

Assessment of spatial variability of soil properties using geospatial techniques for farm level nutrient management

Duraisamy Vasu^{a,*}, S.K. Singh^a, Nisha Sahu^a, Pramod Tiwary^a, P. Chandran^a, V.P. Duraisami^b, V. Ramamurthy^c, M. Lalitha^c, B. Kalaiselvi^c

^a ICAR - National Bureau of Soil Survey and land Use Planning, Nagpur, Maharashtra 440 033, India

^b Directorate of Natural Resource Management, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu 641 003, India

^c Regional Centre, ICAR - National Bureau of Soil Survey and land Use Planning, Bengaluru, Karnataka 560 024, India

ARTICLE INFO

Article history:

Received 31 July 2016

Received in revised form 11 January 2017

Accepted 12 January 2017

Available online 1 February 2017

Keywords:

Deccan plateau

Geostatistical techniques

Site specific nutrient management

Spatial variability

Soil fertility

ABSTRACT

Crop productivity under rainfed farming systems in India is low due to poor water and nutrient management. The available small scale information of soil nutrients is inadequate to effectively manage individual farms held by small and marginal farmers. Large scale spatial variability assessment using grid sampling method is a feasible option to identify critical nutrient deficiency zones. The present study was conducted in a part of semi-arid tropical Deccan plateau region, India, to assess the spatial variability of soil pH, organic carbon (OC), soil available nitrogen (N), phosphorus (P), potassium (K) and sulphur (S). A total of 1508 composite samples (0–15 cm) were collected by adopting 325 × 325 m grid interval (one sample for 10 ha area) and they were analysed for soil fertility parameters. Coefficient of variation (CV) indicated that OC, N, P, K and S were high in heterogeneity (CV > 35%). Moreover, pH, P, K and S were non-normally distributed and log transformation produced normalised dataset. The semivariogram parameters (nugget to sill ratio, range and slope) indicated that the spatial distribution of soil properties were inconsistent. The spatial variability of parameters were mapped by ordinary kriging using exponential (pH and OC) and spherical (N, P, K and S) models selected based on root mean square error (RMSE) and r^2 values. Multi-nutrient deficiencies were observed in most parts of the study area and N was acutely deficient. Farm level nutrient availability status was derived from spatial variability maps and critical nutrient deficiency zones were identified. Nutrient management recommendations based on soil test results were delivered to farmers for adopting need based variable rate of fertilizer application. The generated maps can serve as an effective tool for farm managers and policy makers in site specific nutrient management.

© 2017 Elsevier B.V. All rights reserved.

1. Introduction

Indian agriculture is predominantly rainfall dependent and rainfed farming contributes 45% to the total food grain production. Among the total cultivated area of 141 million hectare (M ha), 61% (86 M ha) is under rainfed farming (Srinivasarao et al., 2015). The Deccan plateau covers an area of 0.42 million km² in central and southern parts of India and is characterised by semi-arid tropical (SAT) climate (Vasu et al., 2016b). Crop productivity is low in most parts of this region with an average of less than 1600 kg ha⁻¹ (ICAR, 2011) due to poor water availability and soil fertility (Sahrawat and Wani, 2013). The SAT soils are low in organic carbon (~0.5%) due to

oxidation enhanced by hyperthermic soil temperature regime and low biomass addition. They are also low in available nitrogen, phosphorus, potassium and sulphur (Sahrawat et al., 2010). The adverse effect of SAT environment is also pronounced in the form of natural soil degradation indicated by increase in subsoil sodicity (Pal et al., 2016), accelerated soil erosion and multi nutrient deficiency (Chauhan et al., 2014).

In general, the rate of fertilizer application is low under rainfed conditions due to uncertain water availability. The deficiencies of major nutrients are considered important but minimum research effort was made to identify the spatial extent of their deficiencies in SAT soils of India (Sahrawat et al., 2013; Sahrawat, 2016). On-farm soil fertility testing across different states in Indian SAT areas during 2001–2012 showed widespread deficiencies of sulphur (46–96%), phosphorus (21–74%) and nitrogen (11–76%) (Sahrawat et al., 2010). Therefore, diagnosis of nutrient related limitations

* Corresponding author.

E-mail address: d.plantdoctor@gmail.com (D. Vasu).

and their management assumes a greater significance to sustain or improve the crop productivity. Assessment of spatial variability of available soil nutrients is a viable option to identify and delineate critical nutrient deficiency zones. This will enable farm managers to strategize site specific nutrient management (SSNM) based on soil and crop requirements.

Large scale mapping was recommended to identify nutrient deficiencies at farm level (Vasuki, 2010). The spatial variability of soil properties can be mapped using interpolation technique (Cambardella and Karlen, 1999). For example, spatial variability of organic matter, pH and potassium were mapped using kriging by Lopez-Granados et al. (2005) in a 40 ha field located in southern Spain. Soil pH, electrical conductivity, organic carbon and exchangeable bases varied highly in acid soils of India (Behera and Shukla, 2015). Using spline method of interpolation, Patil et al. (2011) mapped the spatial variability of organic carbon, available N, P and K of Karlawad village in Dharwad district of Karnataka and found that except K all properties varied to great extent. Thus, geostatistical tools can be effectively used to map soil fertility parameters. However, with fertilizers becoming expensive, farm level information such as farm size, number of crops cultivated in a year, and level of management hold importance in quantifying the farm nutrient use efficiency (Cherry et al., 2012). In the present study, we used farm level information from all the 19 villages of the study area with spatial variability maps for identifying critical nutrient deficiency zones. The study was carried out in a part of

Deccan plateau region with the objectives: (i) to assess the status of soil pH, organic carbon, available N, P, K, and S; (ii) to study the spatial variability of soil fertility parameters, and (iii) to identify critical nutrient deficiency zones for site specific nutrient management.

2. Materials and methods

2.1. Study area, soil sampling, and analysis

The study area, Thimmajipet (16° 35' to 16° 44' N latitude and 78° 07' to 78° 18' 3 E longitude) is located 100 km south from Hyderabad city, and part of Mahabubnagar district, Telangana, India. It comprises of 19 villages, and covers an area of 215 km². The total cultivated area is 15,020 ha with 13,123 farm holdings. The average size of farm holding is 1.2 ha and 68% of the farmers belong to small and marginal category (≤ 2 ha). The major crops grown during southwest monsoon season (June–September) are cotton (*Gossypium hirsutum*), maize (*Zea mays*), pigeon pea (*Cajanus cajan*), sorghum (*Sorghum bicolor*), and castor (*Ricinus communis*). In winter season (October–January), groundnut (*Arachis hypogaea*) is the major crop followed by rice (*Oryza sativa*). The mean temperature is 36 and 25°C during summer and winter, respectively. The mean annual rainfall (MAR) is 550 mm which mostly occurs during southwest monsoon (Vasu et al., 2016a). The data on cultivated area of major crops for both monsoon and winter

