Original Research Article

Predictive mapping of soil micronutrients using geographic information system for site specific management interventions in a semiarid farm, India

ABSTRACT

Deficiency of soil micronutrients has an adverse impact on crop productivity in intensive agriculture. Plant availability, spatial pattern and distribution of soil micronutrients such as iron (Fe), manganese (Mn), zinc (Zn) and copper (Cu) content in surface soils were evaluated for an agricultural farm in semiarid region of India. Other soil properties viz. soil pH, electrical conductivity (EC), soil organic carbon (SOC) content and equivalent calcium carbonate ($CaCO_3$) content at the farm were also analysed to depict the soil chemical environment, controlling micronutrient availability. Plant available micronutrient contents within farm soils had very high data variability (coefficient of variation >30%). Soil available micronutrients content were negatively correlated with soil pH and positively correlated with SOC content. As per semivariogram analysis, plant available Fe, Mn, Zn and Cu content within farm soils had moderate spatial dependency as indicated by nugget to sill ratio between 0.30 and 0.50 and had spatial parameter ranges of 404, 801, 954 and 1529 m, respectively. Prediction map of plant available Fe content by inverse distance weightage (IDW) method showed a few patches of iron deficiency (< 4.50 mg kg^{-1}) and a marginal level (4.50 - 9.00 mg kg^{-1}). Spatial distribution map of plant available Zn content through lognormal ordinary kriging method indicated a patch of marginal Zn level (0.60 - 1.20 mg kg^{-1}) within the farm soils. Farm scale spatial variability maps of plant available Mn and Cu content, generated by ordinary kriging method with good accuracy and effectiveness, indicated its adequate level with respect to crop nutrition. The spatial distribution maps of soil available micronutrients content for the farm could be served as reference for its precise and site specific management for intensive crop cultivation, higher productivity and profitability

Key words: DTPA extractable micronutrient, Semivariogram, Kriging, Inverse distance weightage, Spatial variability mapping, precision nutrient management

1. INTRODUCTION

Trace elements, for example, iron (Fe), manganese (Mn), zinc (Zn) and copper (Cu) are essential micronutrients for plant metabolism as well as human health and application of micronutrient fertilizer in soil improves both soil health, crop production and .country's nutritional security [1]. Soil is the major reservoir of most biologically active micronutrients [2]. These micronutrients are required in very little amount by plants or creatures for its nourishment and wellbeing, but then high level of these or other minor elements can be hazardous [3], [4]. Availability of soil micronutrients is better indicator than its total soil content for the prediction of crop uptake and ecological toxicity. But adoption of intensive and modern cropping practices with high-yielding crop cultivars, unbalanced fertilizer and low manure application resulted in emergence of widespread micronutrient deficiency in soils and crops of India as well as world leading to reduced crop yield, low micronutrient concentration in agricultural produce and subsequently its low supply to food chain [5]–[7]. Agricultural strategies for improving micronutrient concentrations in plant foods had been described in details [8]. Soil test based fertilizer recommendation is also one effective tool to achieve precision farming for maximization of crop productivity, sustainability of soil health and efficient fertilizer management [9]. Digital micronutrient map generated from soil test value using geospatial techniques can be used for preliminary guide or tool for variable rate fertilizer recommendation based on status of soil and crop requirement [10].

Geographic information system (GIS) based geostatistics consists a set of tools, which has been broadly used to show the spatial behaviour and to generate variability map of soil attributes [11]–[14]. Geostatistics enables spatial relationships among sample values to be quantified and used for spatial interpolation of values at unsampled sites with optimal and unbiased estimations [15]. Spatial variability of plant available soil micronutrients was reported at national level [16], state [17], district [18]–[21] and block level [22] for developing right kind of customized fertilizer by fertilizer industries and precise fertilizer distribution by government and fertilizer agencies. Geo-spatial variability of soil micronutrients at regional scale [23], catchment level or watershed level [24] and at farm scale [25], [26] were also reported. Highly detailed maps of soil micronutrient availability at individual fields were being developed for precision agriculture [27]–[29]. At present scenario in India, generation of detailed georeferenced digital maps such as village level and farm scale spatial variability maps of soil micronutrients and development of its prediction model for future use as algorithm in GIS are thrust area for achieving high sustainable agricultural productivity and superior nutritional quality [30]**.** Soil map generated through geospatial techniques portrays the delineated boundary of spatial distribution of the soil micronutrient availability based on a limited number of samples in agricultural and environmental landscapes. This resource inventory data are vital for a superior comprehension of the nature and degree of micronutrient anomaly like deficiencies and toxicities in soil-plant systems and recommendation of best management practices for controlling soil micronutrient availability, increasing crop productivity, sustainability and environmental safety [31], [32].

In the current investigation, an endeavour has been made with three objectives (i) to survey soil micronutrient status for assessment of extent of micronutrient (Fe, Cu, Zn and Mn) availability, deficiency or toxicity; (ii) to characterize its spatial variability through semivariogram model and (iii) to generate micronutrient distribution map using GIS based interpolation tools for site specific micronutrient management at ICAR-Indian Agricultural Research Institute (IARI) farm, New Delhi representing Aravalli plains under semi-arid climatic zone of India.

2. MATERIALS AND METHODS

2.1. Description of study area

A spur of the Aravalli Hills from Rajastan state enters Indian Capital Territory of Delhi through Gurgaon on the southern outskirt and ventures into a prolonged edge of around 5 km width running towards north-east. The greater part of the Delhi Territory consists of a mantle of alluvium which is a consolidated fluvial deposit with nodular calcium carbonate concretions at places. Indian Agricultural Research Institute (IARI) farm is a representative agricultural farm from Delhi under semiarid climate. IARI farm is bounded by longitude 77° $8'$ $40.5''$ - 77° $10'$ $28.1''$ East and latitude 28° $37'$ $22.0''$-28° $38'$ $58.7''$ North at New Delhi with a cultivated area of 278 ha. Soils of IARI farm belongs to coarse loamy/fine loamy, mixed, hyperthermic, Typic/Calcic/Fluventic Haplustepts. The study area is under semi-arid climate with hottest May month and coldest January month. The average annual temperature is 25.5°C. The average summer (May, June and July) and winter (December, January and February) temperature are 33°C and 17.3°C respectively. Annual normal rainfall was 729 mm, of which 612 mm (84%) was received from June to September and rest from November to March months.

There are different administrative blocks (Fig 1) in the cultivated area of the farm such as Main Block (MB), Middle Block (MID), Genetic Block (Gen), Sewage irrigated area

(SA), New Area (NA), Shadipur orchard and block, Top Block (TB), Todapur (TDPR), National Burreau of Plant Genetic Resources (NBPGR) Block, Paddock field, Water Technology (WTC) Block, Precision Farming and Development Centre (PFDC) experimental area, Protected structures under Indo-Israel Project and forest area for efficient execution of farm activities. During *Kharif* season, major cereal crops such as *Oryza sativa* (paddy), *Zea mays* (maize), *Sorghum bicolor*, *Pennisetum glaucum* (bajra); pulses viz. *Glycine max* (soybean), *Vigna radiata* (mung bean), *Cajanas cajan* (arhar), *Vigna unguiculata* (cowpea); vegetables, flowers, etc. were grown, whereas during *Rabi* season, cereals viz. *Triticum aestivum* (wheat), maize etc; oilseeds like *Brassica* sp. (mustard); pulses like *Cicer arietinum* (chickpea), *Pisum sativum* (pea), *Lens culinaris* (lentil), arhar, cowpea; vegetables; flowers; other crops like *Gossypium hirsutum* (cotton), etc. were cultivated. Cultivation of high value off-seasons crops under protected structures and seed production of agri-horticultural crops as per demands of farmers were also being practiced in the farm. Besides the seasonal crops, there were fruit orchards of *Ziziphus mauritiana* (ber), *Mangifera indica* (mango), C*itrus*, *Emblica officinalis* (aonla), *Psidium* (guava), *Syzygium cumini* (jamun), *Vitis vinifera* (grape) etc in Todapur block, Shadipur block and NBPGR block within the farm. *Eucalyptus and Jatropha curcas* are planted in Genetic block whereas natural forest is seen in south east corner of IARI farm.

