Advances in Research

11(5): 1-13, 2017; Article no.AIR.35391
ISSN: 2348-0394, NLM ID: 101666096

Evaluation of Variation in Macronutrients of Soils in Harda District, Madhya Pradesh, India - A Geostatistical Approach

Subhash[1,2*], G. S. Tagore[1], Debabrata Nath[2], M. Mohanty[2] and Nishant K. Sinha[2]

[1]Department of Soil Science and Agricultural Chemistry, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur - 482004 (M.P.), India.
[2]Indian Institute of Soil Science, Bhopal, 462001, India.

Authors' contributions

This work was carried out in collaboration between all authors. Author GST designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors Subhash and GST managed the analyses of the study. Authors Subhash and DN managed the literature searches and communicate with journal. Authors MM and NKS evaluated and edited the manuscript. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AIR/2017/35391
Editor(s):
(1) S. Srinivasa Rao, Department of Chemistry, V. R. Siddhartha Engineering College, Andhra Pradesh, India.
Reviewers:
(1) Sukhwinder Bali, University of Maine Cooperative Extension, USA.
(2) Seref Kilic, Ardahan University, Turkey.
(3) Ahmed Raissouni, University of Abdelmalek Essaâdi, Morocco.
(4) Stanley U. Onwudike, Federal University of Technology, Nigeria.
Complete Peer review History: http://www.sciencedomain.org/review-history/21013

Original Research Article

Received 11th July 2017
Accepted 1st September 2017
Published 15th September 2017

ABSTRACT

GPS based three hundred and three surface soil samples (0-15 cm) were collected from dominant cropping system and analyzed for different soil characteristics in laboratory using standard procedures. The results were statistically interpreted that the N, P, K, and S were found to be deficient in 56.77, 31.68, 6.6 and 52.48 percent soil samples, respectively. Geo-statistical results revealed that the exponential model was found best fit for available N, P, K, and S. Spatial distribution maps showed that soil pH, EC, organic carbon, calcium carbonate, N, P, K, and S spatially varied and were deficient in Hundia, Timarani, Khirkiya and Sirrali. These maps will be helpful for farmer's to decide the quantity of fertilizer to be added to soil to improve fertility status for sustainable crop production and environmental protection.

**Corresponding author: E-mail: smandloi000@gmail.com;*

Keywords: GIS; GPS; macronutrients; mapping; semi-variogram; variability.

1. INTRODUCTION

Increase in human population and disturbance on the earth's ecosystem to produce food and fiber will place greater demand on soils to supply essential nutrients. In India, continuous cropping for enhanced yield removes substantial amounts of nutrients from the soil. Amongst, macronutrients are required in large quantities for growth, increase plant productivity and yield, but these nutrients were deficient in the majority of soybean and chickpea growing areas and where sulphur free fertilizer has been used. Soil fertility maps are meant for highlighting the nutrient needs, based on fertility status of soils to realize good crop yields.

Information related to spatial variability and distribution of soil properties is critical for farmers attempting to increase the efficiency of fertilizers and crop productivity [1]. Geo-statistics has been used extensively to characterize the spatial variability of soil attributes due to its ability to quantify and reducing sampling uncertainties and minimizing investigation costs [2]. [3] and [4] characterized the spatial variability of soil physical, [5] studied the chemical properties and microbiological properties [6].

Classic statistic method is needed for extensive sampling to decline variation correlation. Despite high costs spent in this method, the results are limited only on mean value for specific classes. Some studies were undertaken in traditional survey, mapping of soil fertility and large numbers of samples analyzed, but the latitude and longitude of sampling sites are often time missing. Hence, an attempt was made to use GPS receivers to map the exact location of sampling sites which can be used as input data in GIS and is used to run the queries to know various properties of soil.

2. MATERIALS AND METHODS

2.1 Description Study Area

Geographically, Harda district situated between 21°53' to 22°36' North latitude and 76°47' to 77°30' East longitude with an area of 3330 sq km. It is located in the Narmada river valley and the Narmada forms the northern district boundary. Administratively, the district divided into six blocks, Rahatgaon, Harda, Khirkiya, Hundia, Sirrali and Timarani (Fig. 1). The district feels maximum temperature up to 47℃ and minimum up to 12℃ and an average annual rainfall of 1021.84 mm. The major crops grown in the study area are soybean, wheat, summer mungbean, chickpea, sugarcane and vegetables. The soil map of NBSSLUP Nagpur showed the highest area is dominated by Vertisols followed by Inceptisols and Entisols.

2.2 Land Use and Cropping Pattern

The Land use map was prepared by using Indian remote-sensing satellite-P6, linear imaging self-scanning satellite-III (IRS-P6, LISS-III) satellite imagery. The Satellite data has the characteristics of 23.5 m spatial resolution, four spectral channels green (0.52 µ-0.59 µ), red (0.62 µ-0.68 µ), NIR (0.77 µ-0.86 µ), and SWIR (1.55 µ-1.70 µ) and five days temporal resolution with 141 km swath.

The survey of India topographical maps (1:50000), the digital map of soil and satellite imagery as a secondary data was used from internet. For image processing/analysis ERDAS Imagine 9.3.1 was used. On the basis of the information obtained by the identification of the physical characteristics from the imagery and their verification in the field was done.

The major land-use/land-cover categories were identified and mapped (Fig. 2). From the maps, it is evident that the major area 2082.20 sq km, which was accounted to 62.52%, is occupied by cultivated land. On the basis of information obtained from every sampling site and local agriculture department, the soybean based cropping pattern is dominant existing cropping system viz., soybean-wheat, soybean-wheat-summer mungbean, soybean-chickpea and soybean-fallow. Sugarcane and horticultural crop/orchards-spices crop/vegetables land uses were observed in study area. Based on the interpretation of classified image and calculated area statistics the forest was classified in two categories; dense 20.0% (666.0 sq km) and open 6.96% (231.90 sq km).

Other land use categories are built-up (52.83 sq km) which accounted by 1.59 percent represented to Harda city and some village's settlements. Water bodies were occupied (68.25 sq km) 2.05% of total geographical area. The classified data showed the wasteland in four category i.e., gullied/ravenous land 0.05% (1.82 sq km), sandy area-riverine,0.10% (3.17sq km), dense scrub1.28% (42.72 sq km) and open scrub

1.80%(59.89 sq km) and minimum area covered by mining 0.01% (0.17 sq km) of the TGA.