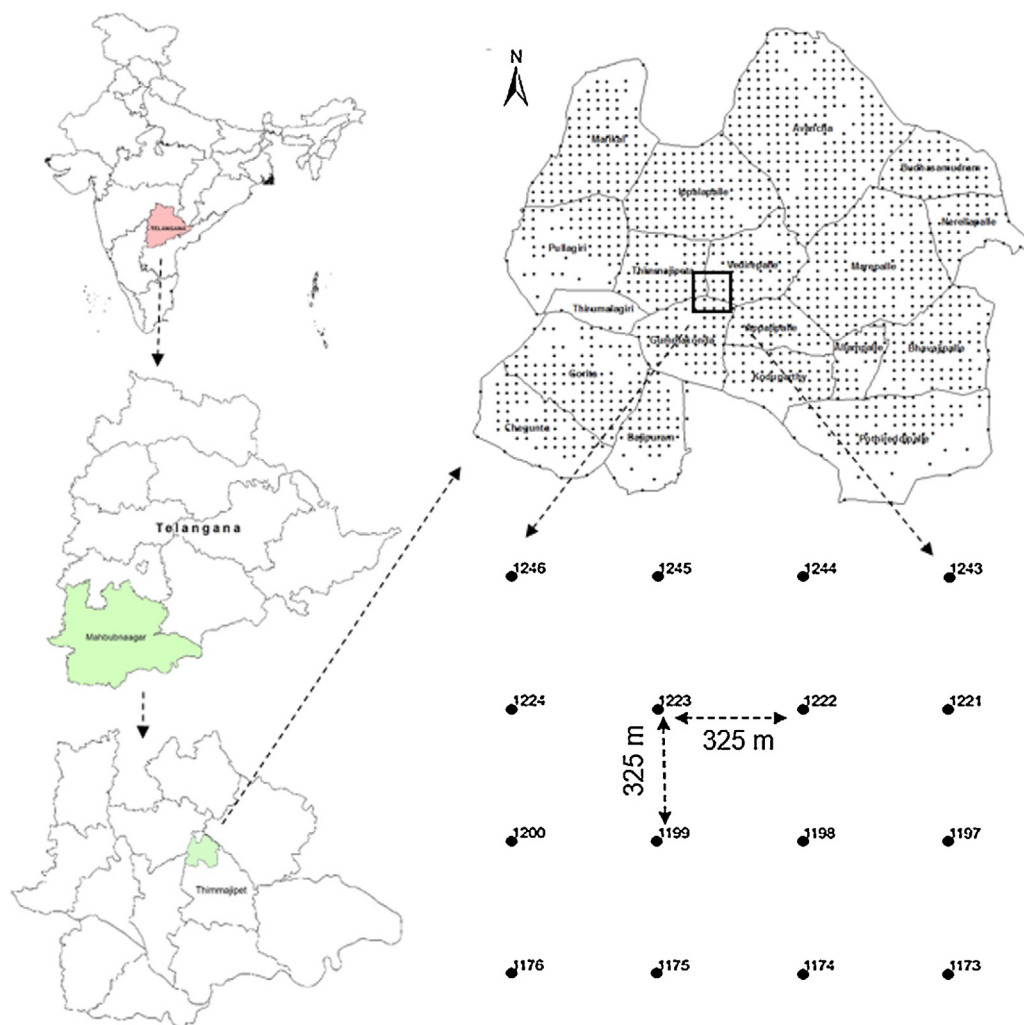


Fig 1. Location of study area and adopted grid sampling scheme.

seasons were obtained from the Department of Agriculture, Government of Telangana, Hyderabad for the period of five years (2009–2014) and the average cultivated area in each village was calculated.

Georeferenced soil samples (0–15 cm) were collected during the month of February 2015 after the harvest of winter crops by grid method. The grid interval was fixed based on the operational guidelines given by Department of Agriculture and Cooperation, Ministry of Agriculture, Government of India (DoAC, 2014; nmsa.dac.gov.in). It recommended 10 and 2.5 ha grid interval for rainfed and irrigated farming systems, respectively. The total cultivated area was divided into grids of 10 ha area (325 × 325 m interval) and a total of 1508 composite samples were collected (Fig. 1). The samples were labelled, air dried and sieved through 2 mm sieve for analysis of soil fertility parameters. The samples were sieved through 100 mesh sieve (0.5 mm) for determining organic carbon (OC) (Walkley and Black, 1934). Soil pH was measured with 1:2 soil water ratio. Soil available nitrogen (N) was estimated by the method of Subbiah and Asija (1956); available phosphorus (P) by Olsen et al. (1954) for neutral and alkaline soils (pH > 6.5) and by Bray and Kurtz (1945) for acid soils (pH < 6.5). Soil available potassium (K) was extracted by 1 N ammonium acetate (pH 7.0) and estimated in flame photometer by the method of Schollenberger and Simon (1945). Available sulphur (S) was extracted by 0.15% CaCl₂ (Williams and Steinbergs, 1959) and measured by turbidimetry method (Chesnin and Yien, 1950) using UV spectrophotometer (Shimadzu UV-2600, A116652).

2.2. Statistical and geostatistical analysis

Descriptive statistics of the analysed soil data viz., minimum, maximum, mean, standard deviation, coefficient of variation, and skewness were determined using STATISTICA 10.0. Normality tests were conducted using Quantile–Quantile (Q–Q) plots and based on skewness, the data of soil fertility parameters were log transformed to normalise the distribution wherever found necessary (Goovaerts et al., 2005). The spatial variability of soil fertility parameters were estimated using geostatistics tool in ArcGIS 10.1 for windows. The structure of the spatial variability was assessed by calculating semivariograms by the formula (Lark, 2000):

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

Modelled semivariograms are directional in the present study. Hence, anisotropy of semivariograms were checked using Geo-statistical Analyst in ArcGIS and the optimum parameters were calculated as described by Bogunovic et al. (2014).

2.3. Spatial variability mapping

Spatial variability of soil fertility parameters were mapped by kriging interpolation method. Circular, Spherical, Exponential, and Gaussian models were tested. Root Mean Square Error (RMSE)

technique was used to select the best kriging model (Li et al., 2011). The RMSE was calculated using the following formula:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N \{z(\chi_i) - \hat{z}(\chi_i)\}^2}$$

The spatial prediction of the values of soil properties at an unsampled point is estimated by the formula (Chilés and Delfiner, 1999):

$$Z(\chi_0) = \sum_{i=1}^n \lambda_i Z(\chi_i)$$

The nugget variance was used to define distinct classes of the spatial dependence for the soil parameters. If the nugget to sill (N:S) ratio was less than or equal to 0.25, the parameter is considered strongly spatially dependent (S); if the ratio was between 0.25 and 0.75, the parameter was considered moderately spatially dependent (M); and if the ratio was greater than 0.75, the variable was considered weakly spatially dependent (W) (Cambardella et al., 1994). If the slope of the semivariograms was close to zero, regardless of the nugget ratio, the variable was considered to be randomly distributed (R).

3. Results and discussion

3.1. Descriptive statistics and distribution of soil fertility parameters

The descriptive statistics of the soil fertility parameters are presented in Table 1. The variability was interpreted using the coefficient of variation (CV). The criteria proposed by Wilding (1985) was used to classify the parameters into most (CV > 35%), moderate (CV 15–35%) and least (CV < 15%) variable classes. Accordingly, OC, N, P, K and S were the most variable and pH was moderately variable. In general, pH and OC are considered to be stable soil parameters (Bouma and Pinke, 1993). However, the moderate (pH) to high variability (OC) observed in this study could be attributed to pedogenic processes influenced by the micro-topographical variations (Vasu et al., 2016b). The CV value observed in the present study is similar to the results of Fu et al. (2010), who recorded CV for P (68%) and K (60%) in a dairy farm in south-eastern Ireland but the values are higher than the observations recorded by Bogunovic et al. (2014) for P (22%) and K (34%). The normality of the distribution was interpreted from the results of Q–Q plots. Organic carbon and N were normally distributed whereas pH, P, K and S were non-normally distributed. The data of pH, P, K and S were log transformed which reduced the skewness (Table 1) and normalised their distribution.

The distribution of OC and N were lined up with the straight lines and the skewness (right for OC; left for N) was caused by few outliers. The distribution of pH followed a pattern. The high degree of variation in the slope of K and S indicate strong skewness. This was caused by the extreme soil test K values of 4 samples (1401, 1453, 1576, 3210 kg ha^{−1}) which could be considered as outliers.

Table 1
Descriptive statistics of soil fertility parameters.