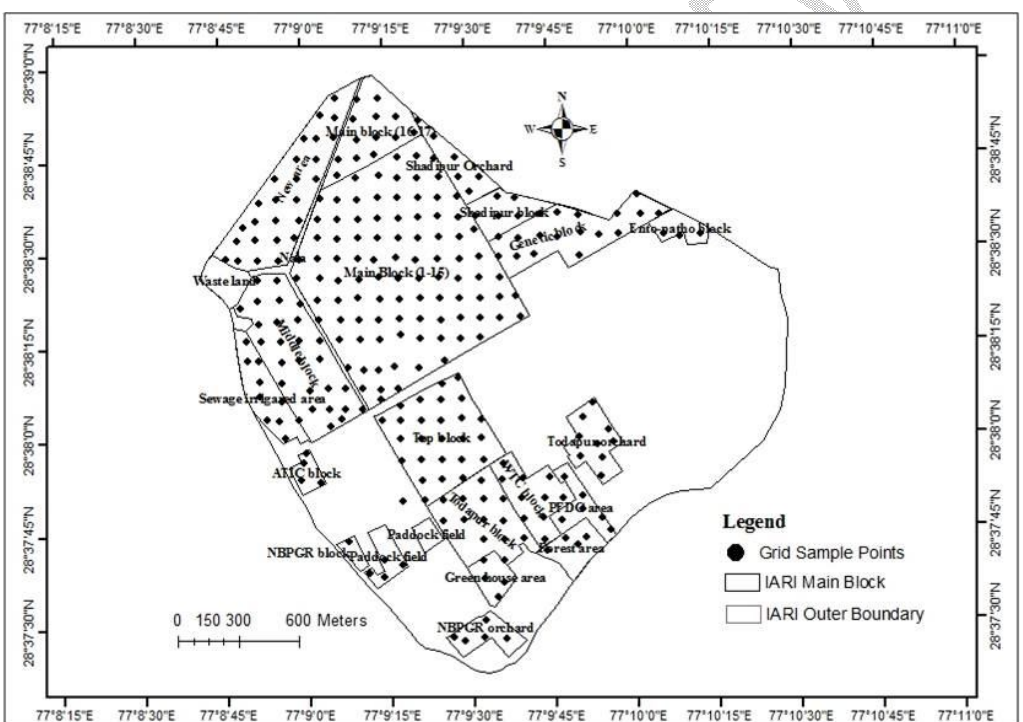


Figure 1 Location, major blocks and collected sample points at ICAR-Indian Agricultural Research Institute farm (IARI), New Delhi

2.2. Sampling design and soil analysis

Geo-coded soil samples were collected in a depth of 0 to 15 cm from 288 locations across area of 278 ha at square grid intersection points of 100 m × 100 m dimension using global positioning system (GPS). Soil pH in 1:2.5 soil water suspensions is determined using a combined electrode in a digital pH meter and electrical conductivity was measured in the supernatant liquid of the soil water suspension (1:2.5) using electrical conductivity meter as per standard guidelines [33]. The soil samples were analysed for soil organic carbon by

Walkley and Black (1934) method [34] and for free carbonate carbon by pressure calcimeter method [35]. Plant available micronutrients in near-neutral and calcareous soils were extracted using most suitable extractant *i.e.* diethylene triamine penta acetic acid - calcium chloride - triethanol amine (DTPA-$CaCl_2$-TEA) solution [36] and its concentration was determined in atomic absorption spectrophotometer (AAS). The DTPA extractable soil iron (Fe), manganese (Mn), zinc (Zn) and copper (Cu) contents are denoted by DTPA-Fe, DTPA-Mn, DTPA-Zn and DTPA-Cu.

2.3. Statistical and geostatistical analysis

Descriptive statistics such as data distribution, central tendency, dispersion and bivariate correlation were analysed using SPSS version 16.0 software. The data distribution pattern of original soil attributes was analyzed with Q-Q plot to understand whether it is normally distributed or not. Data transformation techniques such as natural logarithmic or Box-Cox transformation were used for micronutrients datasets without normal distribution. The coefficients of skewness and kurtosis of original and transformed dataset calculated in exploratory data analysis wizard of ArcGIS software assisted for its interpretation.

The data variogram models were plotted using GS+ software. The test semivariogram is a graphical portrayal of the mean square fluctuation between two neighbouring points of distance h, which is used describe the spatial structure of soil attributes [37]. Semivariance is computed using following equation.

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i)\text{-}z(x_i\text{+}h)]^2 \qquad (1)$$

In the above equation, $\gamma(h)$ is the semivariance expressed as a function of the magnitude of the lag distance or separation vector h, N(h) is the number of observation pairs separated by distance h and $z(x_i)$ is the regionalized variable at location x_i. The omni-directional experimental semivariogram $\gamma(h)$ was being fitted to various theoretical models such as spherical, exponential, linear, or Gaussian to estimate three semivariogram parameters, *i.e.*, nugget (C_0), sill (C_0 + C) and parameter range (A_0) [38]. The sill is sum value of nugget variance (C_0) and structural variance (C). Best fitted semivariogram model for soil micronutrients content was selected on the basis of maximum r^2 value**.**

The deterministic model such as Inverse Distance Weighted (IDW) and geostatistical interpolation technique viz ordinary kriging with inclusion of semivariogram parameters obtained from GS+ program was used to create spatial surfaces from measured points using ArcGIS version 10.4.1 software. The spatial distribution of soil micronutrients was mapped after its back-transformation. Accuracy and effectiveness of interpolation techniques for generation of thematic soil maps was assessed through cross validation approach [39]. The evaluation indices such as mean error (ME) and root mean squared error (RMSE) indicate the accuracy of interpolation, whereas goodness of prediction (G) indicates the effectiveness of interpolation [40]. Mean Error (ME) is the average value of residuals *i.e.* difference between predicted and observed values. Root mean squared error (RMSE) is the square root of the mean of the square of all residuals or errors. Mean error is used to measure average biasness of interpolation. RMSE is good measure of accuracy to compare different interpolation models for a particular soil attribute. The formula of mean error (ME) and RMSE were given below:

$$ME = \frac{\sum_{i=1}^{n} [\hat{z}(x_i) - z(x_i)]}{n} \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} [\hat{z}(x_i) \quad z(x_i)]^2} \qquad (3)$$

where $z(x_i)$ is the observed values of the variable at the location x_i, $\hat{z}(x_i)$ is the predicted values at the location x_i and n is the number of sampling locations.

The G measure gives a sign of effectiveness of interpolation whether it is acceptable over using the sample mean alone as predictor [41].

$$G = \left[1 - \frac{\sum_{i=1}^{N}[z(x_i) - \hat{z}(x_i)]^2}{\sum_{i=1}^{N}[z(x_i) - \bar{z}]^2}\right] \times 100 \qquad (4)$$

Where z is the sample mean. If G = 100, it indicates perfect prediction, while negative values demonstrate that sample mean is itself good estimator of population data rather than following interpolation techniques.

