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ABSTRACT
The present study was to delineate management zones (MZs) in salt affected Mahakalpada block in eastern India by capturing both spatial variability of soil parameters along with satellite derived Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). Grid wise 237 soil samples collected from the study area were analyzed and spatial maps were generated for physicochemical properties, DTPA extractable micronutrients, i.e. iron, zinc, copper, and manganese and major nutrients, i.e. available nitrogen (AN), phosphorous (AP), and potassium (AK). Soil electrical conductivity and AK showed a high CV of 100% and 56.7%, respectively. Principal component analysis was performed using the soil spatial maps, NDVI and EVI maps and only four principal components which produced eigenvalues > 1 and accounting for 75.4% of the total variability were retained for further analysis. Further, fuzzy c-mean clustering was used to delineate the MZs based on fuzzy performance index (FPI) and normalized classification entropy (NCE) was used for identifying the three MZs. There was a significant difference between MZ1 and MZ2 for all the variables except AN and EVI whereas all the variables were significantly different between MZ1 and MZ3 highlighting the usefulness of MZs delineation technique for site-specific nutrient management.

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Site specific management zones; kriging; geostatistics; fuzzy clustering; enhanced vegetation index

Introduction

Around 147 million hectares (Mha) of land in India is affected by land degradation of which 6.7 Mha land is affected by soil salinity (Sharma et al. 2004). Saline soil is distributed in all the continents and poses a major threat to agriculture and cover approximately 7% of the total land area of the Earth (Ghassemi et al. 1995). Soil salinity prevalent in coastal area is mainly due to seawater ingression and intrusion of saline water to its aquifer. Land degradation is a worldwide problem for which non-sustainable land management may be regarded as a major factor (García-Orenes et al. 2009; Rigueiro-Rodríguez et al. 2012; Thapa and Yila 2012; Zema et al. 2012; Zhao et al. 2013). The crop production in these saline and degraded areas is a challenging task due to heterogeneous and spatial variation in soil fertility. Hence, it is very essential to utilize the modern tools and techniques like geostatistics, kriging and remote-sensing, for analyzing the soil fertility so that crop productivity can be maximized without environmental and soil degradation. Understanding spatial variability of nutrients in soils is

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prerequisite for devising location-specific nutrient recommendation with the aim of better farm economy and increased sustainability in crop production (Behera and Shukla 2015; Tripathi et al. 2015a). Site specific nutrient management can be achieved using new approach of delineating management zones (MZs) for highly variable saline soils. A MZ may be defined as a homogeneous sub-region of a heterogeneous field in which variable rate is used for application of an input (Tripathi et al. 2015b). Management zonation is an effective approach to manage soil heterogeneity at a regional scale (Ferguson et al. 2002; Wang et al. 2009). N fertilizer management using soil N-based MZs was very useful as described by Abdul et al. (2007). The use of MZs was suggested as a substitute to grid soil sampling for analyzing spatial variability of soil properties and recommending variable rate fertilizer application (Fleming et al. 2000).

Identification of MZs by cluster algorithm which is a statistical approach is highly adapted. Arno et al. (2011) found fuzzy c-means algorithms as a better option compared to k-means for delineating MZs. Various authors (Wang et al. 2009; Davatgar et al. 2012; Tripathi et al. 2015b) delineated the MZs by using principal component analysis (PCA) and fuzzy c-means clustering. Most methods for delineating MZs use spatial information sources relating to crop yield. Various authors (Franzen et al. 2002; Tripathi et al. 2015b) used soil properties and other inputs such as aerial photographs, topography factors along with crop yield maps to delineate homogenous MZs in agricultural fields. Several factors are responsible for a healthy crop growth and use of Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) from satellite data during peak crop vegetative stage will be highly useful because these are positively correlated with crop growth and yield. Hence, NDVI and EVI may prove to be most suitable variables for delineating MZs. But very few workers (Boydell and McBratney 1999; Scharf et al. 2002) have used satellite data for MZs delineation. Keeping in view the above background, an attempt was made in this study (i) to characterize the spatial variability of soil pH, EC, macro and micronutrients using the geostatistical analysis and (ii) to delineate potential MZs using PCA and fuzzy c-mean clustering by aggregating spatial variation of soil parameters and real-time crop condition based on NDVI and EVI.