Properties	Min	Max	Mean	Std. Dev	CV	skewness	skewness ^b	Normality test
pH	5.5	10.3	6.84	1.18	17.3	2.885	−0.003	Y = 6.8438 + 1.1669*x ^a
OC (%)	0.11	1.61	0.79	0.34	42.6	0.128	–	Y = 0.79 + 0.3339*x
N (kg ha ^{−1})	32.5	497.7	183.1	88.1	48.1	0.528	–	Y = 183.1593 + 86.1324*x
P (kg ha ^{−1})	4.3	88.9	34.9	20.6	59.0	1.812	0.105	Y = 38.4967 + 21.809*x ^a
K (kg ha ^{−1})	36.9	3210.0	291.6	236.0	71.0	12.418	0.889	Y = 234.8838 + 149.0702*x ^a
S (mg kg ^{−1})	0.17	224.0	28.5	27.4	92.9	7.191	0.498	Y = 20.1206 + 16.703*x ^a

^a distribution not normal.

^b after log transformation.

Similar to the findings of the present study, [Sahrawat \(2016\)](#) also reported high available K values as high as 3750 kg ha^{-1} in SAT soils and this could be attributed to the presence of almost unweathered biotites in both silt and clay fractions which release fairly high amount of K ([Pal et al., 1993, 2014](#)). Similarly, soil test values of sulphur for 16 samples ranged from 106 mg kg^{-1} to 224 mg kg^{-1} . These extreme soil test values may not always be an outlier but a form of natural or management induced variation. However, the presence of the outliers in the dataset might change the structure of semivariograms and its properties. Outliers can cause distortion that violates geostatistical theory ([Barnett and Lewis, 1994](#)) and make variogram erratic ([Armstrong and Boufassa, 1988](#)). The nutrients K and S showed high heterogeneity in contrast to other properties. Hence, the outlier values were replaced by maximum values for K and S to avoid the negative influence of outliers on semivariograms. After removing the outlier, the CV changed from 71.0 to 58.7, and from 92.9 to 66.4 for K and S, respectively. The skewness was also reduced ([Table 1](#)) post outlier removal. These changes are the reason for removing the outlier in order to obtain the characteristics of majority of data. It can be controversial how to deal with outliers and if they are not estimation errors, they need to be included if possible ([Fu et al., 2010](#)). But their influence should be limited. Thus, it can be argued that it is one of the limitation of the geostatistical model to accommodate the outliers in spatial variability mapping.

3.2. Spatial variability of soil fertility parameters

The extensive variability of soil nutrients warranted categorisation of soil fertility parameters into different classes in order to identify and delineate areas with their deficiency for their effective management. They were grouped into various classes based on range which represent their magnitude in soil and the area of each class were estimated. The frequency distribution of fertility parameters with their estimated area are presented in [Table 2](#). Soil pH varied from slightly acidic (40%) to neutral (47.6%) and

12.3% of the total area was slightly alkaline. The variation in the pH could be attributed to nature of parent material, micro topography and type of fertilizer used. The acidic to neutral pH is due to low base saturation and highly weathered conditions. However, the alkaline pH of soils in 12.3% area was due to the presence of CaCO_3 in the surface soils. These soil are experiencing semi-arid climatic conditions since the Holocene period and the enhanced accumulation of pedogenic CaCO_3 (PC) in surface layers is due to higher evapotranspiration than precipitation ([Pal et al., 2014](#)). The formation of PC caused the increase in pH of these soils. Moreover, the accumulation of sodium in the surface layers from sodium concentrated groundwater in the study area may also be the cause for alkaline pH of the soils ([Vasu et al., 2015](#)).

In general, SAT soils in India are poor in organic carbon with an average of $\sim 0.5\%$ ([Bhattacharyya et al., 2007; Venkanna et al., 2014](#)). Hence, OC value more than $>0.75\%$ is considered as high under Indian SAT conditions ([Lal, 2015; Prabhavati et al., 2015](#)). Organic carbon varied from very low to high in the study area. A total of 88.1% area were low to medium (<0.5 ; $0.5\text{--}0.75\%$), and 11.2% area were high ($>0.75\%$) ([Table 2](#)). The low OC status of these soils is due to erosion of topsoil and high rate of organic matter decomposition due to semi-arid climate. Available nitrogen was deficient in most of the areas with values $<240 \text{ kg ha}^{-1}$ recorded in 95.7% area. The acute deficiency of nitrogen is due to low OC content, increased rate of mineralisation and insufficient application of N fertilizer to nutrient exhaustive crops like cotton and maize. Moreover, N deficiency was also aggravated by high S content of the soils. The correlation between the estimated properties ([Table 3](#)) showed that N was significantly correlated with OC ($r = 0.744$), sulphur ($r = -0.224$) indicating the influence of OC and S on nitrogen availability.

The available phosphorus was medium in 80.1% of the area and low in 11.1% area. The deficiency of P in the SAT soils under neutral to slightly acidic conditions may be attributed to their inherent low P status, low organic matter, 1:1 type of clay; hydrous oxides of iron and aluminium ([Sanyal and De Datta, 1991](#)) and formation of Ca-P

Table 2
Frequency distribution of soil fertility parameters.

Parameter	Unit	Rating	Class	Area (ha)	% of total area
pH		4.5–5.5	strongly acidic	10.1	0.1
		5.5–6.5	slightly acidic	8630.1	40.0
		6.5–7.5	neutral	10259.2	47.6
		7.5–8.5	slightly alkaline	2651.6	12.3
Organic carbon	(%)	<0.25	very low	149.2	0.6
		$0.25\text{--}0.50$	low	7521.3	34.9
		$0.50\text{--}0.75$	medium	11463.9	53.2
		>0.75	high	2416.6	11.2
Nitrogen	kg ha^{-1}	<120	very low	1377.2	6.4
		120–240	low	19245.7	89.3
		240–360	medium	928.3	4.3
		>360	high	–	–
Phosphorus	kg ha^{-1}	<11	very low	9.1	0.1
		11–22	low	2385.0	11.0
		22–44	medium	17414.8	80.1
		44–88	high	1742.24	8.1
Potassium	kg ha^{-1}	<160	very low	6752.2	31.3
		160–240	low	10414.6	48.3
		240–360	medium	4179.0	19.4
		360–480	high	205.2	0.2
Sulphur	mg kg^{-1}	<5.0	very low	63.4	0.3
		5.0–10.0	low	6761.4	31.4
		10.0–20.0	medium	12790.1	59.3
		20.0–40.0	high	1936.3	9.0

Table 3
Correlation matrix of parameters.

Parameter	pH	OC	N	P	K	S
pH	1					
OC	0.302 [*]	1				
N	0.305 [*]	0.744 [*]	1			
P	0.227 [*]	0.125 [*]	0.139 [*]	1		
K	0.223 [*]	0.145 [*]	0.155 [*]	0.179 [*]	1	
S	−0.053 [*]	−0.010	−0.224 [*]	−0.031	−0.028	1

^{*} significant at 0.05 level.

Table 4
Summary statistics of models of ordinary kriging for parameters.

Parameters	Spherical		Circular		Exponential		Gaussian	
	RMSE	r ²	RMSE	r ²	RMSE	r ²	RMSE	r ²
log pH	1.0101	0.34	1.0114	0.34	0.9930	0.45	1.0238	0.33
OC	0.3103	0.57	0.3104	0.51	0.3098	0.59	0.3106	0.46
log N	0.1556	0.41	0.1850	0.38	0.1904	0.39	0.2008	0.29
log P	0.0899	0.59	0.1004	0.47	0.1112	0.55	0.0991	0.51
log K	0.4420	0.48	0.5231	0.36	0.4960	0.35	0.5200	0.43
log S	0.2789	0.40	0.2991	0.34	0.3101	0.31	0.2980	0.33

in soils containing $\geq 1\%$ CaCO_3 (Bhattacharyya et al., 2007). However, the relatively better availability of phosphorus may be due to dissolution of Ca-P under neutral soil reaction conditions cultivated with deep rooted crops (Pal et al., 2012). This assumption is supported by the fact that P is significantly correlated with soil pH ($r=0.227$). Available potassium was low ($160\text{--}240\text{ kg ha}^{-1}$) in 48.3% and very low ($<160\text{ kg ha}^{-1}$) in 31.3% and medium in 19.3% area (Table 2). Moreover, high values of K ranging from 1401 to 3210 kg ha^{-1} was recorded which has been already discussed in Section 3.1.