3. RESULTS AND DISCUSSION

3.1. Descriptive statistics

Classical statistics are being used to study the central tendency, dispersion of soil attributes, data distribution pattern and its relationship with other soil properties. The measures of central tendency such as average, median and the measures of variability and dispersion such as minimum, maximum, standard deviation and coefficient of variation are presented in Table 1. There was a wide range of variability for the soil attributes such as pH, EC, soil organic carbon (SOC) concentration, equivalent calcium carbonate content and DTPA extractable micronutrient content *i.e.* DTPA-Fe, DTPA-Mn, DTPA-Zn and DTPA-Cu content. The data variability of soil attributes was classified on the basis of coefficient of variation (CV) values as low (<10%), medium(10–20%), high (20–30%), and very high (>30%) variabilities, as per criteria proposed by Gomes and Garcia (2002) [42]. Soils were neutral and alkaline in nature with pH value ranging from 5.79 to 9.10. The low pH variability, as observed by its low coefficient of variation CV 7%, was reduced to major extent because of log-transformation of hydrogen ion concentration. The SOC concentration within surface soils of the farm varied from 0.56 to 11.14 g kg^{-1}, with a mean value of 3.94 g kg^{-1}. The mean concentration of equivalent calcium carbonate was 4.83 g kg^{-1}, with a maximum of 71.50 g kg^{-1}. The average values for plant available Fe (DTPA-Fe), Mn (DTPA-Mn), Zn (DTPA-Zn) and Cu (DTPA-Cu) content within the farm soils were 12.55, 14.20, 3.30 and 2.24 mg kg^{-1} respectively, which are at high level category. As per generalized transition zone of critical limit for available micronutrients in soil [30], high level of DTPA-Fe, DTPA-Mn, DTPA-Zn and DTPA-Cu are >10.5, >9.0, >1.8 and >1.0 mg kg^{-1} respectively. Electrical conductivity, SOC content, effective calcium carbonate content, DTPA-Fe, DTPA-Mn, DTPA-Zn and DTPA-Cu content had very high data variability at the farm. The coefficient of variation (CV) for DTPA-Fe and DTPA-Cu content were 148% and 157% respectively, which were comparatively higher than other soil attributes. After removal of only five numbers of extreme outliers of plant available Cu concentration, the CV value reduced from 157% to 35% with same median values of 1.72 mg kg^{-1}. The comparatively very low or high DTPA-Cu content within a few locations values may not always be an outlier but a form of natural or management induced variation. These outliers or extreme values were removed to minimize the errors of semivariogram models [43], [44]

Table 1 Summary statistics for soil available micronutrient content and other soil properties at ICAR-IARI farm, New Delhi

Soil attributes	Sample No	Mean	Std. Deviation	CV (%)	Min.	Max.	Interquartile Range	Median
pH	288	7.96	0.58	7	5.89	9.10	0.64	8.08
EC (dS m^{-1})	288	0.41	0.18	43	0.08	1.04	0.22	0.39

SOC (g kg^{-1})	288	3.94	1.63	41	0.56	11.14	1.77	3.63
$CaCO_3$ (g kg^{-1})	288	4.83	9.26	192	0.00	71.50	2.94	2.25
Fe (mg kg^{-1})	288	12.55	18.52	148	1.26	135.93	6.83	6.90
Mn (mg kg^{-1})	288	14.20	7.32	52	1.20	72.42	8.48	13.77
Zn (mg kg^{-1})	288	3.30	2.86	87	0.25	19.03	2.66	2.36
Cu (mg kg^{-1})	288	2.24	3.53	157	0.04	56.08	1.32	1.72
Cu (mg kg^{-1}) outlier excluded	283	1.99	1.23	35	0.26	7.99	1.24	1.72

The interrelationship between soil available micronutrient content and soil properties was given in Table 2.

Table 2 Correlation coefficients (r) for relationship of soil available micronutrient content with soil properties

	pH	EC	SOC	$CaCO_3$	DTPA –Fe	DTPA –Mn	DTPA - Zn	DTPA –Cu
pH	1.00							
EC	0.00	1.00						
SOC	-0.29**	0.15*	1.00					
CaCO3	0.23**	0.02	-0.07	1.00				
DTPA-Fe	-0.18**	0.14*	0.20**	-0.06	1.00			
DTPA-Mn	-0.33**	0.01	0.02	-0.16**	0.16**	1.00		
DTPA-Zn	-0.14*	0.10	0.23**	-0.10	0.45**	0.01	1.00	
DTPA-Cu	-0.04	0.07	0.13*	-0.04	0.42**	-0.09	0.41**	1.00

** and * indicate that correlation is significant at 0.01 level and 0.05 level (2-tailed) respectively

There was negative influence of increasing pH on DTPA-micronutrients as indicated by significant and negative correlation coefficient between soil pH and soil available Fe (-0.18**), Mn (-0.33**) and Zn (-0.14*) concentration. It was also observed that the availability of soil Mn content was significantly influenced by $CaCO_3$ content. Soil organic carbon had a positive and significant effect on soil available Fe (0.20**), Zn (0.23**) and Cu (0.13*) content. The similar relationship was also observed and explained that soil organic matter (SOM) had substantial role in heavy metal sorption by soils due to its significant effect on binding of heavy metals in soil as well as metal-organic complex and speciation in soil solution [45], [46]. It was also reported that soil pH and SOM had major significant role on the availability and extractability of soil micronutrients [23], [47], [48].

The original dataset of soil available micronutrient content showed positively skewed and leptokurtic distribution (Table 3).

Table 3 Shape parameters for original and transformed data of soil micronutrient content

Soil attributes	Original data		Log-transformed data		Box-Cox transformation		
	Skewness	Kurtosis	Skewness	Kurtosis	Parameter λ value	Skewness	Kurtosis
Fe (mg kg^{-1})	3.68	17.62	1.18	4.48	-0.50	-0.03	3.19
Mn (mg kg^{-1})	2.13	16.24	-0.71	4.13	0.25	-0.18	3.79

Zn (mg kg^{-1})	2.22	8.92	-0.002	3.00	-	-	-
Cu (mg kg^{-1})	12.59	189.24	-0.02*	3.22*	-	-	-

*Outlier excluded dataset of Cu

The differences in topographic features, land use, vegetation cover, management practices etc may be the underlying reason for soil elements being distributed normally or non-normally [49]. The normal Q-Q plot clearly depicts the distribution pattern of original dataset and Box-Cox transformed or natural logarithmic transformed dataset in Fig 2 and normal distribution of dataset is observed while the points cluster around a straight line. Box-Cox transformation with parameter λ value of -0.50 and 0.25 for soil available Fe (Fig 2b) and Mn content (Fig 2d) respectively showed normal distribution, as observed from a straight diagonal line in concerned Q-Q plots and coefficient of skewness closer to zero & coefficients of kurtosis closer to 3.0. The dataset of soil available Zn content was log normally distributed (Fig 2e). In Q–Q plots of soil available Cu content (Fig 2g), the deviation from straight line was observed and subsequently, a few extreme values or outliers were removed. The dataset of soil available Cu content (Fig 2h) after outlier's removal was also log normally distributed. Box-Cox transformed data of DTPA-Fe and DTPA-Mn as well as logarithmically transformed data of DTPA-Zn and DTPA-Cu were used for geostatistical analysis. Box-Cox and natural logarithmic transformation of non-normal dataset of soil nutrients were followed to stabilize the variance and subsequent geostatistical analysis was also reported by several authors [25], [44], [50].

3.2. Spatial modeling of soil micronutrient content

Spatial modeling through semivariogram analysis of soil available micronutrient content can show a definite spatial structure and nature of spatial dependency. Semivariogram analysis of soil properties like pH, soil organic carbon and macronutrients at ICAR-IARI farm, New Delhi was reported earlier [51]. Semivariogram for Box-Cox transformed data of DTPA-Fe and DTPA-Mn as well as logarithmically transformed data of DTPA-Zn and DTPA-Cu contents was analysed in the geostatistical program. The best fitted semivariogram model of soil available Fe and Zn content was exponential and it was spherical for soil available Mn and Cu content (Fig 3).