Material and methods

Study area

Mahakalpada block was the study area which spreads over 516 km^2 and inhabits 240 villages, situated in the east coast of India. Figure 1 shows the Mahakalpada block which is located between 20º32′ to 20º50′N and 86º45′ to 87º05′ E. A mean annual temperature of 20.5°C prevails in the study area which is humid and receives about 1400 mm rainfall mainly during July to September. Generally, rice cultivation is practiced in the area only in monsoon season primarily due to absence

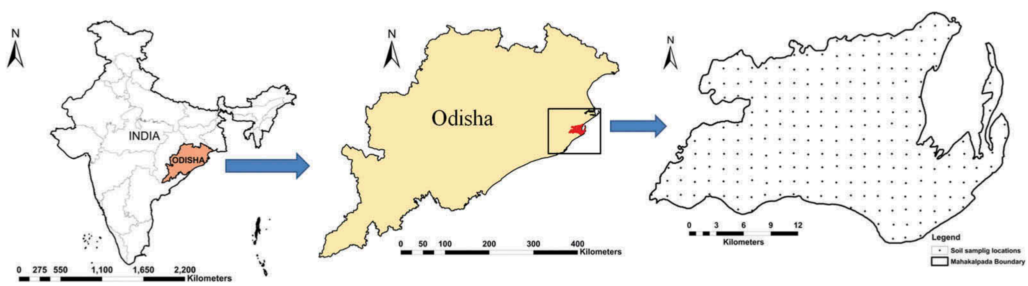

Figure 1. Soil sampling locations in Mahakalpada block of Kendrapada district in coastal Odisha, India.

of irrigation infrastructure and unavailability of freshwater due to saline groundwater. Mostly the farmers apply just nitrogenous fertilizers in less quantity (60 kg ha^{-1} N).

Collection of soil samples

Soil sampling was done on 237 locations in the study area (Figure 1) by following a grid-sampling scheme. Sampling was done from plow layer (0–15 cm). The coordinates of sampling locations were recorded using handheld GPS recorder. Soil samples were air dried in shade and passed through 2 mm sieve.

Analysis of soil properties

Soil samples were analyzed following standard procedures. A soil-water suspension (1:2) was used for measuring the soil pH and EC (Richards 1954). Soil available nitrogen, phosphorus and potassium were estimated using methods of Subbaiah and Asija (1956), Bray and Kurtz (1945) and Black (1965), respectively. DTPA extraction technique (Lindsay and Norvell 1978) was used for estimating iron (Fe), zinc (Zn), copper (Cu) and manganese (Mn) concentration.

Satellite data

The Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices 16-Day L3 Global 250 m in HDF-EOS Data Format (MOD 13Q1) (Huete et al. 1999, 2002) was acquired during peak vegetative stage of rice during the first week of November 2015. Two MODIS vegetation indices, i.e. Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) products were used in this study.

Conventional statistics

Descriptive statistics such as minimum, maximum, mean, standard deviation (SD), coefficient of variation (CV), median, kurtosis and skewness were determined for soil variables. For determining the relationship among nine soil properties, a correlation analysis was performed. Statistical package SAS 9.2 was used for all the statistical analysis.

Geostatistics analysis

Semivariogram modeling was performed for fitting the best semivariogram model for assessing the spatial variation of each soil variable. Best fit semivariogram model was used for ordinary kriging (Krige 1981) to prepare the spatial variability map for each soil variable by interpolation. The accuracy of kriging interpolation was assessed by cross-validation analysis (Schepers et al. 2004). ArcGIS 10 (Geostatistical analyst) was used for semivariogram modeling, kriging and preparing the spatial variability map of soil variables. Spatial dependency of soil properties was assessed based on ratio of nugget to sill as described by Cambardella et al. (1994).

Principal component analysis (PCA)

A multivariate analysis technique, i.e. PCA was used in this study. Principal components (PCs) receiving high eigenvalues best represent the field properties (Schepers et al. 2004). In this study, PCs with eigenvalues ≥ 1.0 were selected for fuzzy clustering (Tripathi et al. 2015b; Shukla et al. 2017).

Fuzzy cluster algorithm

Different unique MZs were delineated using fuzzy k-mean clustering (Brown 1998) by minimizing the within-group variability while maximizing the among-group variability for creating homogenous groups. In this study, FuzMe software was used to divide the study area into 2–8 clusters (Minasny and Mc Bratney 2006) using Fuzzy k-mean (as suggested by De Gruijter and Mc Bratney 1988; Wang et al. 2009). The details for the iteration process of the model used for this study was same as mentioned by various researchers (Minasny and Mc Bratney 2006; Tripathi et al. 2015b). Similar settings for the FuzME software were used following Fridgen et al. (2004) and Reyniers et al. (2006). For deciding the optimum clusters, Fuzzy performance index (FPI) (Mc Bratney and Moore 1985; Boydell and Mc Bratney 1999) and normalized classification entropy (NCE) (Bezdek 1981) were used:

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

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

where c = number of cluster; n = number of observations; μ_{ik} = fuzzy membership; $\log_a$ = natural logarithm. Degree of fuzziness was measured by FPI, values for which may range from 0 (indicating distinct classes) to 1 (indicating no distinct classes). Similarly, NCE gives an account of disorganization produced by different clusters. When FPI and NCE reach at their minimum, optimum number of clusters are identified (Fridgen et al. 2004). For indicating the heterogeneity among different MZs, analysis of variance was used.