The deficiency of K in these soils is due to their poor cation exchange capacity, type and amount of clay (0.7 nm kaolin interstratified with hydroxyl-interlayered vermiculites) and erosion of topsoil (Srinivasarao et al., 2011). Though the SAT soils contain good amount of silt and clay biotite, vermiculite and smectite, weathered vermiculite as mica-vermiculite has high selectivity for K^+ ions which fixes K and may not be extractable by extractant containing monovalent cation like NH_4^+ and Na^+ (Cox et al., 1999; Rees et al., 2013). Available sulphur content varied to great extent and it was low ($<10\text{ mg kg}^{-1}$) in 31.7%, medium ($10\text{--}20\text{ mg kg}^{-1}$) in 59.3% and high ($>20\text{ mg kg}^{-1}$) in 9% area. The poor available S content was due to acidic pH and low organic matter (Srinivasarao et al., 2008; Kumar et al., 2014) and adsorption by CaCO_3 (Ogehe et al., 2012). Moreover, farmers apply only meagre quantity of sulphur and take minimum care for secondary and micronutrients. Hence, deficiency of sulphur is inevitable due to crop uptake and other losses.

Ordinary kriging was used to assess the spatial variability of parameters. The best fit model was selected based on lowest RMSE value and r^2 (Table 4). The properties of calculated semivariograms for fertility parameters indicate different degree of spatial

dependence. The maximum lag distance was 511 m (Table 5) with 12 lag distance classes. The slope close to zero in the semivariogram of S (Fig. 2) indicate that sulphur was randomly distributed. Range is the maximum distance to which parameters are spatially correlated. It indicates the optimum sampling interval for precise assessment of spatial variability. The higher range value than the distance of grid interval (Table 5) indicates that the distribution of all the fertility parameters were inconsistent. Moreover, the heterogeneity observed in the distribution of area in different classes (Figs. 4–6) is an implication of range values. The nugget to sill (N:S) ratio (Table 5) indicates that soil pH, OC and available P were moderately spatial dependent (0.25–0.75) whereas N, K and S were weakly dependent (>0.75). The weak to moderate spatial dependency of the parameters could be attributed to external factors such as variable rate of fertilizer application by the farmers within a village or cropped region.

The reliability of spatial variability maps is dependent on sampling protocol and accuracy of the spatial interpolation. Optimising grid distance is the main bottleneck in the assessment of spatial variability for site specific nutrient management. The sampling interval should be less than half the semivariogram range (Kerry and Oliver, 2004). Many strategies were followed to establish sampling procedures such as N:S ratio (Cambardella et al., 1994); estimation errors (Mohamed et al., 1996); mean squared error (Chang et al., 1999). Among these, N:S ratio is more successful and being used widely (McBratney and Pringle, 1999; Bogunovic et al., 2014). Shukla et al. (2016) used random sampling method and found that range values varied from 5 to 140 km. In the present study, we used 325 m grid interval and observed range values varied from 1160 to 1807 m suggesting that the results of interpolation could be reliable under rainfed conditions. However, Fu et al. (2010) observed ranges of 264 m and 300 m, for P and K, respectively when they adopted 30 m grid interval. Contradictorily, Cambardella and Karlen (1999) recommended a grid interval finer than 15 m to describe variability occurring in intensively cultivated fields. Based on the results of the present study and studies reporting larger (Behera and Shukla, 2015; Sağlam et al., 2011), and smaller grid intervals (Bogunovic et al., 2014; Robinson and Mettermicht, 2006; Cambardella and Karlen, 1999; Cambardella et al., 1994), we hypothesized that strongly spatially dependent parameters may be influenced by intrinsic soil properties and weakly spatially dependent parameters are influenced by soil and crop management practices (Vasu et al., 2016a, 2016b). Moreover, the high nugget effect for the parameters except pH showed irregular distribution of spatial variability, and low correlation (Table 3) between parameters were the result of high heterogeneity. Hence, we assume that a grid interval of 325 m would serve the purpose of spatial variability mapping at farm level under rainfed conditions.

3.3. Spatial distribution of fertility parameters and nutrient management

The spatial distribution information helped to assess the extent and magnitude of soil fertility, especially soil nutrients and their

Table 5
Semivariogram parameters of soil fertility properties.

Fertility Parameters	Lag distance (m)	Range (m)	Nugget (C_0)	Partial sill (C)	Sill $C_0 + C$	N:S ratio	Spatial dependence
pH	324	1272	0.021	0.010	0.031	0.68	Moderate
OC	413	1538	0.196	0.076	0.272	0.72	Moderate
N	292	1167	0.220	0.039	0.259	0.85	Weak
P	455	1160	0.295	0.110	0.405	0.73	Moderate
K	511	1291	0.289	0.067	0.356	0.81	Weak
S	269	1807	0.932	0.159	1.091	0.85	Weak

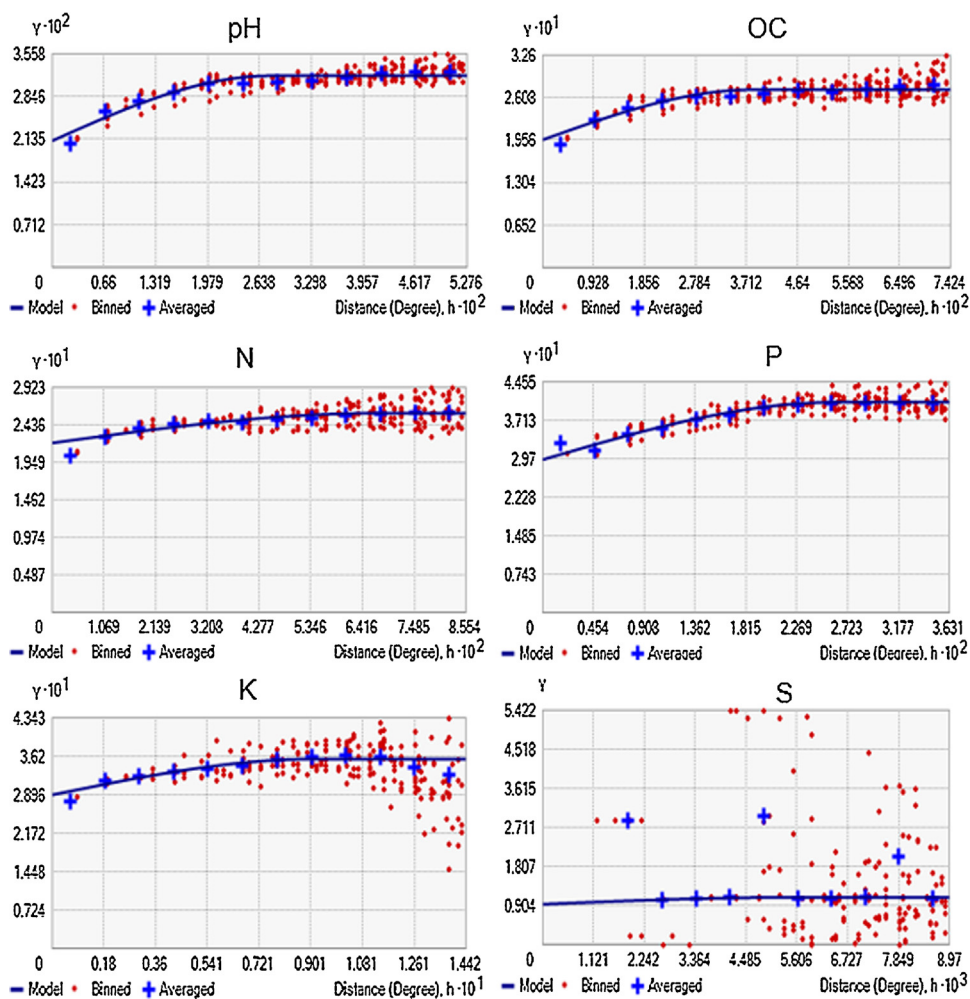


Fig. 2. Calculated semivariograms of soil properties with the lines indicating selected best fit model based on RMSE and r^2 values.