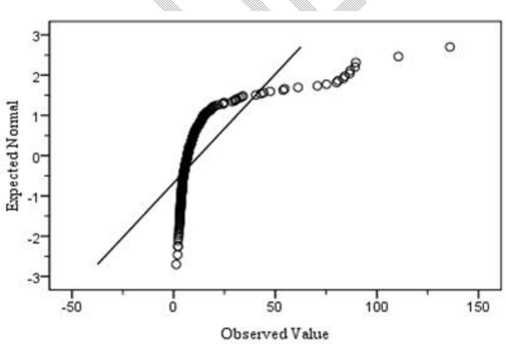


Fig 2a Q-Q_plot of original Fe data

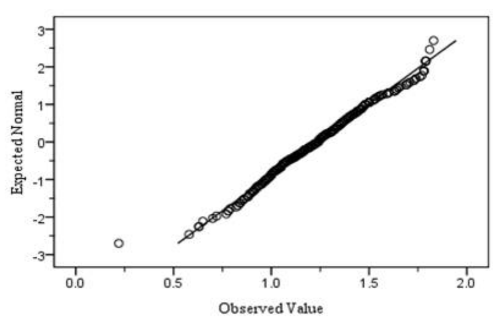


Fig 2b Q-Q plot of Box-Cox transformed (λ=-0.5) Fe data

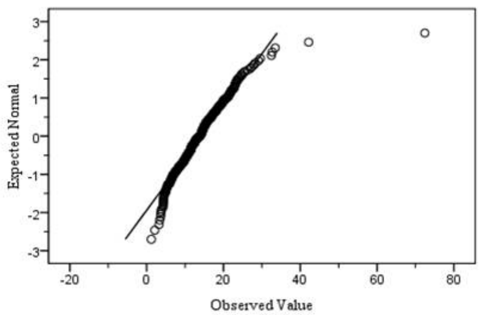


Fig 2c Q-Q plot of original Mn data

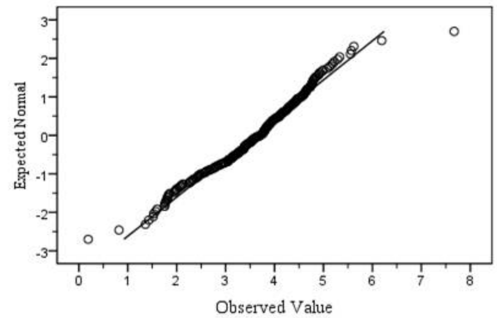


Fig 2d Q-Q_ plot of Box-Cox transformed (λ=-0.25) Mn data

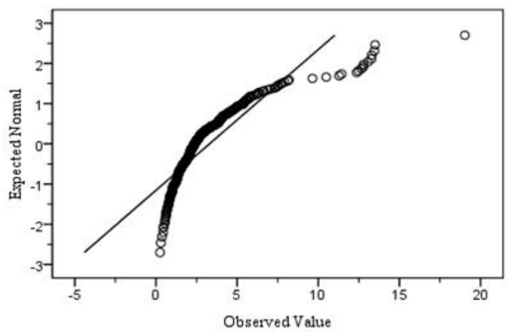


Fig 2e Q-Q_ plot of original Zn data

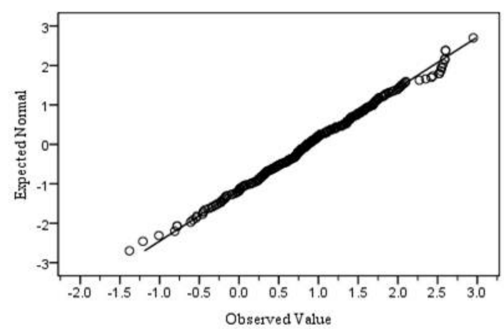


Fig 2f Q-Q_plot of Ln (Zn)

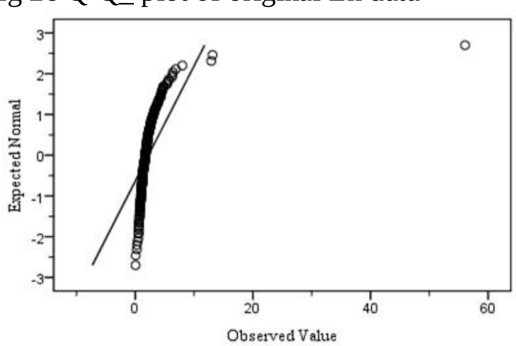


Fig 2g Q-Q_ plot of original Cu data

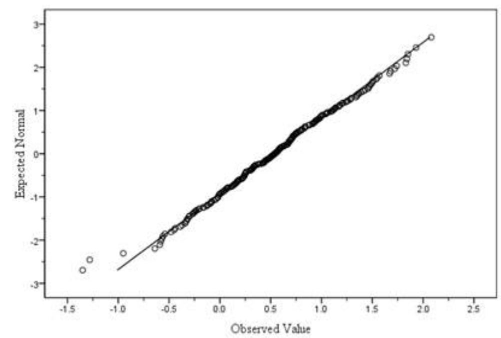
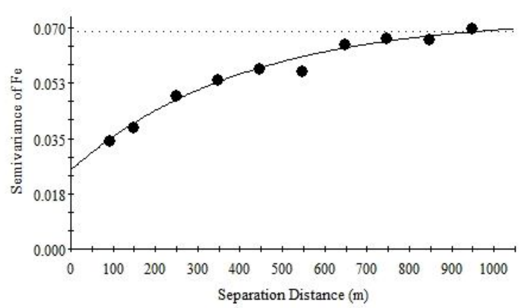
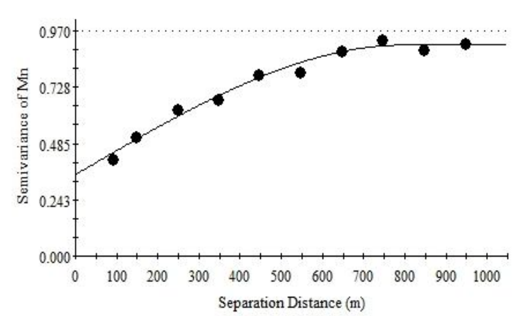


Fig 2h Q-Q plot of Ln (Cu)

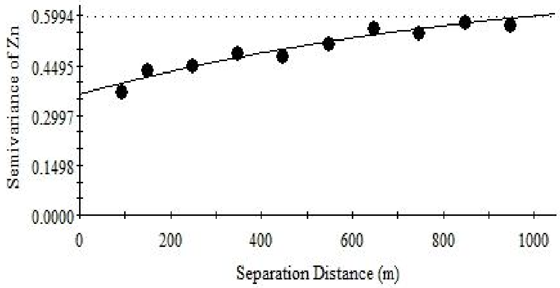
Fig 2 Normal Q-Q plot of original soil micronutrient datasets and its transformed datasets for ICAR-IARI farm soils



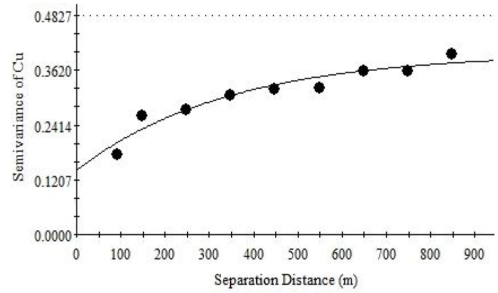
(a)



(b)



(c)



(d)

Fig 3 Experimental semivariograms and fitted models for soil available micronutrients (a) Fe, (b) Mn, (c) Zn and (d) Cu content after data transformation at ICAR-IARI farm. Dashed line indicates the sample variance of transformed dataset.