Results

Descriptive statistics of soil properties

The descriptive statistics for the nine soil variables studied are listed in Table 1. The soil pH which varied from 3.7 to 5.5 for the study area was in acidic range. A high CV of 100% for soil EC (1:2) was recorded which varied from 0.1 dS m^{-1} in western part to maximum of 10.4 dS m^{-1} in eastern part of the study area, nearer to coast. Similar to EC, available potassium (AK) in soil varied from 93 kg ha^{-1} to 1139.4 kg ha^{-1} with a high CV (56.7%). Nitrogen deficiency in soil was prevalent in study area as evident from the low Available nitrogen content in soil. Among major soil nutrients, AP had the highest CV. Among all the nine soil variables, lowest CV (7.1%) was recorded for pH, whereas DTPA extractable Mn had the highest CV (160.4). Except EC, AP, Zn and Mn, medians for all other variables were close to their means (Table 1). Considerable spatial variability of soil properties was evident from the high CV and also from the spatial maps (Figure 2).

Table 1. Descriptive statistics of soil properties.

Variables	Min	Max	SD	Mean	Median	CV (%)	Skewness	Kurtosis
pH (1:2)	3.67	5.46	0.31	4.43	4.45	7.1	0.15	0.19
EC (1:2) (dS m^{-1})	0.13	10.36	1.88	1.88	1.40	100	2.18	6.51
AN (kg ha^{-1})	33.03	238.34	44.55	111.16	105.27	40.1	0.36	0.59
AK(kg ha^{-1})	93.01	1139.42	241.17	425.63	353.65	56.7	1.27	1.09
AP (kg ha^{-1})	2.97	67.05	11.15	17.80	15.75	62.7	1.54	4.08
Zn (mg kg^{-1})	0.23	10.26	1.37	0.93	0.71	148.1	6.08	38.63
Fe (mg kg^{-1})	11.75	81.40	12.74	33.43	30.57	38.1	0.90	1.29
Cu (mg kg^{-1})	0.42	4.45	0.79	2.72	2.89	29	−0.57	0.64
Mn (mg kg^{-1})	0.23	77.85	11.96	7.45	2.81	160.4	4.03	20.76

EC: Electrical conductivity; AN: available nitrogen; AK: available potassium; AP: available phosphorous; Fe, Zn, Cu and Mn represent DTPA extractable iron, zinc, copper and manganese in soil, respectively; CV: Coefficient of variation.