deficiency. The spatial variability maps indicate village wise spatial distribution of fertility parameters. Fig. 3 indicates that soil pH was mostly slightly acidic to neutral in most of the villages and it was alkaline in part of Avancha, Budhasamudram, Nerelapalle,

Marepalle, Pothireddipalle, Koduparthi, Appajipalle and Gorita comprising 12.3% of the total area (Table 2). However, a closer examination of the grid data indicates that pH was as high as 10.3 and it ranged from 8.7 to 10.3 for 32 samples. The interpolation

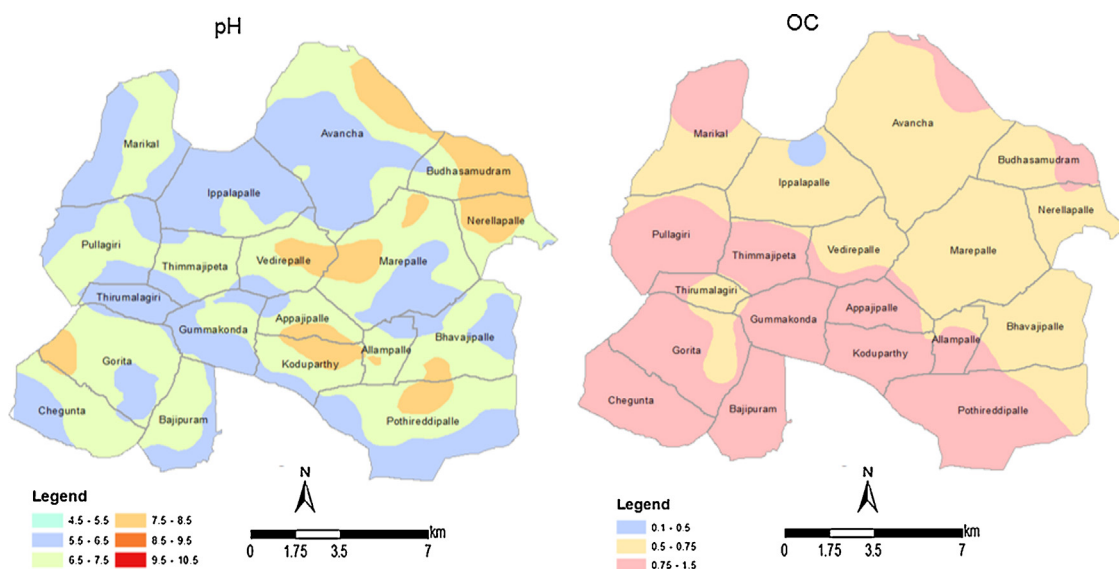


Fig. 3. Spatial variability map of pH and organic carbon by village.

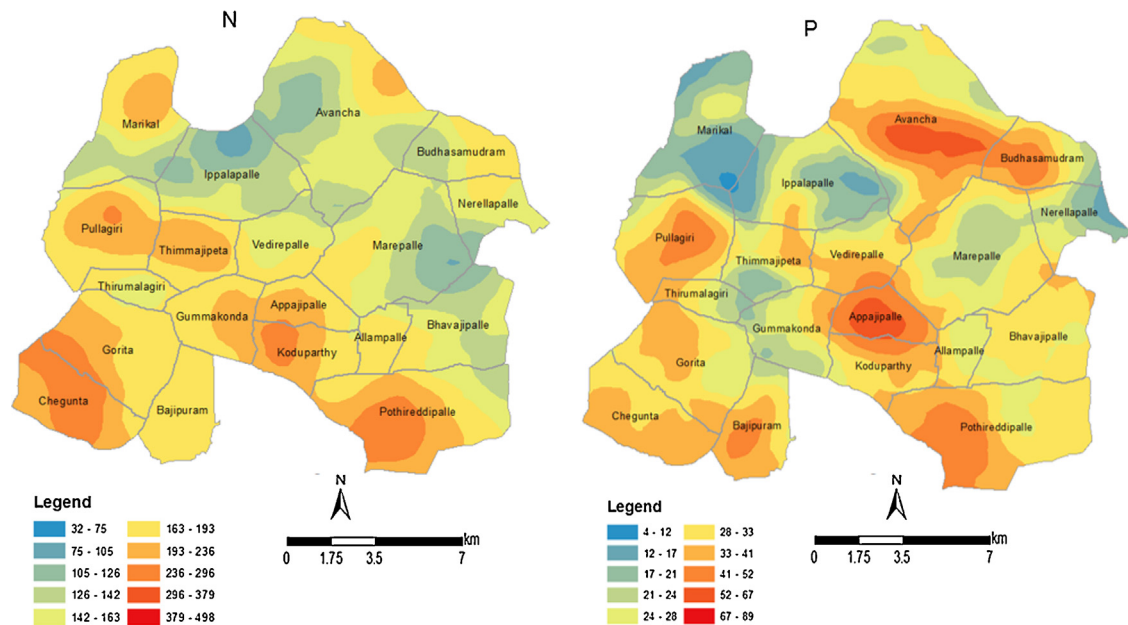


Fig. 4. Spatial variability map of soil available zinc (Zn) and copper (Cu) by village.

resulted in lower pH range class for $\text{pH} > 8.5$ due to spatial correlation of grid data. Organic carbon was high ($> 0.75\%$) in most of the southern and south-western villages and deficient in most of the northern villages (Fig. 3). However, the frequency distribution data shows that 2416.6 ha area was low and 149.2 ha was very low in organic carbon.

Available nitrogen (N) was generally low in northern villages especially in Ippalapalle, Avancha and Marepalle and very low values ($32\text{--}75 \text{ kg ha}^{-1}$) were recorded in some pockets (Fig. 4). It was relatively higher in northern villages as compared to villages of southern side of the study area. But, in general, available N was found be deficient ($< 240 \text{ kg ha}^{-1}$) in all the villages except few field plots. Available phosphorus (P) was medium to high in most of the villages. Fig. 4 shows that P was low ($4\text{--}12 \text{ kg ha}^{-1}$) in few pockets of Marikal, Ippalapalle, Thimmajipet, Gummagonda, Marepalle

and Neralapalle. Available potassium (K) was acutely deficient in villages of western part of the study area (Pullagiri, Marikal, Thirumalagiri, Gorita, Gummagonda and Thimmajipet) and also in some pockets of eastern villages (Fig. 5). It was medium to high in villages of central and northern parts. Fig. 5 indicates that available sulphur (S) ranged from low to medium in all villages with small pockets of high values. It represented the patchy and random distribution of sulphur in surface soils. In Bhavajipalle, Allampalle and Marepalle villages, most of the soils were deficient in sulphur.