2.3 Soil Sampling, Processing and Their Analysis

Sampling sites were randomly distributed over agricultural land by considering of topography and heterogeneity of the soil type. GPS based three hundred and three soil samples (0 to 15 cm) were collected from farmer's field during the off season of 2014. Soil samples were dried and crushed with the help of wooden rod and passed through 2 mm sieve and then used for analysis of soil pH, EC, OC and $CaCO_3$. The available N, P, and K were analyzed using [7,8] and [9] respectively. The available S was determined by the turbidimetric method [10]. The nutrient index (NI) was calculated according to by [11] and classified as low (<1.67), medium (1.67 to 2.33) and high (>2.33).

2.4 Geo-statistical Analysis

It was necessary to normalize the data prior to the geo-statistical analysis because of high skewness and the presence of outliers. Logarithmic transformations were selected to normalize the dataset. When skewness coefficient is lower than 0.5 there is no need to convert data, but if this coefficient is between 0.5 and 1, and more than 1 for normalizing data square root and logarithm must be used, respectively [12]. When this ratio is smaller than 0.25 the concerned parameter has a strong spatial steal structure, between 0.25-0.75 spatial structure is middle, and when it is greater than 0.75 spatial structures is weak [13].

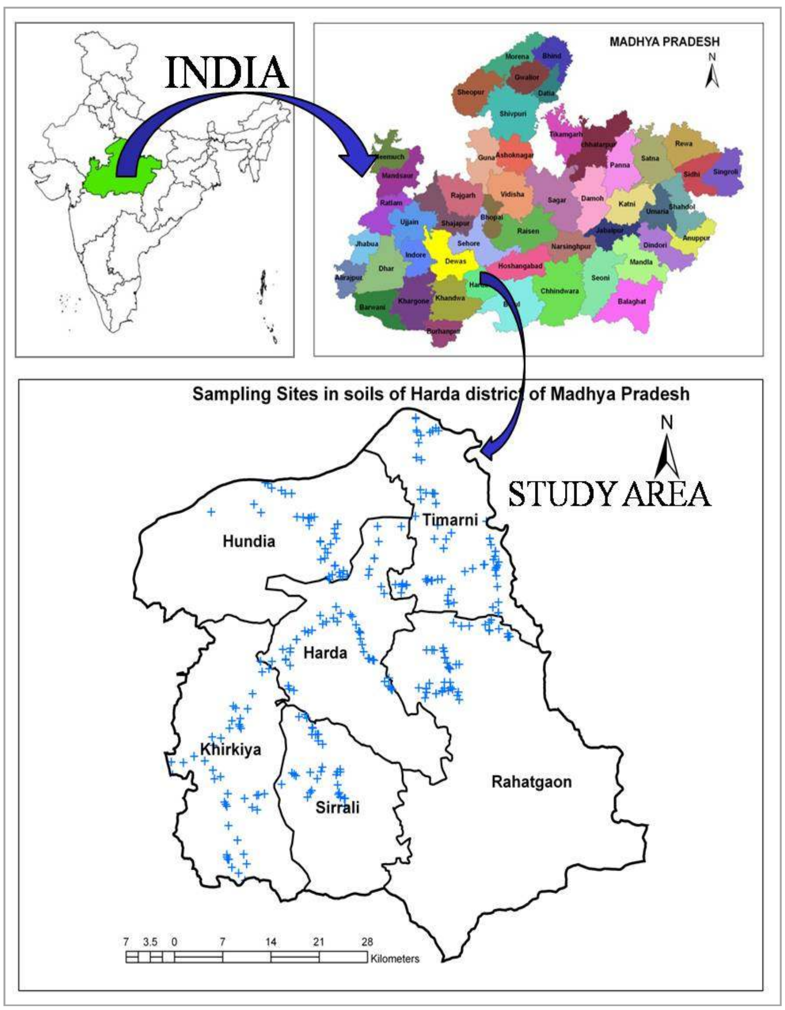

Fig. 1. Location map of study area

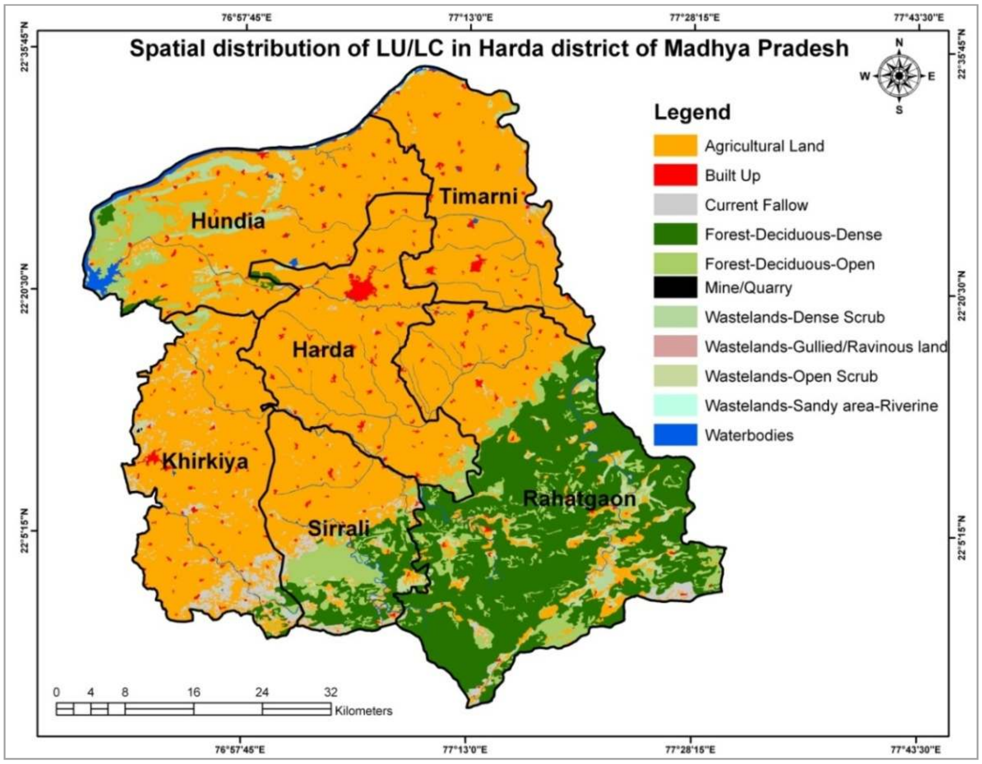

Fig. 2. Land use and its spatial distribution in Harda district

If the data distributions are largely deviate from a normal distribution, data transformations are often performed to reduce the influence of extreme values on spatial analysis [14].

$$f(x) = \ln(x) \quad \lambda=0,$$

Where f(x) is the transformed value and x is the value to be transformed. For a given data set (x_1, x_2,.....x_n), the parameter is estimated based on the assumption that the transformed values (y_1,y_2,.....y_n) are normally distributed. When $\lambda = 0$, the transformed becomes the logarithmic transformation.