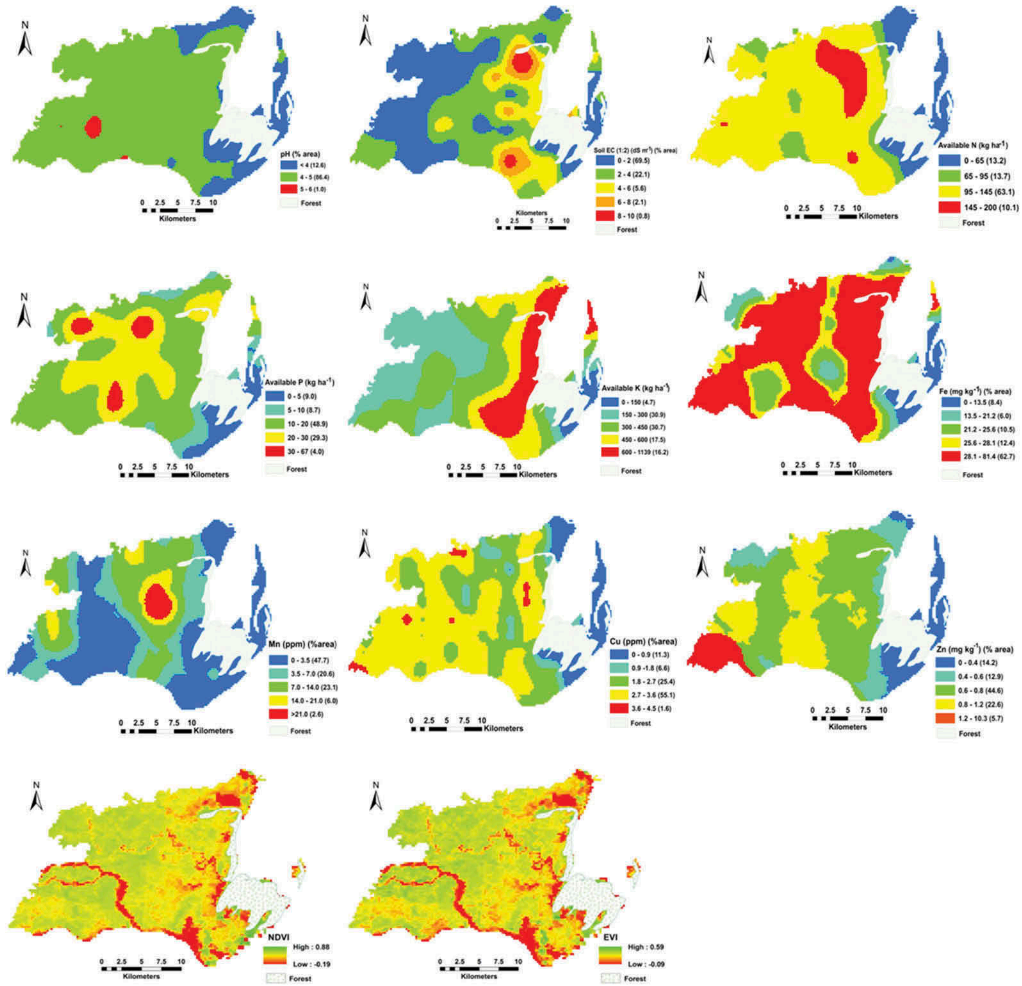

Figure 2. Maps of spatial distribution for nine soil properties, Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) maps for the study area. EC: soil electrical conductivity; AN: available nitrogen; AK: available potassium: AP: available phosphorous; Fe, Zn, Cu and Mn are DTPA extractable iron, zinc, copper and manganese in soil; Values in parenthesis in legends represents the % area for that particular legend class.

Correlation among soil properties and crop growth indicators, i.e. NDVI and EVI are presented in Table 2. It is evident that both NDVI and EVI were significantly correlated with soil properties (except EC and AK). Similarly, AK has negative correlation. EC showed high correlation with AK which was obvious. Except few, almost all of the variables were significantly correlated among each other.

Geostatistics analysis for the soil properties

Geostatistical analysis using Geostatistical Analyst of ArcGIS was performed for identifying the best fit semivariogram models. The best fit semivariogram models for EC, AN, Zn and Mn were spherical models whereas tetraspherical model was found suitable for AP and Fe. The parameters for these semivariogram models are listed in Table 3. Ordinary Kriging technique was used for interpolation of soil properties into 250 m grid cell to represent the nine soil variables on the same spatial resolution as NDVI and EVI. A strong spatial dependence was seen for pH, EC, AN and Zn (nugget/sill ratio <

Table 2. Correlation matrix of the soil properties in the study area.

	pH	EC	AN	AP	AK	Fe	Zn	Cu	Mn	EVI	NDVI
pH	1										
EC	0.10**	1									
AN	0.76**	0.19**	1								
AP	0.70**	−0.04**	0.49**	1							
AK	0.26**	0.55**	0.14**	0.09**	1						
Fe	0.68**	0.36**	0.56**	0.43**	0.56**	1					
Zn	0.38**	−0.04**	0.35**	0.16**	0-.03**	0.34**	1				
Cu	0.80**	0.17**	0.76**	0.48**	0.09**	0.64**	0.41**	1			
Mn	0.32**	0.10**	0.60**	0.24**	−0.02	0.17**	0.06**	0.27**	1		
EVI	0.11**	−0.02	0.11**	0.15**	−0.07**	0.04**	0.01	0.07**	0.06**	1	
NDVI	0.13**	−.024*	0.12**	0.17**	−0.08**	0.07**	0.08**	0.11**	0.05**	0.53**	1

EC: Electrical conductivity; AN: available nitrogen; AP: available phosphorous; AK: available potassium; Fe, Zn, Cu and Mn represent DTPA extractable iron, zinc, copper and manganese in soil, respectively; EVI: Enhanced Vegetation Index; NDVI: Normalized Difference Vegetation Index. (**. Correlation is significant at the 0.01 level; *. Correlation is significant at the 0.05 level)

Table 3. Semivariogram models for soil variables.