Spatial variation of soil nutrients provided information about the deficiency of one or more nutrients in each village (Table 6). Cotton and maize are the major rainy season crops occupying substantial area out of total cultivated area. In the winter season, groundnut is cultivated in maximum area followed by rice. The data presented in Table 6 shows significant reduction in the

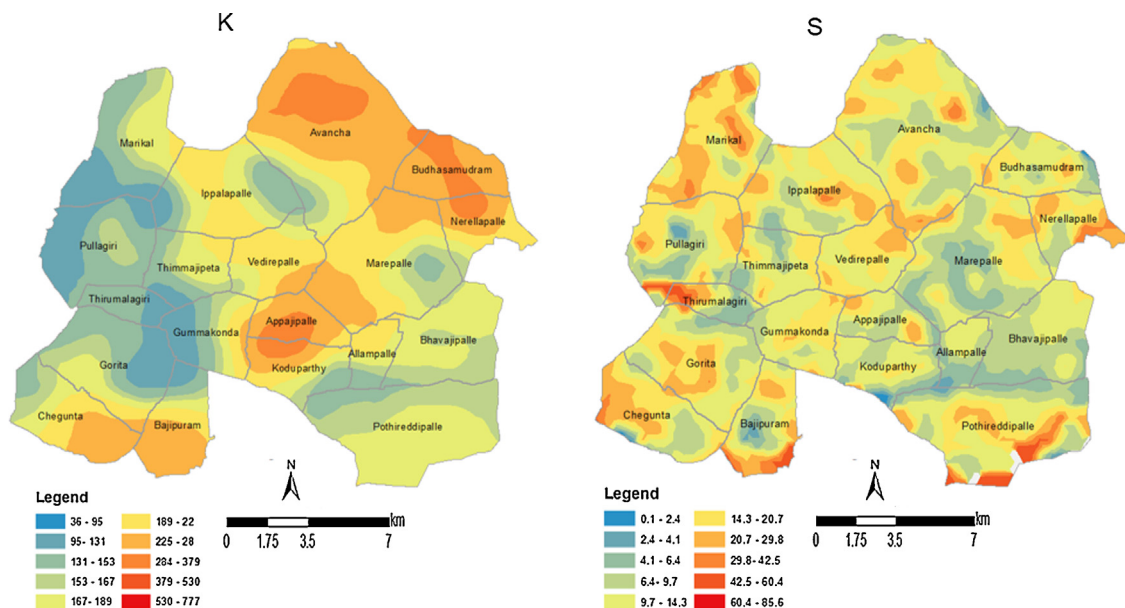


Fig. 5. Spatial variability map of soil available boron (B) by village.

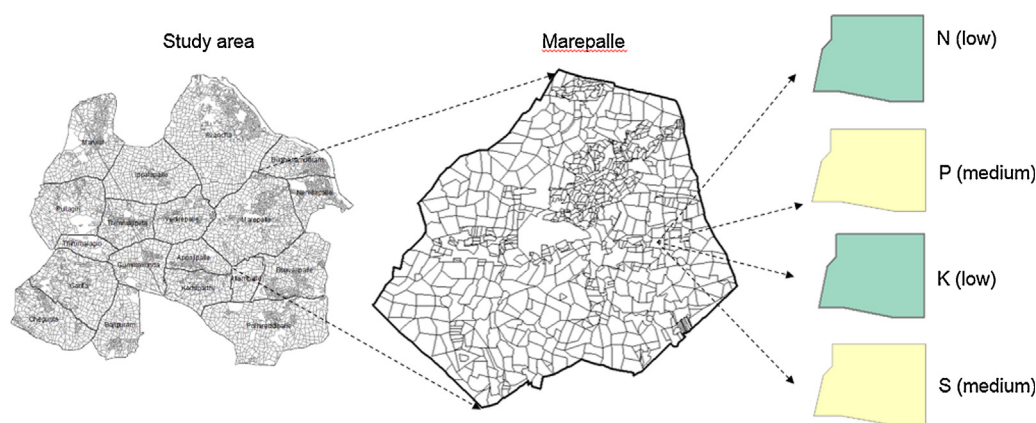


Fig. 6. Cadastral map integrated with spatial variability information (a) in which a selected farm in the Marepalle village (b) showing medium OC (0.6%) and P (17 kg ha⁻¹), low N (79 kg ha⁻¹), K (105 kg ha⁻¹) and S (9.1 mg kg⁻¹).

cultivated area from monsoon to winter, which is due to poor water availability and poor resource available with the farmers. Since cotton and maize are nutrient exhaustive crops, optimum nutrient management coupled with application of organic manures is prerequisite to sustain or increase their yield level. The data in Table 6 shows the occurrence of multi-nutrient deficiency in the villages of the study area except in Vedirepalle and Appajipalle where only N and S were deficient, respectively. The continuous

mining of soil nutrients coupled with low rate of fertilizer application led to the emergence of the multi-nutrient deficiency. Need based application of fertilizers to individual farms is advised for reducing the excess usage of fertilizers. Moreover, the management in the study area is small scale with each farmer operating in small field plots. Hence, use of cadastral information along with spatial variability could pave way for effective nutrient management (Jin and Jiang, 2002). For example, selected farm in

Table 6
Cultivated area (average of five years 2009–2014) in two cropping seasons and identified deficient nutrients by village.

S. No.	Name of Village	Cultivated area (ha)			Major crops		Deficient nutrients
		monsoon	winter	% reduction	monsoon	winter	
1	Pullagiri	398	222	44.2	Maize (47) Cotton (45)	Groundnut (90)	N, K, S
2	Marikal	611	65	89.4	Cotton (54) Maize(31)	Groundnut (90) Rice (31)	N, P, K
3	Ippalapally	543	41	92.4	Cotton (50) Maize(35)	Rice (39) Groundnut (24)	N, P, K, S
4	Avancha	1646	119	92.8	Cotton (77)	Rice(67) Water melon(10) castor (10)	N, S
5	Buddasamudram	514	35	93.2	Cotton (68) Maize(21)	Rice (80) Chillies (41)	N, S,
6	Nerellapally	406	134	67.0	Cotton (67)	Groundnut (60) Rice (19)	N, P, S
7	Marepally	1209	122	89.9	Cotton (74)	Rice (49) Groundnut (39)	N, P, K, S
8	Vedirepally	490	115	76.5	Cotton (47) Maize(44)	Groundnut (66) Rice (11)	N
9	Thimajipet	352	65	81.5	Cotton (47) Maize(43)	Groundnut (66) Rice (25)	P, K, S
10	Thirumalagiri	35	6	82.9	Cotton (40) Maize(34)	–	N, K, S
11	Gorita	793	108	86.4	Cotton (60) Maize(29)	Rice (56) Groundnut (26)	N, K, S
12	Cheguntha	518	118	77.2	Cotton (56) Maize(33)	Rice (68) Groundnut (24)	K, S
13	Bajipuram	482	85	82.4	Cotton (54) Maize(32)	Rice (52) Groundnut (38)	N,K, S
14	Gummakonda	453	98	78.4	Cotton (50) Maize(41)	Groundnut (74) Rice (16)	N, P, K
15	Appajipally	371	49	86.8	Cotton (48) Maize(42)	Groundnut (65) Rice (20)	S
16	Koduparthi	462	96	79.2	Cotton (50) Maize(41)	Groundnut (71) Rice (15)	K, S
17	Allampally	234	17	92.7	Maize(43) Cotton (37)	–	N, K, S
18	Bawajipally	600	68	88.7	Cotton (42) Maize(39)	Groundnut (41) Rice (30)	N, K, S
19	Pothriddipally	629	90	85.7	Maize(43) Cotton (35)	Groundnut (49) Rice (27)	N, K

Figures in parenthesis indicate percentage of area to the total cultivated area in each village.

the Marepalle village (Fig. 6) shows that OC was medium; N (79 kg ha^{-1}), K (105 kg ha^{-1}), and S (9.1 mg kg^{-1}) were deficient, and P was medium (17 kg ha^{-1}). Cotton is the major crop grown during the rainy season in the farm. Studies on nutrient uptake and yield response of cotton to soil test based fertilizer application in the SAT regions of India showed that application of farm yard manure (5 t ha^{-1}), 60 kg N , $30 \text{ kg P}_2\text{O}_5$, $40 \text{ kg K}_2\text{O}$ and 12 kg S as major nutrients is recommended to achieve optimum yield (Katharine et al., 2013; Gudadhe et al., 2015). Similarly, nutrient management recommendations were issued to farmers in the form of soil test report cards prepared in local language based on soil test results of soil fertility parameters. The nutrient database generated can be used for village level developmental planning and monitoring of soil fertility for sustaining the crop productivity.