Geo-statistical tool in GIS 9.3.1 was used to analyze the spatial correlation structures. Ordinary Kriging was used for the spatial interpolation because it is best at providing an unbiased prediction for specific unsampled locations and minimizing the influence of outliers [1]. Semi-variogram $y(h)$ is computed as half the average squared difference between the soil properties of data pairs.

The semi variance $y(h)$ is estimated as: equation as:

$$y(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [\mathrm{z(x_i)} - \mathrm{z(x_i + h)}]^2,$$

Next, this was fitted with a theoretical model, such as Exponential, Spherical and Gaussian models [15]. Choice of the best-fitted model was based on the lowest residual sum of square (RSS) and the largest coefficient of determination (R^2). The model provided information about the spatial structure as well as the input parameters (i.e. nugget, sill and range) for the Kriging interpolation. Nugget is the variance at distance zero, sill is the semi- variance value at which the semi-variogram reaches the upper bound after its initial increase, and the range is a value (x axis) at which one variable becomes spatially independent.

The nugget to sill ratio was used to define different classes of spatial dependence for the soil properties. Nugget/sill ratio of 25%, 25-75% and >75% were classified as having strong, moderate and weak spatial dependence, respectively, according to [16].

2.5 Validation Indices

Mean absolute error (MAE) and mean squared error (MSE), measure the accuracy of prediction, whereas goodness of prediction (G) measure the effectiveness of prediction given by [17] and [18].

$$\text{MAE} \quad = \frac{1}{N}\sum_{i=1}^{N}[|\mathrm{z}(\mathrm{x_i}) - \hat{\mathrm{z}}(\mathrm{x_i})|]$$

Where zˆ (xi) is the predicted value at location i. Small MAE values indicate few errors. The MAE measure, however, does not reveal the magnitude of error that might occur at any point and hence MSE was calculated,

$$\text{MSE} \quad = \frac{1}{N}\sum_{i=1}^{N}[\mathrm{z}(\mathrm{x_i}) - \hat{\mathrm{z}}(\mathrm{x_i})]^2$$

Where z is the sample means If G = 100, it indicates perfect prediction, while negative values indicate that the predictions are less reliable than using sample mean as the predictors.

$$G = \left(1 - \frac{\sum_{i=1}^{N}[\mathrm{z}(\mathrm{x_i}) - \hat{\mathrm{z}}(\mathrm{x_i})]^2}{\sum_{i=1}^{N}[\mathrm{z}(\mathrm{x_i}) - \bar{\mathrm{z}}]^2}\right) \times 100$$

Squaring the difference at any point gives an indication of the magnitude, such as small MSE values indicate more accurate estimation, point-by-point. The G measure gives an indication of how effective a prediction might be, relative to that which could have been derived from using the sample mean alone [19].

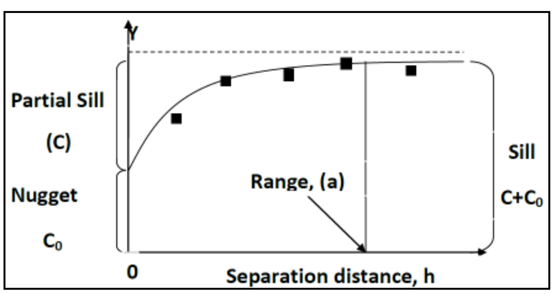

Fig. 3. Semi-variogarm parameters

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics of Soil Properties

The descriptive statistics of soil properties presented in Table 1 showed the pH, EC, OC and $CaCO_3$ varied from 6.4 to 8.9, 0.09 to 0.98 dSm^{-1}, 2.35 to10.16 g kg^{-1} and 5.0 to 115.0 g kg^{-1} with the mean values of 7.6, 0.2 dSm^{-1}, 5.32 g kg^{-1} and 37.4 g kg^{-1}, respectively. The available N, P, K, and S varied from 87.8-326.1 kg ha^{-1}, 4.94-76.85 kg ha^{-1}, 161.3-885.9 kg ha^{-1} and 1.0-89.0 mg kg^{-1} with mean value of 231.3 kg ha^{-1}, 23.8 kg ha^{-1}, 472 kg ha^{-1} and 28.2 mg kg^{-1}, respectively.

Considering the coefficient of variation CV <10% as low, 10 to 100% as moderate, >100% as high variability, $CaCO_3$ had the largest variation (CV = 83.40 percent) followed by EC (CV = 60.00 percent), OC (CV =24.06 percent) and pH had least variability (CV = 6.70 percent). The available P had the highest variability (CV=71.19 percent) followed by available K (CV=32.15 percent) and N had the lowest variability (CV= 18.62 percent). The S was found to be moderately variable (CV = 61.03 percent). Data revealed the skewness coefficients ranged from -0.35 to 3.70. Data showed the higher for EC, $CaCO_3$, and available P are largely deviated from normally distribution.

3.2 Nutrients Status and Spatial Distribution

Data presented in Table 2 showed that the soil pH varied from 6.5 to 8.40, 6.60 to 8.40, 6.40 to 7.80, 6.90 to 8.70, 6.50 to 8.10 and 6.60 to 8.90 with mean value of 7.63, 7.60, 7.18, 7.85, 7.60 and 7.77 in Harda, Hundia, Khirkiya, Rahatgaon, Sirrali and Timarani block, respectively. The EC of the soil varied from 0.10 to 0.59, 0.10 to 0.93, 0.09 to 0.37, 0.10 to 0.59, 0.10 to 0.30 and 0.10 to 0.98 dSm^{-1} with mean value of 0.19, 0.27, 0.17, 0.19, 0.17 and 0.22 dSm^{-1} in Harda, Hundia, Khirkiya, Rahatgaon, Sirrali and Timarani block, respectively. The soils were neutral to slightly alkaline in reaction, electrical conductivity indicated the order Hundia > Harda=Timarani > Rahatgaon > Khirkiya=Sirrali. Similar results were reported by [20].

The organic carbon in soil ranged from 2.92 to 10.16, 3.46 to 7.83, 2.35 to 6.95, 2.81 to 9.38, 2.52 to 8.31 and 2.48 to 8.46 g kg^{-1} with the mean value of 5.64, 5.54, 4.23, 5.25, 5.24 and 5.82 g kg^{-1} in Harda, Hundia, Khirkiya, Rahatgaon, Sirrali and Timarani block, respectively. Considering <5.0 g kg^{-1} as the threshold value of organic carbon, 75.9% soil samples showed low in Khirkiya block might be due to unbalanced fertilization and high summer temperature, resulting in rapid decomposition of it. In Rahatgaon and Sirrali block about 43.3 and 43.4% soil samples were low; whereas 32.5, 25.5 and 22.5 per cent soil samples were collected from Hundia, Harda, and Timarani respectively was found to be low. [21] who reported the amount of SOC in soils of India is relatively low ranging from 0.1 to 1% and typically, < 0.5%. [22] and [23] reported similar results.