S. No.	Soil Variable	Model type	Sill	Nugget	Nugget/Sill	Range (m)
	pH	Stable	0.77	0.15	0.20	5175
	EC	Spherical	2.77	0.20	0.07	4950
	AN	Spherical	2178.25	232.96	0.11	5004
	AP	Tetraspherical	83.42	31.89	0.38	4096.80
	AK	Gaussian	47,280	17,754	0.38	6425
	Zn	Spheirical	0.817	0.12	0.14	3966
	Fe	Tetraspherical	182.05	74.17	0.41	9215
	Cu	Gaussian	0.63	0.34	0.54	4096
	Mn	Spherical	83.54	43.60	0.52	7963

EC: Electrical Conductivity; AN: available nitrogen; AK: available potassium; AP: available phosphorous; Fe, Zn, Cu and Mn represent DTPA extractable iron, zinc, copper and manganese in soil, respectively.

25%) (Table 3). Other soil properties showed moderate spatial dependence (nugget/sill ratio as 25–75%).

The maps of spatial variability for all soil properties are depicted in Figure 2. Comparatively, high levels of AK and soil salinity was recorded in the areas near sea coast and low AK content and soil EC was found in the areas away from sea coast, whereas reverse trend was recorded for AN, AP and all micronutrients contents (Figure 2).

In the present study, NDVI and EVI from MODIS satellite data were used to reflect the status of crop growth. The NDVI and EVI images at the maximum vegetative growth stage of rice are given in Figure 2. The north-west and south-west part of the study area were having low soil EC and higher NDVI values, whereas, lower NDVI values were recorded in the east and north-east part, where higher soil EC was observed. For EVI also similar trend was observed.

Principal component analysis

Principal Component Analysis (PCA) was performed for aggregating and summarizing the spatial variation in the 11 variables which included nine soil properties, NDVI and EVI, considered for this study. Only four principal components which produced eigenvalues greater than 1 and accounting for 75.4% of the total variability were retained for further analysis (Table 4). Maps for the four PCs are shown in Figure 3. Principal component 1 (PC 1) dominated by pH, AN, Fe and Cu, explained 37.8% of the total variability (Table 4). Consequently, the spatial maps of pH, AN, Fe and Cu were same as the kriged map of PC 1. The second PC (PC 2) dominated by AP explained 16.1% of total variance and there was a similarity between the kriged map of PC2and map of AP. The PC3 (dominated by EC and AK) and PC4 (dominated by Mn) explained additional 12.2% and 9.5% of total variance, respectively.

Table 4. Principal component analysis of the variables and loading coefficients for the first four principal components.

Principal component	Eigenvalues	Component loading (%)	Cumulative loadings (%)
PC 1	4.13	37.57	37.57
PC 2	1.78	16.14	53.71
PC 3	1.34	12.19	65.89
PC 4	1.05	9.54	75.43
PC 5	0.83	7.54	82.96
PC 6	0.51	4.59	87.55
PC 7	0.50	4.50	92.05
PC 8	0.39	3.58	95.63
PC 9	0.23	2.11	97.74
PC 10	0.14	1.28	99.01
PC 11	0.11	0.99	100.00

PC loadings for each variable

	pH	EC	AN	AP	AK	Fe	Zn	Cu	Mn	NDVI	EVI
PC1	0.92	0.29	0.87	0.67	0.36	0.81	0.45	0.86	0.46	0.19	0.17
PC2	0.07	−0.68	0.09	0.26	−0.74	−0.32	0.17	0.07	0.17	0.52	0.51
PC3	−0.10	0.38	−0.15	−0.01	0.38	0.12	−0.29	−0.17	−0.15	0.65	0.67
PC4	−0.08	0.18	0.26	−0.02	−0.07	−0.21	−0.53	−0.11	0.77	−0.08	0.00

EC: Electrical Conductivity; AK: available potassium; AP: available phosphorous; AN: available nitrogen; Fe, Zn, Cu and Mn represent DTPA extractable iron, zinc, copper and manganese in soil, respectively; NDVI: Normalized Difference Vegetation Index; EVI: Enhanced Vegetation Index.