4. Conclusions

Given the increasing cost of input management in agriculture, precise nutrient management is the need of the hour to increase farm nutrient use efficiency viz-à-viz sustaining the agricultural productivity in rainfed farming systems. In the present study, pH, P, K and S did not follow normal distribution and log transformation effectively shifted the data to normality with low skewness values. The observed outliers were collective but inconsistent to the rest of the dataset. Hence, it could be attributed to farm management practices such as fertilizer addition and intensive cultivation. Moreover, the study also revealed that while outliers are reality, dropping them from the spatial variability analysis is one of the limitation of geostatistics. Most of the soil fertility parameters (OC, N, K and S) are low in concentration except P and their deficiency is attributed to semi-arid climate, poor recycling and low level of management. Since the range values of the analysed soil properties varied from 1160 to 1807 m, 325 m grid interval could be reliable to assess spatial variability in the region of study. The study also helped to identify and delineate critical nutrient deficiency zones. The generated maps can serve as an effective tool in site specific nutrient management. This is a prerequisite in rainfed farming systems in order to optimise the cost of cultivation as well as to address nutrient deficiency.

Acknowledgements

The authors thank Department of Agriculture, Government of Telangana, Hyderabad for the financial assistance to this work. The authors are also thankful to technical laboratory staff of Head Quarters and Regional Centre, ICAR-NBSS & LUP, Bengaluru for their assistance during the laboratory analysis of soil samples. We also thank reviewers and editor, whose comments enormously helped in improving this manuscript.

References

- Armstrong, M., Boufassa, A., 1988. Comparing the robustness of ordinary kriging and lognormal kriging: outlier resistance. *Math. Geol.* 20 (4), 447–457.
- Barnett, V., Lewis, T., 1994. *Outliers in Statistical Data*, Third ed. Wiley, New York.
- Behera, S.K., Shukla, A.K., 2015. Spatial distribution of surface soil acidity electrical conductivity, soil organic carbon content and exchangeable potassium, calcium and magnesium in some cropped acid soils of India. *Land Degrad. Dev.* 26, 71–79.
- Bhattacharyya, T., Pal, D.K., Easter, M., et al., 2007. Modelled soil organic carbon stocks and changes in the Indo- Gangetic Plains India from 1980 to 2030. *Agric. Ecosyst. Environ.* 122, 84–94.
- Bogunovic, I., Mesic, M., Zgorelec, Z., Jurisic, A., Bilandzija, D., 2014. Spatial variation of soil nutrients on sandy-loamy soil. *Soil Tillage Res.* 144, 174–183.
- Bouma, J., Pinke, P.A., 1993. In: Robert, P.C., Rust, R.H., Larson, W.E. (Eds.), *Soil Specific Crop Management*. ASA, CSSA, SSSA, Madison, WI 1996, p. 207.
- Bray, R.H., Kurtz, L.T., 1945. Determination of total, organic and available forms of phosphorus in soils. *Soil Sci.* 59, 39–45.
- Cambardella, C.A., Karlen, D.L., 1999. Spatial analysis of soil fertility parameters. *Precis. Agric.* 1, 5–14.
- Cambardella, C.A., Moorman, T.B., Novak, J.M., Parkin, T.B., Karlen, D.L., Turco, R.F., Konopka, A.E., 1994. Field-scale variability of soil properties in Central Iowa. *Soil Sci. Soc. Am. J.* 58, 1501–1511.
- Chang, J., clay, D.E., Carlson, C.G., Malo, D., Clay, S.A., 1999. Precision farming protocols: part 1. Grid distance and soil nutrient impact on the reproducibility of spatial variability measurements. *Precis. Agric.* 1, 277–289.
- Chauhan, B.S., Kaur, P., Mahajan, G., Randhawa, R.K., Singh, H., Kang, M.S., 2014. Global warming and its possible impact of agriculture in India. *Adv. Agron.* 123, 66–121.
- Cherry, K., Mooney, S.J., Ramsden, S., Shepherd, M.A., 2012. Using field and farm nitrogen budgets to assess the effectiveness of actions mitigating N loss to water. *Agric. Ecosyst. Environ.* 147, 82–88.
- Chesnin, L., Yien, C.H., 1950. Turbidimetric determination of available sulphates. *Soil Sci. Soc. Am. Proc.* 15, 149–151.
- Chil  s, J.P., Delfiner, P., 1999. *Geostatistics: Modelling Spatial Uncertainty*. Wiley, New York.
- Cox, A.E., Joern, B.C., Brouder, S.M., Gao, D., 1999. Plant-available potassium assessment with a modified sodium tetraphenylboron method. *Soil Sci. Soc. Am. J.* 63, 902–911.
- Department of Agriculture and Cooperation (DoAC) Ministry of Agriculture and Farmers Welfare, 2014. National Mission for Sustainable Agriculture. Operational Guidelines. . <http://www.jkapsd.nic.in/PDF/nmsagidelines.pdf>.
- Fu, W., Tunney, H., Zhang, C., 2010. Spatial variation of soil nutrients in a dairy farm and its implications for site-specific fertilizer application. *Soil Tillage Res.* 106, 185–193.
- Goovaerts, P., Avruskin, G., Meliker, J., Slotnick, M., Jacquez, G., Nriagu, J., 2005. Geostatistical modelling of the spatial variability of arsenic in groundwater of southeast Michigan. *Water Resour. Res.* 41, W07013.
- Gudadhe, N., Dhinde, M.B., Hirwe, N.A., 2015. Effect of integrated nutrient management on soil properties under cotton chickpea cropping sequence in vertisols of Deccan plateau of India. *Indian J. Agric. Res.* 49 (3), 207.
- ICAR, 2011. Vision 2030. . <http://www.icar.org.in/files/ICAR-Vision-2030.pdf>.
- Jin, J., Jiang, C., 2002. Spatial variability of soil nutrients and site specific nutrient management in the P.R China. *Comput. Electron. Agric.* 36, 165–172.
- Katharine, S.P., Shanthi, R., Maragatham, S., Natesan, R., Ravikumar, V., Dey, P., 2013. Soil test based fertilizer prescriptions through inductive cum targeted yield model for transgenic cotton on Inceptisol. *IOSR J. Agric. Vet. Sci.* 6 (5), 36–44.
- Kerry, R., Oliver, M.A., 2004. Average variograms to guide soil sampling. *Int. J. Appl. Earth Obs.* 5 (4), 307–325.
- Kumar, H., Sahu, K.K., Kurre, P.K., Goswami, R.G., Kurrey, C.D., 2014. Correlation studies on available sulphur and soil properties in soils of Dabhra block under Janjgir-Champa district in Chhattisgarh. *Asian J. Soil Sci.* 9, 217–220.
- Lal, 2015. Soil carbon sequestration in agroecosystems of India. *J. Indian Soc. Soil Sci.* 63 (2), 125–143.
- Lark, R.M., 2000. Estimation of the variograms of soil properties by the method-of-moments and maximum likelihood; a comparison. *Eur. J. Soil Sci.* 51, 717–728.
- Li, X.F., Chen, Z.B., Chen, H.B., Chen, Z.Q., 2011. Spatial distribution of soil nutrients and their response to land use in eroded area of South China. *Proc. Environ. Sci.* 10, 14–19.
- Lopez-Granados, F., Jurado-Exposito, M., Pena- Barragan, J.M., Garcia-Torres, L., 2005. Using geostatistical and remote sensing approaches for mapping soil properties. *Eur. J. Agron.* 23, 279–289.
- McBratney, A.B., Pringle, A.J., 1999. Estimating average and proportional variograms of soil properties and their potential use in precision agriculture. *Precis. Agric.* 1125 doi:<http://dx.doi.org/10.1023/A:1009995404447>.
- Mohamed, S.B., Evans, L.J., Shiel, R.S., 1996. Mapping techniques and intensity of soil sampling for precision farming. In: Robert, P.C., Rust, R.H., Larson, W.E. (Eds.), *Precision Agriculture, Proceedings of the 3rd International Conference*. ASA, CSSA, SSSA, Madison, WI, pp. 217.
- Ogeh, J.S., Uzu, F., Obi-ljeje, O.D., 2012. Distribution of sulphur in soils formed from different parent materials in southern Nigeria. *Niger. J. Basic Appl. Sci.* 20 (1), 73–77.
- Olsen, S.R., Cole, C.V., Watanabe, F.S., Dean, L.A., 1954. Estimation of available phosphorus in soils by extraction with sodium bicarbonate. Circular of United States Department of Agriculture, , pp. 939.
- Pal, D.K., Deshpande, S.B., Durge, S.L., 1993. Potassium release and adsorption reactions in two ferruginous soils (polygenetic) soils of southern India in relation to their mineralogy. *Pedologie (Ghent)* 43, 403–415.
- Pal, D.K., Wani, S.P., Sahrawat, K.L., 2012. Vertisols of tropical indian environments. *Pedol. Edaphology Geoderma* 189–190, 28–49.
- Pal, D.K., Wani, S.P., Sahrawat, K.L., Srivastava, P., 2014. Red ferruginous soils of tropical Indian environments: a review of the pedogenic processes and its implications for edaphology. *Catena* 121, 260–278.
- Pal, D.K., Bhattacharyya, T., Sahrawat, K.L., Wani, S.P., 2016. Natural chemical degradation of soils in Indian semi-arid tropics and remedial measures. *Curr. Sci.* 110 (9), 1675–1682.
- Patil, S.S., Patil, V.C., Al-Gaadi, K.A., 2011. Spatial variability in fertility status of soil surface soils. *World Appl. Sci. J.* 14 (7), 1020–1024.
- Prabhavati, K., Dasog, G.S., Patil, P.L., Sahrawat, K.L., Wani, S.P., 2015. Soil fertility mapping using GIS in three agro-climatic zones of Belgaum district, Karnataka. *J. Indian Soc. Soil Sci.* 63 (2), 173–180.
- Rees, G.L., Pettygrove, G.S., Southard, R.J., 2013. Estimating plant-available potassium in potassium-fixing soils. *Commun. Soil Sci. Plant Anal.* 44, 741–748.
- Robinson, T.P., Mettermicht, G., 2006. Testing the performance of spatial interpolation techniques for mapping soil properties. *Comput. Electron. Agric.* 50, 97–108.