The semivariogram reaches an asymptote at effective range for the spherical models while in case of exponential model, the sill ($C+C_0$) never meets the asymptote and it is within 5% of the asymptote at distance of effective range (A). The coefficient of determination (r^2) for best fitted curve was 0.99 for DTPA-Cu, 0.98 for DTPA-Fe and Mn, and 0.93 for DTPA-Zn content. It showed that the preferably selected theoretical models *i.e.* exponential and spherical model reflected a specific pattern of spatial structure for soil micronutrient content in the farm. Similarly, the best fitted spatial modeling of soil micronutrients as observed by several authors were spherical model [22], [50] and exponential model [23], [26], [52].

The variability of soil available micronutrient contents, which was caused by soil micro-scale processes and measured error, controlled the nugget value. The proportion of nugget value (C_0) to total sill of soil available Fe, Mn, Zn and Cu content were 0.34, 0.38, 0.50 and 0.30 respectively (Table 4). In the present farm scale study, the spatial variability arising from the random components was less as indicated by low nugget proportions. Sill value is the semivariance value on Y axis that fitted semivariogram model attains at the parameter range value correspond to X axis [53]. The nugget/sill ratios of soil available micronutrient (Fe, Mn and Cu) content were between 25 to 75%, which demonstrated moderate spatial autocorrelation, as per standard classification [54], for soil available micronutrient content. The moderate spatial dependency of soil micronutrient content was mainly controlled by both structural (parent material, topography, soil type, soil texture and mineralogy) and extrinsic factors (cropping system, tillage, fertilizer application, soil & water management and agricultural management practices etc). It indicated that although the soil available micronutrients in the farm were controlled by several factors including cropping systems, its management etc, it had not yet arrived the degree of eliminating the original spatial pattern. The findings broadly align with the observations provided by Ramzan & Wani (2018) [25].

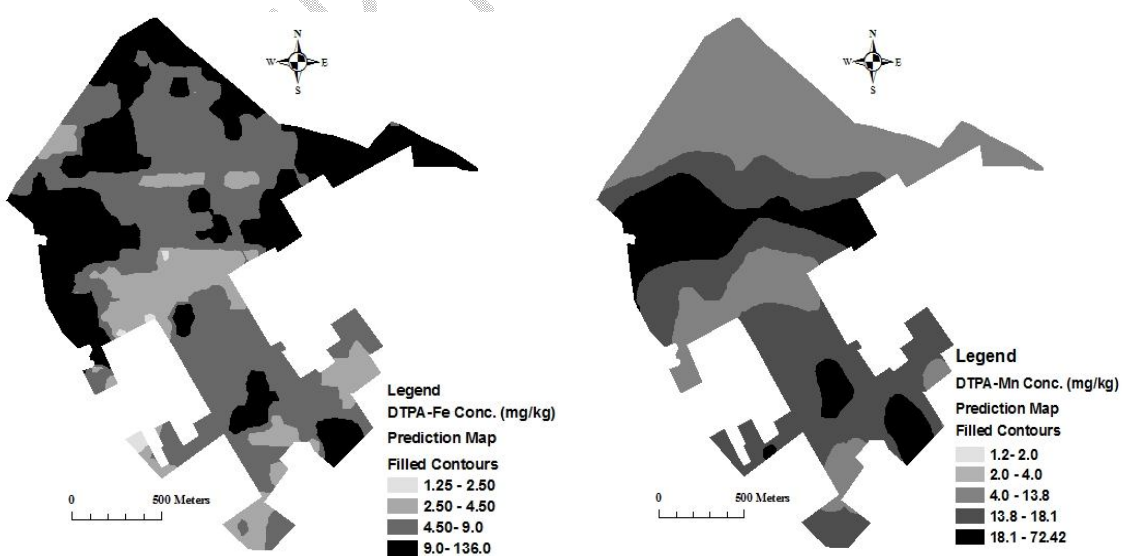
Table 4 Parameters for best fitted semivariogram model of soil attributes at ICAR- IARI farm, New Delhi

Soil attributes	Best fitted model	Nugget (C_0)	Sill (C_0+C)	Parameter range (A_0) (m)	Nugget/Sill *i.e.* $C_0/(C_0+C)$	r^2
DTPA-Fe	Exponential	0.025	0.074	404	0.34	0.98
DTPA-Mn	Spherical	0.350	0.910	801	0.38	0.98
DTPA-Zn	Exponential	0.363	0.727	954	0.50	0.93
DTPA-Cu	Spherical	0.107	0.351	1529	0.30	0.99

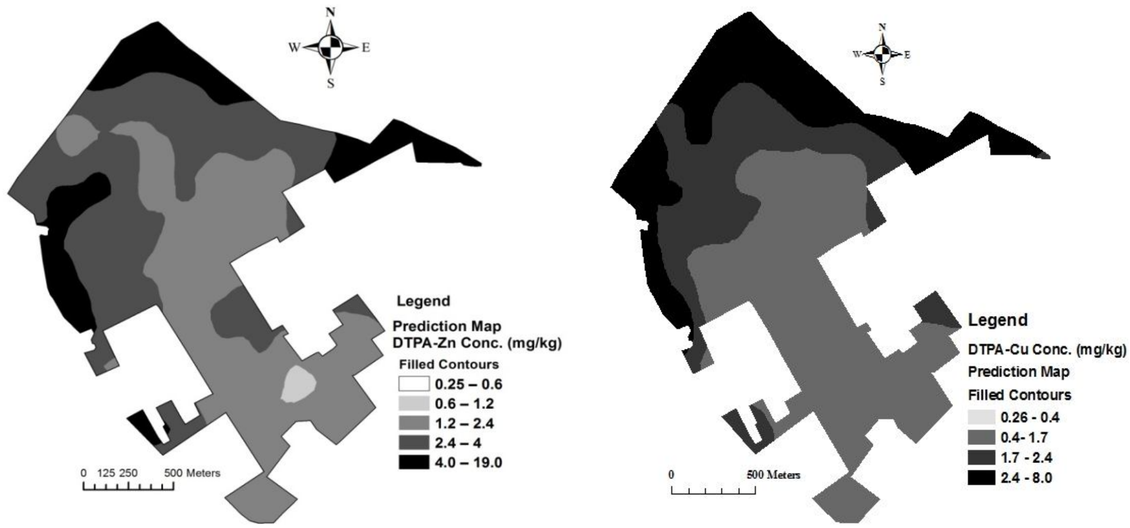
The spatial range is the largest distance, within which soil attributes are spatially autocorrelated and is used as decisive tool for selecting sampling design and mapping of soil properties [43]. It was related to the interaction among various soil factors, soil processes, and resultant soil properties, which are variable at different scale of survey under study [55]. The effective range (A) for spherical model is same value of parameter range (A_0) [56]. The effective range (A) for exponential model is equal to three time of parameter range ($3A_0$), which is the distance at which the sill ($C+C_0$) is within 5% of the asymptote. The spatial ranges or effective ranges of soil available Fe, Mn, Zn and Cu content were 1212, 801, 2856 and 1529 m, respectively. From Table 4, the spatial range of available micronutrient contents in the farm was in the sequence of available Zn>Cu >Fe> Mn content. The effective range of available Zn was very high and it had spatial autocorrelation throughout the farm. Spatial range of soil attributes may be controlled by scale of soil survey. Smaller spatial range of soil available micronutrient content was reported by several authors viz. 100-150 m by Dafonte et al. (2010) [57], 135-171 m by Najafian et al. (2012) [58], 194-299 m by Weindorf & Zhu (2010) [59], 120–243 m by Wani et al. (2013) [60]. Similar spatial range of soil available micronutrient content was reported by several authors viz. 495–2110 m by Dharejo et al. (2011) [61], 1596 to 3019 m by Vasu et al. (2021) [22] . Higher spatial range of soil available micronutrient content at block level, district and country level soil survey was also reported by other authors [23], [50], [55].

