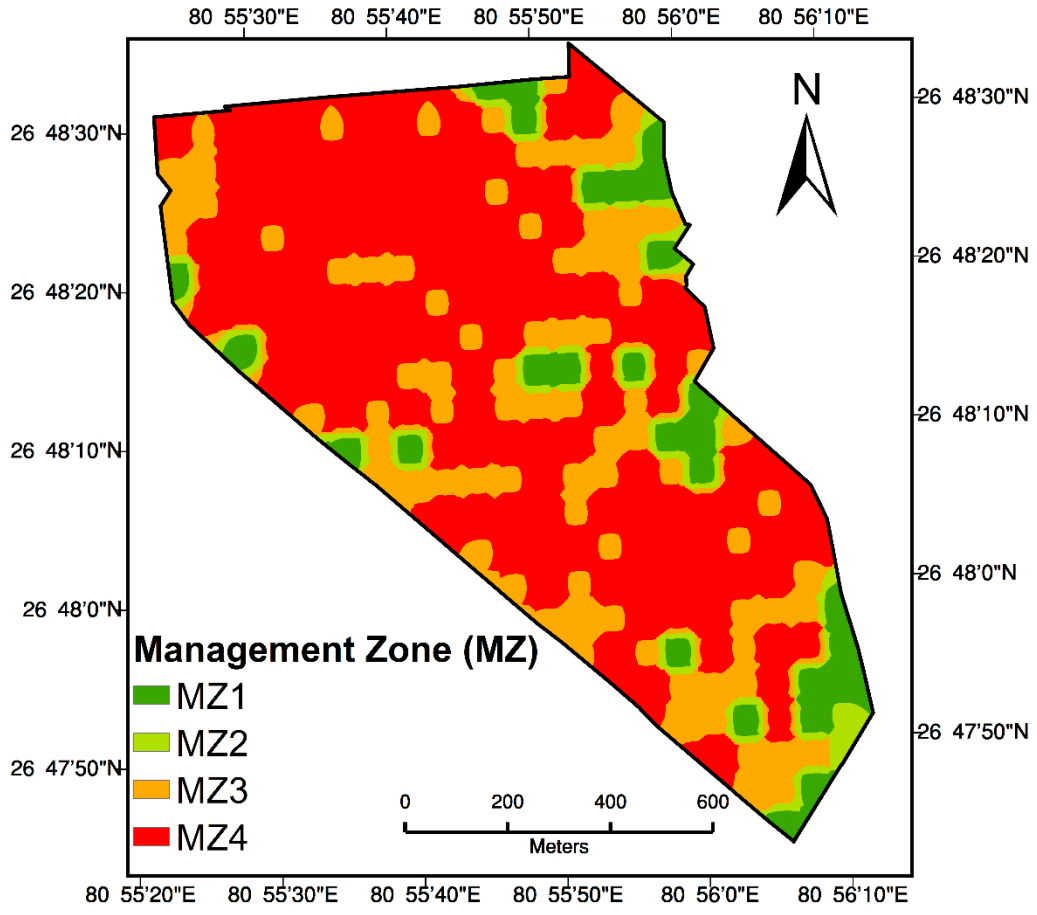
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744 Fig. 5. Predicted spatial distribution map of soil textural class (a), soil pH (b), electrical
745 conductivity (c), soil organic carbon (d), available nitrogen (e), phosphorus (f), potassium (g),
746 sulphur (h), zinc (i) copper (j) iron (k) and manganese (l) in Indo-Gangetic plain Zone



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748 Fig. 6. Fuzzy performance index (FPI) and normalized classification entropy (NCE) for
749 optimum cluster in study area