- Sağlam, M., Ozturk, H.S., Ersahin, S., Ozkan, A.I., 2011. Spatial variation of soil physical properties in adjacent alluvial and colluvial soils under ustic moisture regime. *Hydrol. Earth Syst. Sci. Discuss.* 8 (2) .
- Sahrawat, K.L., Wani, S.P., 2013. Soil testing as a tool for on-farm soil fertility management: experience from the semi-arid zone of India. *Commun. Soil Sci. Plant Anal.* 44, 1011–1032.
- Sahrawat, K.L., Wani, S.P., Pardhasaradhi, G., Murthy, K.V.S., 2010. Diagnosis of secondary and micronutrient deficiencies and their management in rain fed agro-ecosystems: case study from Indian semi-arid tropics. *Commun. Soil Sci. Plant Anal.* 41, 346–360.
- Sahrawat, K.L., Wani, S.P., Pardhasaradhi, G., 2013. Balanced nutrient management: effects on plant zinc. *J. SAT Agric. Res.* 11.
- Sahrawat, K.L., 2016. How fertile are semi-arid tropical soils. *Curr. Sci.* 100 (9), 1671–1674.
- Sanyal, S.K., De Datta, S.K., 1991. Chemistry of phosphorus transformations in soil. *Adv. Soil Sci.* 16, 1–119.
- Schollenberger, C.J., Simon, R.H., 1945. Determination of exchange capacity and exchangeable bases in soil by ammonium acetate method. *Soil Sci.* 59, 13–24.
- Shukla, A.K., Behera, S.K., et al., 2016. Spatial variability of soil micronutrients in the intensively cultivated Trans-Gangetic Plains of India. *Soil Tillage Res.* 163, 282–289.
- Srinivasarao, Ch., Wani, S.P., Sahrawat, K.L., Rego, T.J., Pardhasaradhi, G., 2008. Zinc, boron and sulphur deficiencies are holding back the potential of rainfed crops in semi-arid India: experiences from participatory watershed management. *Int. J. Plant Prod.* 2, 89–99.
- Srinivasarao, Ch., Venkateswarlu, B., Lal, R., Singh, A.K., Kundu, S., Vittal, K.P.R., et al., 2011. Long-term manuring and fertilizer effects on depletion of soil organic carbon stocks under pearl millet–cluster bean–castor rotation in western India. *Land Degrad. Dev.* doi:http://dx.doi.org/10.1002/ldr.1158.
- Srinivasarao, Ch., Lal, R., Prasad, J.V.S.N., et al., 2015. Potential and challenges of rainfed farming in India. *Adv. Agron.* 133, 1–69.
- Subbiah, B.V., Asija, C.L., 1956. A rapid procedure for the estimation of available nitrogen in soils. *Curr. Sci.* 25, 32.
- Vasu, D., Singh, S.K., Tiwary, P., Butte, P.S., Duraisami, V.P., 2015. Evaluation of groundwater quality for irrigation in Thimmajipet mandal, Mahabubnagar district. *Andhra Pradesh J. Agric. Sci.* 1 (4), 1–6.
- Vasu, D., Singh, S.K., Ray, S.K., Duraisami, V.P., Tiwary, P., Chandran, P., Nimkar, A.M., Anantwar, S.G., 2016a. Soil quality index as a tool to evaluate crop productivity in semi-arid Deccan plateau. *India Geoderma* 282, 70–79.
- Vasu, D., Singh, S.K., Tiwary, P., Chandran, P., Ray, S.K., Duraisami, V.P., 2016b. Pedogenic processes and soil-landform relationships for identification of yield limiting properties. *Soil Res.* doi:http://dx.doi.org/10.1071/SR16111.
- Vasuki, N., 2010. Micronutrient management for enhancing crop production – future strategy and requirement. *J. Indian Soc. Soil Sci.* 58 (1), 32–36.
- Venkanna, K., Mandal, U.K., Raju, A.J.S., Sharma, K.L., Adake, R.V., Pushpanjali Reddy, B.S., Masane, R.N., Venkatravamma, K., Babu, P.D., 2014. Carbon stocks in major soil types and land-use systems in semiarid tropical region of southern India. *Curr. Sci.* 106 (4), 604–611.
- Walkley, A., Black, I.A., 1934. An examination of the Degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. *Soil Sci.* 37, 29–38.
- Wilding, L.P., 1985. Spatial Variability: its documentation, accommodation, and implication to soil surveys. In: Nielsen, D.R., Bouma, J. (Eds.), *Soil Spatial Variability*. Pudoc, Wageningen, Netherlands.
- Williams, C.H., Steinbergs, A., 1959. Soil sulphur fractions as chemical indices of available sulphur in some Australian soils. *Aust J. Agric. Res.* 10, 340–352.