The $CaCO_3$ content in soil varied from 5 to 115, 30 to 107.00, 5 to 110, 5 to 75, 5 to 105 and 5 to 115 g kg^{-1} with an average value of 54.02, 79.05, 34.81, 18.02, 44.17 and 28.52 g kg^{-1} in Harda, Hundia, Khirkiya, Rahatgaon, Sirrali and Timarani block, respectively. The soils of entire district are non calcareous except soils of Harda and Hundia blocks its value soils are weakly to moderately calcareous in nature due to the presence of excess calcium carbonate >50 g kg^{-1}.

The available N content in soils of Harda, Hundia, Khirkiya, Rahatgaon, Sirrali, and Timarani blocks varied from 163.07 to 301.06, 150.53 to 301.06, 137.98 to 263.42, 137.98 to 326.14, 150.53 to 313.60 and 87.81 to 326.14 kg ha^{-1} with a mean values of 253.16, 218.27, 207.67, 227.45 240.84 and 238.51 kg ha^{-1}, respectively. However, available phosphorus content in soils of corresponding blocks varied from 6.95 to 76.85 7.04 to 57.82, 5.94 to 54.07, 5.69 to 63.56, 4.94-55.31 and 6.69 to 60.03 kg ha^{-1} with a mean value of 28.69, 39.32,15.94, 19.82,18.22 and 22.79 kg ha^{-1}.

Status of the available K in the soils of Harda, Hundia, Khirkiya, Rahatgaon, Sirrali and Timarani blocks varied from 198.24 to 863.52, 172.48 to 885.92, 161.28 to 841.12, 176.96 to 846.72, 287.84 to 857.92 and 244.16 to 885.00 kg ha^{-1} with a mean value of 497.42,398.0, 447.46, 468.43, 488.10 and 508.32 kg ha^{-1}, respectively.

The available S content in soils of Harda, Hundia, Khirkiya, Rahatgaon, Sirrali, and Timarani block, varied from 1.76 to 62.50, 1.12 to 87.60, 3.21 to 82.40, 4.51 to 86.20, 2.08 to 41.50 and 1.76 to 89.1 mg kg^{-1} with a mean value of 20.92, 16.29, 23.96, 31.72, 16.34 and 26.72 mg kg^{-1} respectively. Considering 10 mg kg^{-1} as the threshold value, 52.48 percent samples were found deficient, 28.05% medium and 19.47% adequate in soils of Harda district. Low and medium availability S in soils may be due to lack of sulphur addition and continuous removal of S by crops. Similar finding was reported by [24,25] and [26]

3.3 Percent Sample Deficiency and Nutrient Index

Data presented in Table 2 showed the percent deficiency and NI of N in soils of Harda district was in the order of Khirkiya (75.93 and 1.24) > Hundia (72.50 and 1.28) > Rahatgaon (62.00 and 1.38)> Timarani (53.52 and 1.46)> Sirrali (46.67 and 1.53)>Harda (30.91and 1.69), respectively. This might be due to low statusand its continuous removal by crop.

The P was deficient in soil samples (59.26%) from Khirkiya, (43.33%) Sirrali, (36.00%), Rahatgaon and (28.17%), Timarani blocks. The low content of available phosphorous could be ascribed to the high amount of free oxides of Ca^{2+}, Mg^{2+} and Na^{+} which induce the fixation and subsequent precipitation of phosphorus as well as to the low amount of organic matter.

Table 1. Descriptive statistics of soil attributes (n=303)

Parameters	**Physico-chemical properties**				**Available nutrients (kg ha^{-1})**			**S**
	pH	**EC (dSm^{-1})**	**OC (g kg^{-1})**	**$CaCO_3$ (g kg^{-1})**	**N**	**P**	**K**	**(mg kg^{-1})**
Minimum	6.4	0.09	2.35	5.0	87.8	4.9	161.3	1.0
Maximum	8.9	0.98	10.16	115.0	326.1	76.8	885.9	89.0
Mean	7.6	0.20	5.32	37.3	231.3	23.8	472.0	28.25
S.D.	0.51	0.12	1.28	31.15	43.06	16.98	151.8	17.24
Skewness	-0.45	3.7	0.13	0.83	-0.35	0.85	0.41	0.19
β	-0.48	17.39	0.26	-0.45	-0.12	-0.56	-0.1	-1.28
CV%	6.7	60	24.06	83.4	18.62	71.19	32.15	61.03
PS_Low					56.77	31.68	6.6	52.48
PS_Medium					43.23	25.74	29.7	28.05
PS_High					0	42.57	63.7	19.47
NI					1.43	2.11	2.57	1.66

S.D. = Standard deviation, CV = Coefficient of variation, PS_Low= Percent sample low, NI= Nutrient Index, β = Kurtosis, n = no of soil sample

Table 2. Status and spatial distribution of physico-chemical properties and macronutrients