3.3. Spatial distribution map of soil micronutrients for plant availability and site specific management

Spatial variability of plant available micronutrient such as Fe, Mn, Zn and Cu contents at IARI farm soils are depicted in the concerned map (Fig 4) generated using GIS software. Spatial distribution of soil properties like pH, EC, soil organic carbon content and plant available macronutrients content were also reported earlier for ICAR-IARI, New Delhi farm [51], [62]. Soil available micronutrient content in present context had been categorized as very low, low, marginal and adequate level. Southern portion of Main Block and Middle Block, a portion of Todapur orchard and NBPGR orchard in IARI



(a) (b)



(c) (d)

Fig 4 Spatial distribution map of DTPA extractable soil micronutrient (a) Fe, (b) Mn, (c) Zn and (d) Cu content at ICAR-IARI farm, New Delhi

farm was observed as low level or deficient (< 4.50 mg kg^{-1}) zone of soil DTPA-Fe content. Major area of Main Block, Top Block, WTC Block and PFDC block had soil DTPA-Fe content in marginal amount (4.50-9.00 mg kg^{-1}). Major area of the farm had adequate or sufficient (>9.00 mg kg^{-1}) amount of plant available Fe content. Soil iron deficiency in the farm can be explained by alkaline soil pH (7.7) and low soil organic carbon (SOC) content, as DTPA-Fe content was also negatively correlated with pH and positively correlated with SOC content, which had similarity with findings of other author [50]. The deficient and marginal zone of plant available Fe content within the farm need proper soil, irrigation water, crop residue management and micronutrient fertilization for maintaining sustained high crop productivity. Application of green manure or organic manures in soil and foliar spray of 1-2% unneutralized ferrous sulphate three to four times effectively alleviate iron deficiency or iron chlorosis of several crops such as rice, pearl millet, soybean, citrus and horticultural crops [63].

There was no zone of low level (< 0.60 mg kg^{-1}) for plant available Zn content at the farm soils although a few soil samples had low level of Zn content as observed in its minimum value. It may be because of inherent averaging process of spatial prediction model [64]. Marginal (0.60-1.20 mg kg^{-1}) level of DTPA-Zn content was observed within WTC and Todapur block of IARI southern part. Basal application of 25 and 12.5 kg zinc sulphate per hactre to soil through broadcast and its incorporation or its band placement below the seed was recommended for soils with low and marginal level of available soil zinc respectively to get optimum yields. While considering the dose and frequency of zinc application for sandy loam alkaline alluvial soils of IARI farm, 5.5 kg Zn ha^{-1} for first four crops and repeat application of 5.5 and 2.75 kg ha-1 for next 8 and 12 crops, respectively were recommended for higher crop response and optimum yield [63]. The farm soil had adequate amount (>1.20 mg kg^{-1}) of soil available Zn content with comparatively higher value (4.10-19.00 mg kg^{-1}) at northern, eastern *i.e.* Genetics Block, western fringe *i.e.* sewage irrigated area and a patch within NBPGR Block. The higher available Zn values were mainly obtained in northern orchards, paddy cultivated area and sewage irrigated area.

There was no observed area with low (< 2.00 mg kg^{-1}) and marginal (2.00-4.00 mg kg^{-1}) level of soil available Mn content. The farm had soil available Mn content in adequate amount (> 4.00 mg kg^{-1}) with respect to crop nutrition. Soil DTPA-Mn content was observed to be high (18.10-72.42 mg kg^{-1}) in stripe of northern middle portion of IARI farm, patches in forest area, Top Block and Todapur Block. Similarly, soil DTPA-Cu content was also in adequate amount (> 0.40 mg kg^{-1}) in the farm with higher value (2.4 - 8.0 mg kg^{-1}) at margin area in northern portion of the farm. Overall, the concentration of these soil micronutrients in availability form within the farm was not in toxic level or pollution level.

The generated spatial distribution and variability map for different soil micronutrients is of great use for planning appropriate agricultural strategies including fertilization for different crop cultivation. High soil pH, low soil organic carbon and non-replenishment of iron and zinc after crop uptake are a few reasons for deficient or marginal zone of soil available iron and zinc content in the farm as indicated by significant correlation coefficients and similar findings were also reported by other authors [22]. As the soils are heterogeneous and variable in respect to micronutrients distribution and hence site-specific fertilization can be adopted rather than conventional practices of nutrients management for higher crop productivity with environmental and economical sustainability. Sources, optimum dose, method and frequency of micronutrient fertilizer application in Indian soils had been elaborately described for field usable practices [63].

3.4. Assessment of spatial interpolation method

The evaluation indices resulting from cross validation of spatial distribution maps of soil available micronutrient contents for inverse distance weighted (IDW) and ordinary kriging interpolation techniques in GIS software are shown in Table 5. For all the soil micronutrients (Fe, Mn, Zn & Cu), the G values were greater than zero in both method (IDW and OK). It indicated that spatial prediction using IDW & OK method was more effective than assuming sample mean as the property value for any unsampled location. The interpolation of soil DTPA-Fe content by IDW technique was preferred as compared to ordinary kriging. Both mean error (ME) and root mean square error (RMSE) values of DTPA-Fe concentration were lower in case of IDW method as compared to that of ordinary kriging. The goodness of prediction (G) value in IDW method of soil DTPA-Fe prediction was 45% which was comparatively higher than that of ordinary kriging method. So, accuracy and effectiveness of IDW method is more than kriging method in case of soil DTPA-Fe content.

Table 5 Evaluation performance of inverse distance weighted (IDW) and ordinary kriging (OK) interpolation of soil micronutrients through cross validation approach

Soil attributes	Interpolation techniques	Mean Error (ME)	Root mean square error (RMSE)	Goodness of prediction G (%)
DTPA-Fe	IDW	-0.2939	13.68	45
	OK	-2.7620	16.24	23
DTPA-Mn	IDW	0.1040	5.52	43
	OK	-0.0225	5.78	37
DTPA-Zn	IDW	-0.0904	2.71	10
	OK	-0.0798	2.70	11
DTPA-Cu	IDW	-0.2191	3.46	4
	OK	-0.0058	0.83	54

Ordinary kriging technique was used for interpolation of soil DTPA-Mn, DTPA-Zn and DTPA-Cu content. The ME value of prediction for DTPA-Mn content through kriging method is lower than that of IDW method. The G value of prediction for DTPA-Mn content through kriging method was 37%, which was good enough for generation of spatial distribution map after considering its moderate spatial dependency. The ME and RMSE values of prediction for DTPA-Zn content through lognormal kriging method is lower than that of IDW method. The prediction of DTPA-Cu content by lognormal kriging method after outlier removal improved the G value upto 54% and also significantly reduced the ME and RMSE value to lesser values *i.e.* -0.0058 and 0.83 respectively. Hence, accuracy and effectiveness of lognormal kriging method was better than IDW method for prediction of soil DTPA Zn and DTPA-Cu content.