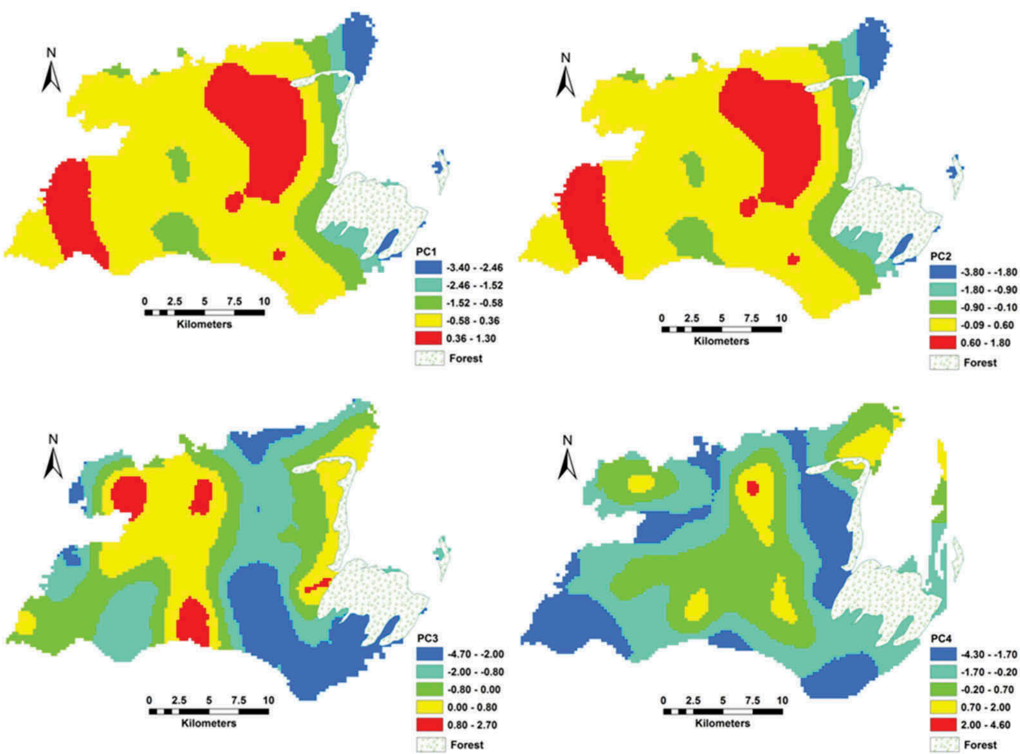

Figure 3. Maps of four Principal components produced by principal component analysis.

Delineating MZs by clustering analysis

Principal component scores for the first four PCs were used for performing the fuzzy c-means clustering using FuzMe software for dividing study area into MZs. FPI and NCE were plotted against

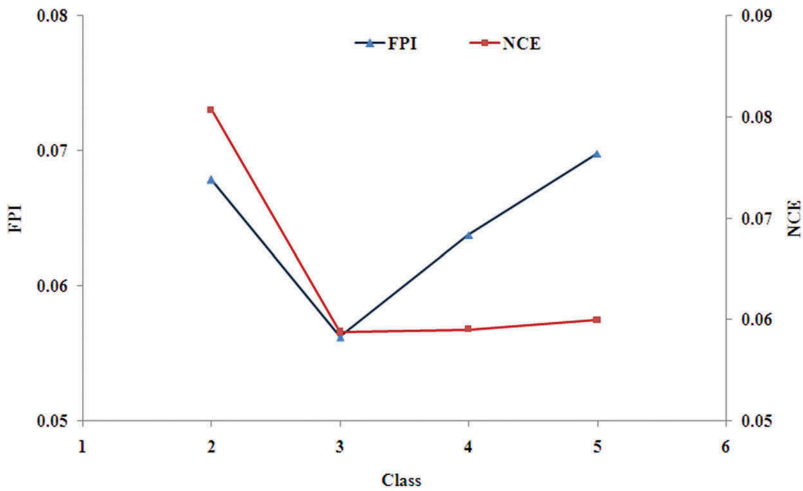

Figure 4. Fuzzy performance index (FPI) and normalized classification entropy (NCE) calculated for the study area for identifying the optimum number of clusters.

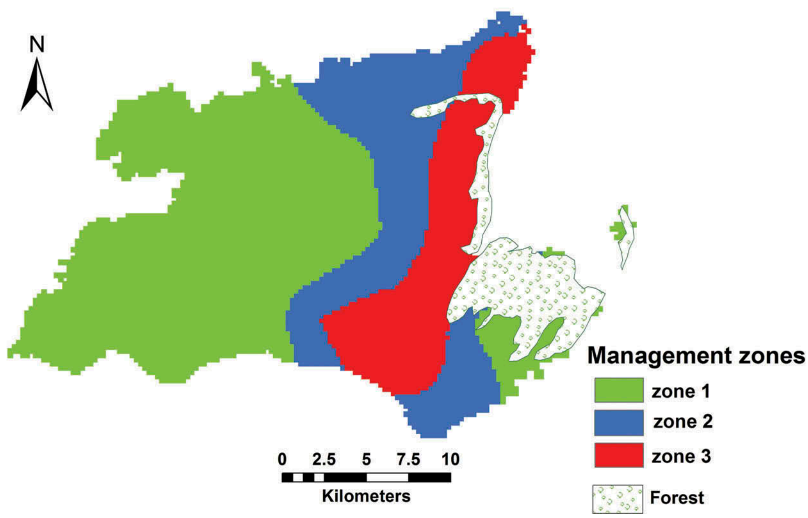

Figure 5. Management zones map for three clusters.