Blocks	Physico-chemical properties				Available nutrients (kg ha^{-1})			S
	pH	EC (dSm^{-1})	OC (g kg^{-1})	$CaCO_3$ (g kg^{-1})	N	P	K	(mg kg^{-1})
Harda (n=55)	6.5-8.4 (7.63)	0.1-0.59 (0.18)	2.92-10.16 (5.64)	5-115 (54.2)	163.07-301.06 (253.16)	6.95-76.85 (28.69)	198.24-863.52 (497.42)	1.76-62.5 (20.92)
Percent sample deficiency					**30.91**	**14.55**	**3.64**	**41.82**
Nutrient Index					**1.69**	**2.15**	**2.75**	**1.67**
Hundia (n=40)	6.6-8.4 (7.6)	0.1-093 (0.27)	3.46-7.83 (5.54)	30-107 (79.05)	150.53-301.06 (218.27)	7.04-57.82 (39.32)	172.48-885.92 (398)	1.12-87.6 (16.29)
Percent sample deficiency					**72.50**	**10.00**	**17.50**	**75.0**
Nutrient Index					**1.28**	**2.5**	**2.23**	**1.33**
Khirkiya (n=54)	6.4-7.8 (7.18)	0.09-0.37 (0.17)	2.35-6.95 (4.23)	5-110 (34.81)	137.98-263.42 (207.67)	5.94-54.07 (15.94)	161.28-841.12 (447.46)	3.21-82.4 (23.96)
Percent sample deficiency					**75.93**	**59.26**	**12.96**	**51.85**
Nutrient Index					**1.24**	**1.69**	**2.48**	**1.63**
Rahatgaon (n=53)	6.9-8.7 (7.85)	0.1-0.59 (0.19)	2.81-9.38 (5.25)	5-75 (18.02)	137.98-326.14 (227.45)	5.69-63.56 (19.82)	176.96-846.72 (468.43)	4.51-86.2 (31.72)
Percent sample deficiency					**62.00**	**36.00**	**6.00**	**43.00**
Nutrient Index					**1.38**	**1.79**	**2.53**	**1.93**
Sirrali (n=30)	6.5-8.1 (7.6)	0.1-0.3 (0.17)	2.52-8.31 (5.24)	5-105 (44.17)	150.53-313.6 (240.84)	4.94-55.31 (18.22)	287.84-857.92 (488.1)	2.08-41.5 (16.34)
Percent sample deficiency					**46.67**	**43.33**	**0.00**	**63.33**
Nutrient Index					**1.53**	**1.67**	**2.57**	**1.4**
Timarani (n=71)	6.6-8.9 (7.77)	0.1-0.98 (0.22)	2.48-8.46 (5.82)	5-115 (28.52)	87.81-326.14 (238.51)	6.69-60.03 (22.79)	244.16-885 (508.32)	1.76-89.1 (26.72)
Percent sample deficiency					**53.52**	**28.17**	**1.41**	**50.70**
Nutrient Index					**1.46**	**1.9**	**2.73**	**1.82**

n= no of soil samples

In Harda and Hundia only 14.55 and 10.0% soil sample found deficient. This high available P content is attributed to the regular application of phosphatic fertilizers and the immobile nature of phosphate ions in soils, which must have resulted in the accumulation of P in soils. Similarly, the NI indicated as 2.15, 2.5, 1.69, 1.79, 1.67 and 1.9 in Harda, Hundia, Khirkiya, Rahatgaon, Sirrali, and Timarani block, respectively. This might be due to calcareousness of soil. This is supported by the result reported by [27].