4. CONCLUSIONS

Classical statistical analysis showed that average concentration of plant available Fe, Mn, Zn and Cu within the farm soil were 12.55, 14.20, 3.30 and 2.24 mg kg^{-1}, respectively. Soil properties like pH and SOC content significantly influenced the available soil micronutrients content. The semivariograms of soil available Fe and Zn content were best fitted with exponential model while soil available Mn and Cu content was best fitted with spherical semivariogram model. Semivariogram analysis showed that soil available Fe, Mn, Zn and Cu content had moderate spatial dependency within the parameter ranges of 404, 801, 954 and 1529 m respectively. Inverse distance weightage (IDW) method predicted the soil available Fe content with higher accuracy and effectiveness as compared to kriging method. As per cross-validation of kriged maps for soil available Mn, Zn and Cu content, its spatial interpolation using semivariogram parameters is more preferable than assuming mean of the observed value for unsampled location. Spatial distribution map delineated a few patches of iron deficient and marginal level of soil available Fe content and marginal level of available zinc content towards crop nutrition and it needs attention for soil management and application of iron and zinc micronutrient fertilizer for higher crop productivity. The farm had adequate level of soil available Mn and Cu content with respect to crop nutrition. The soil micronutrients distribution map of the farm can be used confidently for precision micronutrient management for sustainable crop cultivation. In future, the geo-referenced spatial database can be used for development of predictive equation through calibration of DTPA extractable micronutrients, total micronutrient content and readings of micronutrient sensors attached to IoT for smart agriculture monitoring stations.

Disclaimer (Artificial intelligence)

Option 1: Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

REFERENCES

[1] Shukla AK, Behera SK, Pakhre A, Chaudhari SK. Micronutrients in soils, plants, animals and humans. Indian J. Fertil. 2018;14(4):30-54.

[2] Mitchell RL, Burridge JC. Trace elements in soils and crops. Philos. Trans. R. Soc. London. B, Biol. Sci. 1979;288(1026):15-24.
DOI: https://doi.org/10.1098/rstb.1979.0087

[3] Welch RM. Micronutrient nutrition of plants. Crit. Rev. Plant Sci. 1995;14:49–82.

[4] Sagwal A, Wadhwa P, Shubham, Kaushal S. Essentiality of micronutrients in soil: a review. Int. J. Plant Soil Sci. 2023;35(24):56–65.

[5] Fageria NK, Baligar VC, Clark R. Micronutrients in Crop Production. Advances in Agronomy. 2002;77:185–268.

DOI: http://dx.doi.org/10.1016/s0065-2113(02)77015-6
[6] Shukla AK, Behera SK, Satyanarayana T,. Majumdar K. Importance of micronutrients in Indian agriculture. Better Crop - South Asia. 2019;11(1):6–10.
[7] Kavitha C, Sujatha MP, Tata R. Spatial variations in soil micronutrients as influenced by agro ecological conditions in a tropical humid region. Trop. Ecol. 2019;60(3):362–78.
DOI: http://dx.doi.org/10.1007/s42965-019-00037-w
[8] Graham RD, Welch RM, Bouis HE. Addressing micronutrient malnutrition through enhancing the nutritional quality of staple foods: Principles, perspectives and knowledge gaps. Advances in Agronomy. 2001;70:77–142.
DOI: http://dx.doi.org/10.1016/s0065-2113(01)70004-1
[9] Ramamurthy V, Naidu LGK, Ramesh Kumar SC, Srinivas S, Hegde R. Soil-based fertilizer recommendation for precision farming. Curr. Sci., 2009;97(5):641–7,
[10] Zhuo Z, Xing A, Li Y, Huang Y, Nie C. Spatio-temporal variability and the factors influencing soil-available heavy metal micronutrients in different agricultural sub-catchments. Sustainability. 2019;11(21):5912.
DOI: http://dx.doi.org/10.3390/su11215912
[11] Trangmar BB, Yost RS, Uehara G. Application of Geostatistics to Spatial Studies of Soil Properties. Adv. Agron. 1985;38:45–94.
DOI: http://dx.doi.org/10.1016/s0065-2113(08)60673-2
[12] Burrough PA. Soil variability: A late 20th century view. Soils Fertil. 1993;56:529–62
[13] Kingsley J, Lawani SO, Esther AO, Ndiye KM, Sunday OJ, Penížek V. Predictive mapping of soil properties for precision agriculture using geographic information system (GIS) based geostatistics models. Mod. Appl. Sci. 2019;13(10):60.
DOI: http://dx.doi.org/10.5539/mas.v13n10p60
[14] Gökmen V, Sürücü A, Budak M, Bilgili AV. Modeling and mapping the spatial variability of soil micronutrients in the Tigris basin. J. King Saud Univ. - Sci. 2023;35(6):102724
DOI: http://dx.doi.org/10.1016/J.JKSUS.2023.102724
[15] Goovaerts P. Geostatistics in soil science: state-of-the-art and perspectives. Geoderma. 1999;89(1–2):1–45.
DOI: http://dx.doi.org/10.1016/s0016-7061(98)00078-0
[16] Shukla AK, Behera SK. Micronutrient research in India: retrospect and prospects. Preprints of Seminar Papers. 2017;SII-4/2
DOI: http://dx.doi.org/10.13140/RG.2.2.20370.76489
[17] Singh MV. Micronutrient fertility mapping for Indian Soil. Tech. Bull. AICRP Micronutr. IISS, Bhopal. 2008;7:1–60.
[18] Sharma PK, Sood A, Setia RK, Verma VK, Mehra D, Tur NS, Nayyar VK. Use of information technology for mapping of DTPA-extractable micronutrients in soils of Amritsar district, Punjab. J. Indian Soc. Soil Sci., 2006;54:465–74.
[19] Kumar M, Singh SK, Raina P, Sharma BK. Status of available major and micronutrients in arid soils of Churudistrict of western Rajasthan. J. Indian Soc. Soil Sci., 2011;59:188–92.
[20] Sikarwar A, Shukla V, Bhardwaj S, Prajapati R, Mishra R, Sikaniya Y, Nagwanshi A. Spatial variability of soil micronutrient properties using geostatistical approach and geographic information system technique. Int. J. Plant Soil Sci. 2023;35(22):908–22,
DOI: http://dx.doi.org/10.9734/IJPSS/2023/V35I224202
[21] Satish Y, Shekhar S, Singh A, Rathod S, Chouksey N. Spatial variability of soil micronutrients in Raichur district of Karnataka. Int. J. Stat. Appl. Math. 2023;8(4S):560–7.