750 Fig. 7. Soil
751 management zone map with four optimized cluster in Indo-Gangetic plain Zone

752 Table 1. Descriptive statistics of soil properties of study area

Variables	Unit	Minimum	Maximum	Mean	SE	SD	CV (%)	Skewness	Kurtosis
Sand	%	9.52	51.52	29.12	0.70	10.83	37.19	0.37	-0.80
Silt	%	22.00	78.00	52.85	0.70	10.85	20.52	-0.45	-0.36
Clay	%	8.48	24.48	17.83	0.21	3.31	18.56	-0.57	-0.03
pH	-	7.10	8.80	8.07	0.02	0.32	3.97	-0.41	-0.22
EC	dSm^{-1}	0.06	0.61	0.16	0.01	0.07	43.75	1.89	6.41
SOC	%	0.27	0.86	0.52	0.01	0.09	17.31	0.14	0.90
AN	$kg\ ha^{-1}$	194.43	301.05	240.63	1.31	20.28	8.43	0.23	-0.41
AP	$kg\ ha^{-1}$	7.68	32.75	17.19	0.30	4.71	27.40	0.37	-0.23
AK	$kg\ ha^{-1}$	106.77	1345.76	227.74	7.78	120.51	52.92	6.34	54.04
AS	$kg\ ha^{-1}$	3.53	69.82	10.16	0.39	6.03	59.35	5.08	42.50
Zn	$mg\ kg^{-1}$	0.24	3.16	0.95	0.03	0.53	55.79	1.46	2.23
Cu	$mg\ kg^{-1}$	0.58	6.04	2.13	0.06	0.94	44.13	1.38	2.04
Fe	$mg\ kg^{-1}$	2.32	60.64	17.02	0.62	9.62	56.52	1.44	2.61
Mn	$mg\ kg^{-1}$	2.04	50.52	11.96	0.57	8.81	73.66	1.28	1.17

753 Note. EC: electrical conductivity; SOC: soil organic carbon; AN: available carbon, AP: available phosphorus;
754 AK: available potassium; AS: available sulphur; Zn, Cu, Fe and Mn: DTPA-extractable zinc, copper, iron and
755 manganese, respectively, SE: standard error; SD: standard deviation; CV: coefficient of variation. Values are
756 based on 240 georeferenced soil samples (N=240).

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Table2. Semivariogram parameters of soil properties of study area

Variables	Type of Transformation	Model	Nugget	Partial Sill	Sill (Nugget + Partial Sill)	Nugget/Sill	Nugget/Sill (%)	Range (m)	Moran's I test value	p-value	Spatial Autocorrelation	Spatial Dependence
Sand	None	Hole-effect	110.67	19.90	130.57	0.85	84.76	433.97	0.045	0.326	Absent	Weak
Silt	None	Hole-effect	114.60	15.92	130.52	0.88	87.80	386.78	0.004	0.871	Absent	Weak
Clay	None	Rational Quadratic	6.83	6.19	13.02	0.52	52.46	412.48	0.237	0.000	Present	Moderate
pH	Box-Cox	Pentaspherical	89,874,014.08	31,327,761.97	121,201,776.10	0.74	74.15	708.00	0.134	0.003	Absent	Moderate
EC	Log	K-Bessel	0.09	0.085	0.18	0.53	52.50	460.51	0.326	< 0.001	Present	Moderate
SOC	None	J-Bessel	0.01	0.001	0.01	0.88	87.50	343.72	0.048	0.2752	Absent	Weak
AN	Box-Cox	Exponential	354.46	82.040	436.50	0.81	81.21	840.00	0.067	0.1362	Absent	Weak
AP	Box-Cox	Rational Quadratic	2.68	1.501	4.18	0.64	61.46	308.42	0.170	< 0.001	Present	Moderate
AK	Box-Cox	J-Bessel	128.96	128.198	257.15	0.51	51.45	281.90	0.352	< 0.001	Present	Moderate
AS	Box-Cox	Circular	0.03	0.811	0.84	0.04	3.55	188.88	0.184	< 0.001	Present	Strong
Zn	Box-Cox	Hole-effect	0.26	0.023	0.28	0.92	91.94	415.57	0.063	0.1568	Absent	Weak
Cu	Box-Cox	Rational Quadratic	0.06	0.046	0.10	0.55	55.43	338.49	0.344	< 0.001	Present	Moderate
Fe	Log	J-Bessel	0.18	0.121	0.30	0.60	59.31	286.53	0.238	< 0.001	Present	Moderate
Mn	Box-Cox	Gaussian	0.07	0.058	0.13	0.56	55.77	306.98	0.259	< 0.001	Present	Moderate