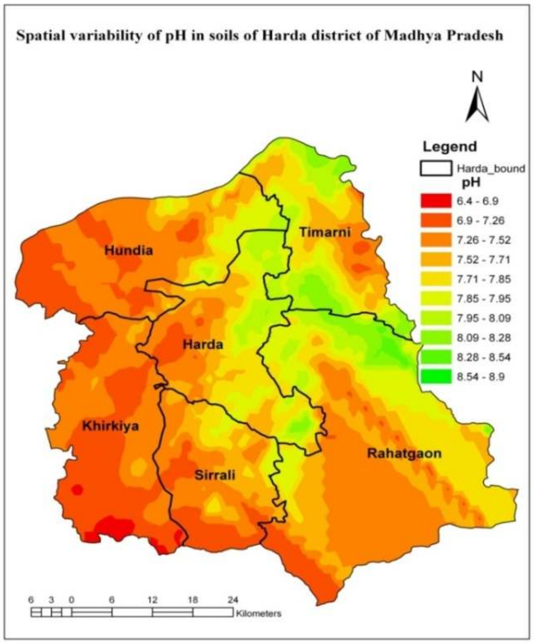

Fig. 4(a). Spatial variability of pH

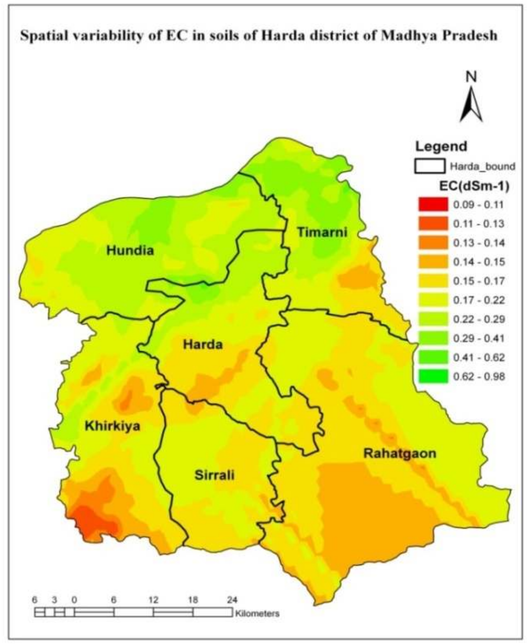

Fig. 4(b). Spatial variability of EC

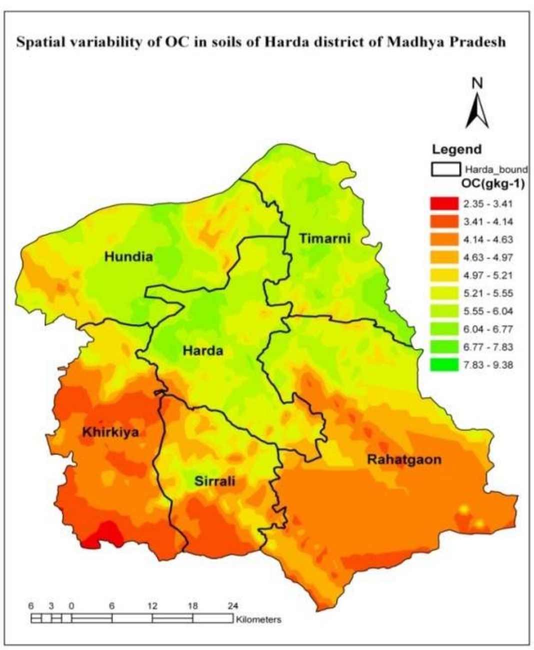

Fig. 4(c). Spatial variability of OC

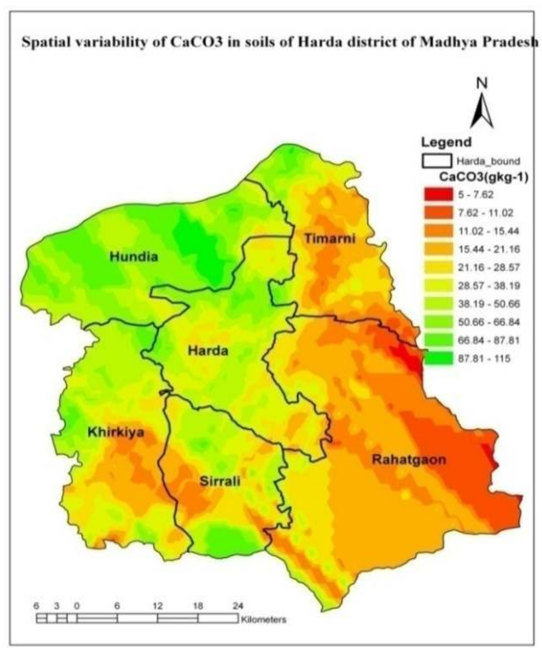

Fig. 4(d). Spatial variability of $CaCO_3$

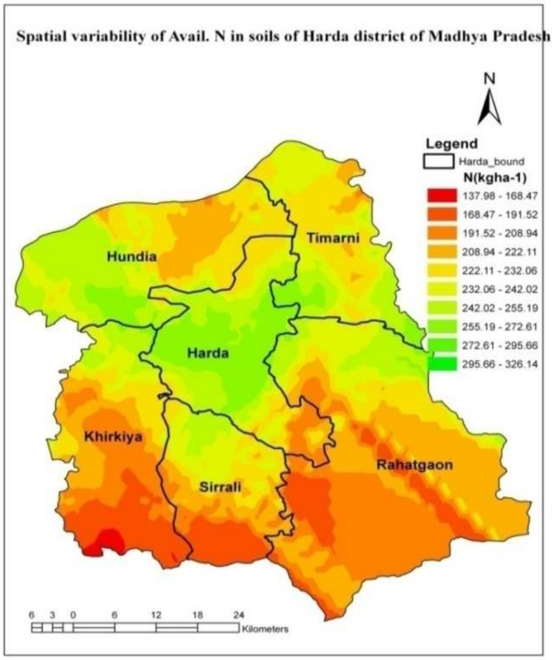

Fig. 4(e). Spatial variability of Avail. N

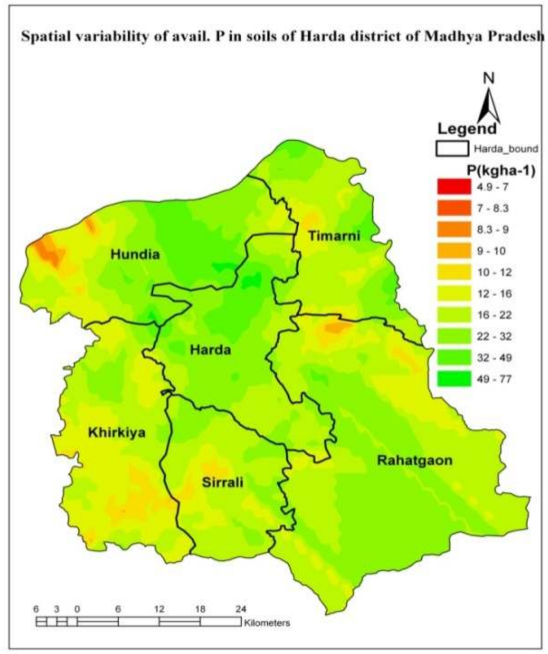

Fig. 4(f). Spatial variability of Avail. P

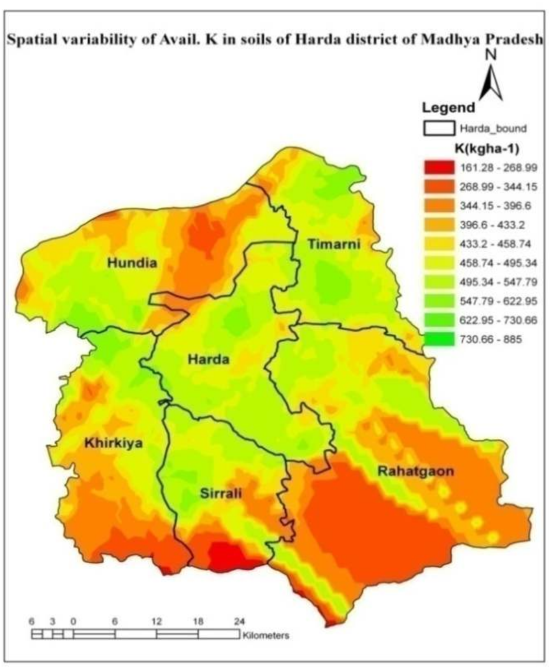

Fig. 4(g). Spatial variability of Avail. K

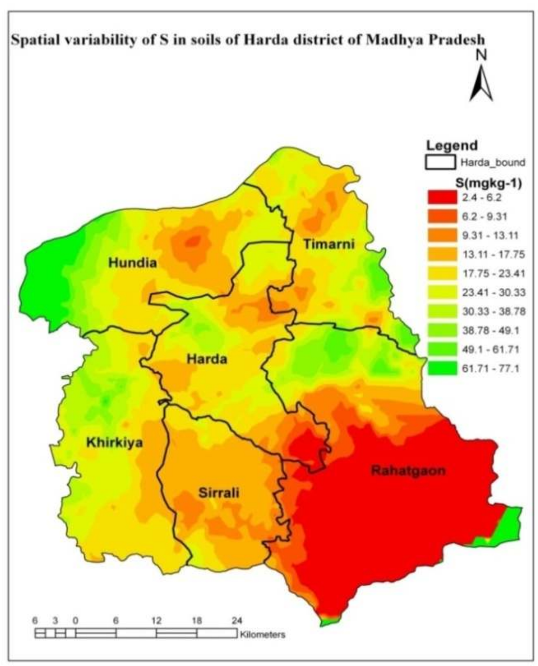

Fig. 4(h). Spatial variability of Avail. S

The deficiency of K was high in Hundia (17.5%) followed by Khirkiya (12.96%), Rahatgaon (6.0%), Harda (3.64%), Timarani (1.41%) and none in Sirrali block. However, the NI in soils of Hundia, Khirkiya, Rahatgaon, Sirrali Timarani, and Harda block as 2.23, 2.48, 2.53, 2.57, 2.73 and 2.75. The available potassium content as a whole district is generally medium to high and

Table 3. Characteristics of the models fitted to variogram and evaluation criteria for cross-validation

Variables	pH	EC	OC	$CaCO_3$	N	P	K	S
Transformation	None	None	None	Log	None	Log	None	Log
Range(m)	4256.5	6947.2	1950.2	2090.9	6603.5	3053.5	5275.9	3570.5
Nugget	0.08	0.01	0.76	0.5	1252.9	0.26	18290	0.23
Partial Sill	0.12	0.01	0.52	0.17	415.43	0.17	3340.2	0.3
Sill	0.2	0.01	1.28	0.66	1668.3	0.43	21630	0.54
NS Ratio	0.38	0.48	0.59	0.75	0.75	0.60	0.85	0.44
MAE	0	0	0.02	1.84	0.18	0.13	1.43	0.59
MSE	0.15	0.01	1.09	685.92	1423.4	234	20788	221.72
G	44.39	20.03	27.24	28.49	18.89	16.49	4.72	20.81

NS Ratio = Nugget Sill ratio, MAE = Mean absolute error, MSE = Mean squared error, G = goodness of prediction

only 6.6% soil samples were tested low. Only soils of Hundia block was found medium with NI value (NI=2.23), and that of rest blocks was high (>2.33). The high status of K in these soils may be due to the predominance of K rich micaceous and feldspars minerals in parent material. Similar results were reported by [28].