the number of classes and optimum number of clusters was determined as three when both the indices, i.e. FPI and NCE were minimum (Figure 4). The resulting MZs map is shown in Figure 5. A t-test was performed for assessing the effectiveness of this methodology for delineating the MZs. It was evident from the t-test (Table 5) that there was heterogeneity in different variables among different MZs. A significant difference (p < 0.05) between MZ1 and MZ2 was recorded for all the variables except AN and EVI whereas all the variables were significantly different between MZ1 and MZ3.

NDVI, EVI along with soil properties for delineating MZs

The resultant MZs map showing three MZs is illustrated in Figure 5. Significant difference among the mean values of variables of three MZs was seen when t-test was performed to assess the

Table 5. Soil pH, Electrical conductivity and nutrient status in management zones.

	pH	EC (1:2) (dS m^{-1})	AN (kg ha^{-1})	AP (kg ha^{-1})	AK (kg ha^{-1})	Zn (mg kg^{-1})	Fe (mg kg^{-1})	Cu (mg kg^{-1})	Mn (mg kg^{-1})	NDVI	EVI
Zone 1	4.09a	1.27c	104.58a	19.85a	381.85b	0.74c	31.09a	2.53a	6.40a	0.60a	0.33b
Zone 2	3.88b	1.78a	103.61a	15.44b	397.74a	0.85b	29.95b	2.34b	5.99b	0.58b	0.32b
Zone 3	3.88b	1.55b	92.51b	15.29b	394.58a	0.94a	29.91b	2.15c	4.66c	0.57c	0.31c

Values in a column followed by different letters are significantly different at $p < 0.05$; EC: Electrical Conductivity; AN: available nitrogen; AK: available potassium; AP: available phosphorous; Fe, Zn, Cu and Mn represent DTPA extractable iron, zinc, copper and manganese in soil, respectively; NDVI: Normalized Difference Vegetation Index; EVI: Enhanced Vegetation Index.

heterogeneity among three MZs classes (Table 5). The AN content was low whereas AK content was sufficient in all the three MZs. Significant difference was recorded in AP levels between Zone 1 and other two zones. In this study, satellite derived NDVI and EVI data were used for assessing the crop condition along with the soil properties, which forms a robust method for delineating the MZs.

Discussion

A high CV of 100% for soil EC (1:2) in the study area may be due to narrow creeks and estuaries which are prevalent near the eastern coast of India. The high tides in these estuaries and creeks resulted in intrusion of saline water to freshwater river and also causes the increase in topsoil salinity mainly in dry season (January to May) near the sea coast. Moreover, different crop management practices followed may have resulted in high spatial variation in soil EC at smaller distances. Mahmut and Cevat (2003) also recorded high coefficients of variations (CVs) of EC. A high CV (56.7%) recorded for available potassium (AK) in soil may be due to presence of K^+ ions introduced through KCl and K_2SO_4 salts present in saline water which may have created high AK concentration in the soils. Nitrogen deficiency in soil may be attributed to low organic carbon as well as less or no application or very less application of fertilizers. Among major soil nutrients, AP had the highest CV which may be attributed to diverse land use pattern and heterogeneous soil and crop management practices followed in the study area. Our findings were similar to Karaman et al. (2001), who recorded that among soil properties, AP was more variable compared to others. Considerable spatial variability of soil properties was evident from the high CV and also from the spatial maps (Figure 2). Hence, the site specific nutrient management by creating soil nutrient MZs may be a better option for improving the crop productivity.

It is evident that both NDVI and EVI were negatively correlated with EC because soil salinity is one of the factors for reduced growth of crops in coastal saline areas. Similarly, AK has negative correlation because AK is not a limiting factor and it is almost in the high range in all over the study area. EC showed high correlation with AK which was obvious. Principal component analysis was performed for summarizing the sources of variability in the data.