Table 3. Summarization of principal component analysis for soil properties

PC	Eigenvalues	Variance (%)	Cumulative (%)
1	2.358	16.840	16.840
2	2.019	14.421	31.261
3	1.516	10.832	42.092
4	1.302	9.298	51.390
5	1.213	8.661	60.051
6	1.098	7.844	67.895

PC matrix

Variables	PC1	PC2	PC3	PC4	PC5	PC6
Sand	-0.812	0.305	0.415	-0.057	-0.171	-0.101
Silt	0.739	-0.330	-0.551	-0.030	0.047	0.159
Clay	0.284	0.057	0.444	0.289	0.432	-0.188
pH	0.064	-0.480	0.296	0.199	0.248	0.146
EC	0.575	0.220	0.345	-0.425	0.058	-0.344
SOC	0.182	0.375	0.333	-0.246	0.422	0.460
AN	-0.019	0.563	-0.052	-0.186	0.182	0.562
AP	0.276	0.157	0.305	0.474	-0.317	0.085
AK	0.342	0.167	0.245	-0.172	-0.649	0.176
AS	0.361	0.456	-0.079	-0.322	0.112	-0.504
Zn	0.272	0.502	-0.124	0.354	-0.263	-0.067
Cu	0.411	0.350	0.042	0.332	-0.082	0.158
Fe	-0.109	0.439	-0.217	0.542	0.328	-0.194
Mn	-0.351	0.500	-0.548	-0.107	0.024	0.001

Note. EC: electrical conductivity; SOC: soil organic carbon; AN: available carbon, AP: available phosphorus; AK: available potassium; AS: available sulphur; Zn, Cu, Fe and Mn: DTPA-extractable zinc, copper, iron and manganese, respectively. Values are based on 240 georeferenced soil samples (N=240).

Table 4. Mean values of the soil properties in different management zones

Management Zone (MZ)	Samples	Sand	Silt	Clay	pH	EC	OC	AN	AP	AK	AS	Zn	Cu	Fe	Mn
		%				dSm^{-1}	(%)	kg ha-1						mg kg^{-1}	
MZ1	28	28.73^{a}	53.57^{a}	17.69^{a}	7.98^{a}	0.19^{b}	0.52^{a}	251.21^{a}	19.31^{b}	364.41^{b}	9.63^{a}	1.37^{a}	2.58^{a}	14.31^{a}	13.01^{a}
MZ2	2	25.52^{a}	56.00^{a}	18.48^{a}	8.10^{a}	0.27^{a}	0.53^{a}	241.48^{a}	25.06^{a}	1312.40^{a}	14.18^{a}	1.16^{a}	1.30^{b}	2.34^{b}	2.12^{b}
MZ3	83	28.22^{a}	53.76^{a}	18.02^{a}	8.01^{a}	0.16^{b}	0.53^{a}	241.01^{a}	17.03^{b}	240.00^{c}	11.66^{a}	1.01^{a}	2.26^{ab}	17.73^{a}	12.56^{a}
MZ4	127	31.01^{a}	51.11^{a}	17.94^{a}	8.13^{a}	0.15^{b}	0.51^{a}	238.04^{a}	16.69^{b}	172.52^{d}	9.22^{a}	0.82^{a}	1.96^{ab}	17.38^{a}	11.50^{a}

Note. 1. MZ: management zone; EC: electrical conductivity; SOC: soil organic carbon; AN: available carbon, AP: available phosphorus; AK: available potassium; AS: available sulphur; Zn, Cu, Fe and Mn: DTPA-extractable zinc, copper, iron and manganese, respectively.

2. Values in the same column superscripted with different letters are significantly different (P= 0.05).