The deficiency of S was high in Hundia (75%) followed by Sirrali (63.33%), Khirkiya (51.85%), Timarani (50.70%), Rahatgaon (43%) and Harda block (41.82%). respectively. The NI value of S in soils low in Sirrali (1.27), followed by Hundia (1.33), Rahatgaon (1.42), Khirkiya (1.63), Harda (1.67) and Timarani (1.82).

In Harda district as a whole, 56.77,31.68,6.60 and 52.48% soil samples rated as low, 43.23, 25.74, 29.70 and 28.05 soil samples rated as medium and 0, 42.57, 63.70 and 19.47% soil samples rated as high of N, P, K, and S, respectively. The NI 1.43 and 1.66 for N and S was found to be low and 2.11 for P as rated medium whereas 2.57 rated as high for K. In this work the N is practically low in all the blocks of Harda district and P status was medium (2.11) except Hundia block (2.50), but [29] reported a wide spread deficiency of P in 98% of districts in India. [30] reported NPK fertility status it was 1.66, 2.35 and 1.98 (L-H-M). In our study for Harda district it was 1.43, 2.11 and 2.57. So the result revealed that there was L-M-H fertility status of N, P and K. According to [31], the NPK status of Karnataka was L-L-H. In Uttar Pradesh, the NPK status was L-M-M [32].

3.4 Spatial Variability Maps

In the present study, natural logarithmic transformation was used to reduce the skewness of the data distributions of $CaCO_3$, P, K, and S. Ordinary Kriging was chosen to create the spatial distribution maps of soil characteristics with the maximum search radius being set to the autocorrelation range of the corresponding variable. No apparent anisotropy was found for any studied variable through experimental variograms. So, all variograms were in isotropic form and fitted using basic math models, such as Spherical, exponential, Gaussian and linear based on the values of weighted residual sums of squares, goodness (G) and relative spatial structure indicator (Nugget/Sill) that indicated spatial dependency for Kriging interpolation.

Geo-statistical result revealed that the exponential model was best fitted for pH, EC, OC, $CaCO_3$, AN, AP, K, and S [33]. The nugget/sill ratio for pH, EC, OC, P, and S fell between 38% and 75% and exhibit moderate spatial dependency. However, $CaCO_3$, N, and K were showed >75%, which showed weak spatial dependency [34]. Reported exponential model and that it exhibited moderate spatial dependence, with a nugget/sill ratio of 0.462. Strong spatial dependence of soil properties could be attributed to intrinsic factors, and a weak spatial dependence could be attributed to extrinsic factors [16]. In addition, spatial dependence is defined as weak if the best fit semi-variogram model has an $R^2 < 0.5$ [35] Prediction map created using the geo-statistics tool of Arc GIS software. [36] by using several interpolation methods such as ordinary kriging and IDW drew similar value maps for potassium and phosphorus content of soils. Correlation ranged for pH, EC, OC, $CaCO_3$, N, P, K, and S were 4256.5, 6947.2, 1950.2, 2090.9, 6603.5, 3053.5, 5275.9 and 3570.5 m, respectively (Table 3). Apparently, pH, EC, N, and K are auto correlated in longer ranges than OC, $CaCO_3$, P, and S. This result is consistent with their CV values. The results are also supported by [37]. Similar result was reported by [38] and [39].

It is obvious from the data that there was no mean absolute error for pH and EC. However, mean squared error was noticed high for K followed by N, $CaCO_3$, P, S, OC, pH and EC. Again, the goodness of fit (G) was positive and highest for pH followed by $CaCO_3$, OC, S, EC, N, P and K.

Kriged maps were showed in Fig. 4a (pH), 4b (EC), 4c (OC), 4d ($CaCO_3$), 4e (AN), 4f (AP), 4g (AK) and 4h (AS). The Kriged map of spatial variability of soil nutrient could be used as a basis for consideration in variable rate fertilization, especially for N and P in order to supply the optimum requirements for plant growth that can be optimized crop production. Fertilization based on maps with recommendations related to soil fertility may lead to reduced fertilizer inputs without reducing yield.

4. CONCLUSION

The soils of Harda district were found neutral to alkaline in soil reaction, safe in electrical conductivity, low to medium in organic carbon content and non-calcareous to calcareous in nature. Results revealed the severity of deficiency occurred in the order N > P and K and NI status of N, P and K as low, medium and high (L-M-H). Geo-statistical result showed the exponential model best fitted for pH, EC, OC, $CaCO_3$, AN, AP, K and S. The nugget/sill ratios for pH, EC, OC, P, and S fell between 38% and 75%, which exhibit moderate spatial dependency. Spatial variability maps of soil nutrients prepared will be helpful for making better future sampling designs and management decisions.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Tesfahunegn GB, Tamene L, Vlek Paul LG. Catchment-scale spatial variability of soil properties and implications on site-specific soil management in northern Ethiopia. Soil & Tillage Research. 2011; 117:124–139.
2. Cambule AH, Rossiter DG, Stoorvogel JJ, Smaling EMA. Soil organic carbon stocks in the Limpopo National Park, Mozambique: Amount, spatial distribution and uncertainty. Geoderma. 2014;213:46–56.
3. Li L, Phoon K, Quek S. Simulation of non-translation processes using non gaussian Karhunen–Loeve expansion. Computers and Structures. 2007;85(5–6):264–276.
4. Weindorf DC, Zhu Y. Spatial variability of soil properties at Capulin Volcano, New Mexico, USA: Implications for sampling strategy. Pedosphere. 2010;20(2):185–197.
5. Liu ZP, Shao MA, Wang YQ. Spatial patterns of soil total nitrogen and soil total phosphorus across the entire Loess Plateau region of China. Geoderma. 2013; 197–198:67–78.
6. Cao SK, Chena KL, Cao GC, Zhang L, Ma J, Yang L, Lu BL, Chen L, Lu H. The analysis of characteristic and spatial variability for soil organic matter and organic carbon around Qinghai Lake. Procedia Env. Sci. 2011;10:678 –684.
7. Subbiah BV, Asija GL. A rapid procedure for the determination of available nitrogen in soils. Curr. Sci. 1956;25:259-260.
8. Olsen SR, Cole CV, Vatanabe FS, Dean LA. Estimation of available phosphorus in soil by extraction with sodium bicarbonate. Circ. U.S Dept. Agric. 1954;939:1-19.
9. Jackson ML. Soil chemical analysis prentice hall of India Private Limited New Delhi; 1973.
10. Chesnin L, Yien CH. TurbidImetric determination of available suiphates. Soil Sci. Soc. Am. Proc. 1951;15:149-151.
11. Parker FW, Nelson WL, Winter Eric, Miller LE. The broad interpretation of soil test information. Agronomy J. 1951;43:105-112.
12. Robinson TP, Metternicht G. Testing the performance of spatial interpolation techniques for mapping soil properties. Computer and Electronics in Agriculture, 2006;50:97-108.
13. Shi J, Wang H, Xu J, Wu J, Liu X, Zhu H, Yu C. Spatial distribution of heavy metals in soils: A case study of Changxing, China. Environmental Geology. 2007;52:1-10.
14. Webster R, Oliver MA. Statistical methods in soil science and resource survey. Oxford University Press, New York, NY; 2001.
15. Goovaerts P. Geo-statistics in soil science: State-of-the-art and perspectives. Geoderma. 1999;89:1-45.
16. Cambardella CA, Moorman TB, Novak JM, Parkin TB, Karlen DL, Turco RF, Konopka AE. Field scale variability of soil properties