Spherical model was the best fit semivariogram models for soil variables except AP and Fe, which is similar to findings of other researchers (Lopez-Granados et al. 2002; Liu et al. 2008; Jiang et al. 2012) who also reported that spherical model was best fitted for most of the soil properties studied. As Goovaerts (1997) suggested, the soil properties under study had spatial autocorrelation for which proximity to creeks or river soil and crop management practices, cropping and farming systems practiced may be responsible. A strong spatial dependence for pH, EC, AN and Zn (nugget/sill ratio < 25%) may be attributed to several factors such as proximity of the study area to sea coast, presence of many creeks, diverse soil and crop management practices. Moderate spatial dependence (nugget/sill ratio as 25–75%) for other soil variables may also be due to soil fertilization, different cropping systems and agricultural methods, and prevailing hydrological situation in this region. Similar results were reported by several authors (Amirinejad et al. 2011; Jiang et al. 2012). Further, the large nugget showed by AN, AP, AK, Fe and Mn may be due to nutrient cycling pattern, differences in hydrological behavior, interaction between biotic and abiotic factors.

Nitrogen content in almost all the areas was low because farmers do not apply chemical fertilizers or apply in very less quantity. Due to heterogeneous management of cultivated rice fields in the area and no incorporation of residues and organic manures in the field, the organic carbon content is also low which may be another reason for low AN content.

Indices like Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are used to monitor crop growth because these are positively correlated to crop cover, leaf area index and crop biomass. Lower NDVI and EVI values in the east and north-east part may be due to higher soil EC which affects negatively to crop growth. The unusual high NDVI and EVI values in south-east part near coast were due to permanent vegetation and forest areas. As an important index to reflect crop acreage and growth, NDVI and EVI images along with distributions map of AN, AP, AK, pH, Fe, Cu, Mn, Zn (Figure 3) were used in PCA to reduce the dimensionality into four transformed principal component images. The similar concept was used by (Li et al. 2007) in which NDVI was used along with EC, TN, OM and CEC to reduce the dimensionality into two principal components.

Principal component 1 (PC 1) dominated by pH, AN, Fe and Cu, has similar spatial map as the spatial maps of pH, AN, Fe and Cu. Similarly, the map of other principal components was similar to spatial maps of soil variables dominating respective PCs.

The use of MZs which are easy to understand, may help farmers for site-specific nutrient recommendation for increasing crop productivity instead of using a single recommendation for the whole area. Considering the mobility of soil nutrients in soil especially nitrogen, real time in season satellite data, i.e. NDVI and EVI may be immensely useful to improve upon the soil fertility based MZs for recommending variable fertilizer application for efficient site-specific nutrient management. Further studies need to be undertaken according to the cropping system followed in the area for addressing the temporal variability in soil properties and crop growth condition in the field while delineating the MZs.

Various researchers (Wang et al. 2009; Davatgar et al. 2012; Shukla et al. 2017) also conducted analysis of variance and found significant difference among different MZs. The farmers in the study area mostly cultivate rice for so many years without adding very little or no chemical fertilizers hence the soil AN was low in all the three MZs. The less salinity in zone 1 may be attributed to less intrusion of saline water through subsurface flow and also through creeks, which is prevalent in zone 2 and 3. DTPA extractable Fe, Zn, Mn and Cu content were not limitations for the growth and development of rice crop, but a high variability was recorded for these nutrients in three zones (Doberman and Fairhurst 2000).

In this study, satellite derived NDVI and EVI data were used for assessing the crop condition along with the soil properties, which forms a robust method for delineating the MZs. This needs to be further strengthened by using multiple year satellite data and soil data for assessing the temporally stable properties and help in identifying the properties which are more variable with space and time. Salinity alone is not the yield governing factor as evident from the NDVI and EVI values of Zone1 and Zone 2 which further enhances the need for delineating MZs for identifying the spatial variation of soil properties and crop condition.

Conclusion

In this study, nine soil properties and satellite derived NDVI and EVI data having information for real time crop condition were used and study area was classified into three MZs. Geostatistical analysis was used to create spatial variability map whereas principal component analysis was used to reduce the dimensionality and fuzzy c-means clustering algorithm finally was used to classify the study area into an optimum number of clusters. The present study revealed a wide variation in the values of the soil properties in the study area. Soil EC was negatively and significantly correlated with NDVI which depicts the crop growth condition. Low available nitrogen content in soil was a major limitation for higher crop productivity hence nitrogen management was most crucial for enhancing the rice production. Being simple and economically feasible, farmers may easily adopt the concept of MZs for implementing site-specific fertilizer recommendation based on the mean values of soil nutrients in each zone for maximizing the rice productivity which will ultimately increase the farmer's income.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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