in Central Iowa soils. Soil Sci. Soc. Am. J. 1994;58:1501–1511.

17. Davis BM. Uses and abuses of cross-validation in geo-statistics Math. Geol. 1987;19:241–248.
18. Santra AK, Pan S, Samanta AK, Das S, Halder S. Nutritional status of forage plants and their use by wild elephants in South West Bengal, India. Tropical Ecology. 2008;49(2):251-257.
19. Agterberg FP. Trend surface analysis. In spatial statistics and models (Eds. Gaile, G. L. and Willmott, C. J.), Reidel, Dordrecht, The Netherlands. 1984;147–171.
20. Singh RP, Mishra SK. Available macro nutrients (N, P, K and S) in the soils of Chiraigaon block of district Varanasi (U.P.) in relation to soil characteristics. Indian J. Sci. Res. 2012;3(1):97-100.
21. Swarup A. Effect of gypsum, green manure, farmyard manure and zinc fertilization on the zinc, iron and manganese nutrition of wet land rice on a sodic soil. J. Indian Soc. Soil. Sci. 2000; 39:530-535.
22. Sharma BD, Arora H, Kumar R, Nayyar VK. Relationships between soil characteristics and total and DTPA-extractable Micronutrients in Inceptisols of Punjab. Commun. Soil Sci. Plan. 2004; 35(5-6):799-818.
23. Rashmi K, Shankar MA, Shashidhar KR, Narayanaswamy TK. Growth and foliar constituents of mulberry (M5) cultivated under organic based nutrient management. Int. J. Indust. Entomol. 2009;19(1):165-169.
24. Rathore GS, Khamparia RS, Gupta GP, Sinha SB. Availability of micronutrients in some alluvial soils and their effect on wheat. J. Ind. Soc. Soil Sci. 1995;28:248-250.
25. Singh S, Sarkar AK. Status of plant available sulphur in soil of Gumla and Lohardaga districts of Chotanagpur region. J. Ind. Soc. Soil Sci. 1999;46(3):556-558.
26. Singh K, Bansal SK. Effect of continuous cropping for twenty years on some properties of the intensively cultivated alluvial soils and nutrients indexing of rice. J. Ind. Soc. Soil Sci. 2007;55(3):265-269.
27. Ghosh S. Spatial variation of soil ph and soil phosphorous and their interrelationship in the plateau area of West Bengal, India. International J. of Recent Scientific Research. 2015;6(3):3208-3212.
28. Ravikumar MA, Patil PL, Dasog GS. Mapping of nutrients status of 48A Distributary of Malaprabha right bank command of Karnataka by GIS technique. Major Nutrient Karnataka. J. Agric. Sci. 2007;20(4):735-737.
29. Tiwari KN. Phosphorous needs of Indian soils and crops. Better Crops Intern. 2001; 15:2.
30. Pathak H. Trend of fertility status of Ind. soils. Curr. Adv. in Agril. Sci. 2010;2(1): 10-12.
31. Ravikumar P, Somashekar RK. Spatial distribution of macronutrients in soils of Markandeya river basin, Belgaum, Karnataka, India. Proceedings of the Intern. Academy of Ecology and Environ. Sci. 2014;4(2):81-94.
32. Kumar P, Kumar A, Dyani BP, Kumar P, Shahi UP, Singh SP, Kumar R, Kumar Y, Sumith R. Soil fertility status in some soils of Muzaffarnagar District of Uttar Pradesh, India, along with Ganga canal command area. African J. Agril. Res. 2013;8(14): 1209-1217.
33. Liu Yinghui, Key Jeffrey R, Frey Richard A, Ackerman Steven A, Paul W. Nighttime Menzel. Polar cloud detection with MODIS. Remote Sensing of Environment. 2004;92: 181 – 194.
34. Zhang H, Zhuang Shunyao, Qian Haiyan, Wang Feng, Ji Haibao. Spatial variability of the topsoil organic carbon in the Moso bamboo forests of southern china in association with soil properties. Plos One a Peer-Reviewed, Open Access Journal. 2015;10(3):0119175.
35. Duffera M, White JG, Weisz R. Spatial variability of southeastern us coastal plain soil physical properties: Implications for Site-specific Management, Geoderma. 2007;137:327–339.
36. Kravchenko AN, Bullock DG. A Comparative study of interpolation method for mapping soil P and K contents. In: Proceedings of 4th International Conference on Precision Agriculture, 11-15 Jun, St. Paul, Minnesota, USA. 1999;267-279.
37. Reza SK, Sarkar D, Baruah U, Das H. Evaluation and comparison of ordinary Kriging and inverse distance weighing methods for prediction of spatial variability of some chemical parameters of Dhalai district, Tripura. Agropedology. 2010;20: 38–48.

38. Liu Z, Zhou W, Jianbo Shen, Ping He, Lei Q, Liang G. A simple assessment on spatial variability of rice yield and selected soil chemical properties of paddy fields in South China. Geoderma. 2014;235–236: 39–47.
39. Tripathi R, Nayak AK, Shahid M, Lal B, Gautam P, Raj R, Mohanty S, Kumar A, Panda BB, Sahoo RN. Delineation of soil management zones for a rice cultivated area in eastern India using fussy clustering. Catena. 2015;133:128-136.

Peer-review history:
The peer review history for this paper can be accessed here:
http://sciencedomain.org/review-history/21013