[22] Vasu D, Sahu N, Tiwary P. Chandran P. Modelling the spatial variability of soil micronutrients for site specific nutrient management in a semi-arid tropical environment. Model. Earth Syst. Environ. 2021;7(3):1797–812.
DOI: http://dx.doi.org/10.1007/s40808-020-00909-4
[23] Shukla AK, Behera SK, Lenka NK, Tiwari PK, Prakash C, Malik RS, Sinha NK, Singh VK, Patra AK, Chaudhary SK. Spatial variability of soil micronutrients in the intensively cultivated Trans-Gangetic Plains of India. Soil Tillage Res. 2016;163:282–9.
DOI: http://dx.doi.org/10.1016/J.STILL.2016.07.004
[24] Gurjar DS, Sudhishri S, Mishra AK, Kaur R, Khanna M. Geo-spatial variability in soil health of Biwan watershed located at Mewat district of Haryana, India. Indian J. Agric. Sci. 2018;88(5):714–9.
DOI: http://dx.doi.org/10.56093/ijas.v88i5.80060
[25] Ramzan S, Wani MA. Geographic information system and geostatistical techniques to characterize spatial variability of soil micronutrients including toxic metals in an agricultural farm. Commun. Soil Sci. Plant Anal. 2018;49(4):463–77.
DOI: http://dx.doi.org/10.1080/00103624.2018.1431264
[26] Buttar TS, Sharma V. Spatial variability of soil micronutrients under paddy (*Oryza sativa*)-wheat (*Triticum aestivum*) cropping system in irrigated plains. Indian J. Agric. Sci. 2023;93(4):403–8.
DOI: http://dx.doi.org/10.56093/IJAS.V93I4.110157
[27] Berndtsson R, Bahri A, Jinno K. Spatial dependence of geochemical elements in a semiarid agricultural field: II. geostatistical properties. Soil Sci. Soc. Am. J. 1993;57(5):1323–9.
DOI: http://dx.doi.org/10.2136/sssaj1993.03615995005700050027x
[28] Paz A, Taboada MT, Gómez MJ. Spatial variability in topsoil micronutrient contents in a one□hectare cropland plot. Commun. Soil Sci. Plant Anal. 1996;27(3-4):479–503.
DOI: http://dx.doi.org/10.1080/00103629609369570
[29] Srivastava AK, Das SN, Malhotra SK, Majumdar K. SSNM-based rationale of fertilizer use in perennial crops : a review. Indian J. Agric. Sci. 2014;84(1):3-17.
DOI: http://dx.doi.org/10.56093/ijas.v84i1.37139
[30] Shukla AK, Behera SK. All India Coordinated Research Project on Micro- and Secondary Nutrients and Pollutant Elements in soils and plants : research achievements and future thrusts. Indian J. Fertil. 2019;15(5):522–43.
[31] White JG, Zasoski RJ. Mapping soil micronutrients. F. Crop. Res. 1999;60(1–2):11–26.
DOI: http://dx.doi.org/10.1016/s0378-4290(98)00130-0
[32] Wu C, Luo Y, Zhang L. Variability of copper availability in paddy fields in relation to selected soil properties in southeast China. *Geoderma*, 2010;156(3–4):200–6.
DOI: http://dx.doi.org/10.1016/j.geoderma.2010.02.018
[33] Jackson ML. Soil Chemical Analysis. New Delhi: Prentice Hall of India Pvt. Ltd; 1973.
[34] Walkley A, Black IA. An examination of the Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. Soil Sci. 1934;37:29–38
[35] Piper CS. Soil and plant analysis. Mumbai: Hans Publishers; 1966.
[36] Lindsay WL, Norvell WA. Development of a dtpa soil test for zinc, iron, manganese, and copper. Soil Sci. Soc. Am. J., 1978;42(3): 421–8.
DOI: http://dx.doi.org/10.2136/sssaj1978.03615995004200030009x
[37] Burgess TM, Webster R. Optimal interpolation and isarithmic mapping of soil

properties. I: The semivariogram and punctual kriging. J. Soil Sci. 1980;31(2):315–31. DOI: http://dx.doi.org/10.1111/j.1365-2389.1980.tb02084.x
[38] Isaaks EH, Srivastava RM. An introduction to applied geostatistics. New York: Oxford University Press; 1989.
[39] Davis BM. Uses and abuses of cross-validation in geostatistics. Math. Geol. 1987;19(3):241–8.
DOI: http://dx.doi.org/10.1007/bf00897749
[40] Voltz M, Webster R. A comparison of kriging, cubic splines and classification for predicting soil properties from sample information. J. Soil Sci. 1990;41(3):473–90.
DOI: http://dx.doi.org/10.1111/j.1365-2389.1990.tb00080.x
[41] Schloeder CA, Zimmerman NE, Jacobs MJ. Comparison of methods for interpolating soil properties using limited data. Soil Sci. Soc. Am. J. 2001;65(2):470–9.
DOI: http://dx.doi.org/10.2136/sssaj2001.652470x
[42] Gomes FP, Garcia CH. Estatrstica aplicada a experimentos agronomicos e florestais. Piracicaba: FEALQ; 2002. Português.
[43] Fu W, Tunney H, Zhang C. Spatial variation of soil nutrients in a dairy farm and its implications for site specific fertilizer application. Soil Tillage Res. 2010;106:185–93.
DOI: http://dx.doi.org/10.1016/j.still.2009.12.001
[44] Bogunovic I, Mesic M, Zgorelec Z, Jurisic A, Bilandzija D. Spatial variation of soil nutrients on sandy-loam soil. Soil Tillage Res. 2014;144:174–83.
DOI: http://dx.doi.org/10.1016/j.still.2014.07.020
[45] Lo KSL, Yang WF, Lin YC. Effects of organic matter on the specific adsorption of heavy metals by soil. Toxicol. Environ. Chem. 1992;34(2–4):139–53.
DOI: http://dx.doi.org/10.1080/02772249209357787
[46] Tella M, Bravin M, Thuriés L, Cazevieille P, Chevvasus-Rosset C, Collin B, Chaurand P, Legros S, Doelsch E. Increased zinc and copper availability in organic waste amended soil potentially involving distinct release mechanisms. Environ. Pollut. 2016;212:299–306.
[47] Kabata-Pendias A, Pendias H. Trace Elements in Soils and Plants. Florida: CRC Press Inc; 2001.
[48] Behera SK, Singh MV, Singh KN, Todwal S. Distribution variability of total and extractable zinc in cultivated acid soils of India and their relationship with some selected soil properties. Geoderma 2011;162(3–4):242–50.
DOI: http://dx.doi.org/10.1016/j.geoderma.2011.01.016
[49] Tesfahunegn GB, Tamene L, Vlek PLG. A participatory soil quality assessment in northern Ethiopia's Mai-Negus catchment. Soil Tillage Res. 2011;86:1–13.
DOI: http://dx.doi.org/10.1016/j.still.2011.09.005
[50] Foroughifar H, Jafarzadeh AA, Torabi H, Pakpour A, Miransari M. Using geostatistics and geographic information system techniques to characterize spatial variability of soil properties, including micronutrients. Commun. Soil Sci. Plant Anal. 2013;44(8):1273–81.
DOI: http://dx.doi.org/10.1080/00103624.2012.758279
[51] Gorai T, Ahmed N, Sahoo RN, Pradhan S, Datta SC, Sharma RK. Site specific nutrient management of an intensively cultivated farm using geostatistical approach. *Proc. Natl. Acad. Sci. India Sect. B Biol. Sci.*, 2015;87(2):477–88.
DOI: http://dx.doi.org/10.1007/s40011-015-0590-1
[52] Liu XM, Xu JM, Zhang MK, Huang JH, Shi JC, Yu XF. Application of geostatistics and GIS Geography, technique to characterize spatial variabilities of bioavailable micronutrients in paddy soil. Environ. Geogr. 2004;46:189–94.
DOI: http://dx.doi.org/10.1007/s00254-004-1025-0

[53] Webster R, Oliver MA. Geostatistics for Environmental Scientists. Chichester, UK: John Wiley & Sons; 2001.
[54] 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.
[55] Shu-ying W, Tong-quan Y, Jian-li W, Liu Y, Kai Y, Ping L. Preliminary study on spatial variability and distribution of soil available microelements in Pinggu county, Beijing, China. Agric. Sci. China. 2008;7(10):1235–44.
DOI: http://dx.doi.org/10.1016/s1671-2927(08)60170-4
[56] Robertson GP. *GS+: Geostatistics for the Environmental Sciences*. Michigan USA: Gamma Design Software, Plainwell; 2008.
[57] Dafonte JD, Guitián MU, Paz-Ferreiro J, Siqueira GM, Vázquez EV. Mapping of soil micronutrients in an european atlantic agricultural landscape using ordinary kriging and indicator approach. Bragantia, 2010;69(suppl):175–86.
DOI: http://dx.doi.org/10.1590/s0006-87052010000500018
[58] Najafian A, Dayani M, Motaghian HR, Nadian H. Geostatistical assessment of the spatial distribution of some chemical properties in calcareous soils. J. Integr. Agric. 2012;11(10):1729–37.
DOI: http://dx.doi.org/10.1016/s2095-3119(12)60177-4
[59] Weindorf DC, Zhu Y. Spatial variability of soil properties at capulin volcano, new mexico, usa: implications for sampling strategy. Pedosphere. 2010;20(2):185–97.
DOI: http://dx.doi.org/10.1016/s1002-0160(10)60006-9
[60] Wani MA, Wani JA, Bhat MA, Kirmani NA, Zahid MW, Bhat SN. Mapping of soil micronutrients in Kashmir agricultural landscape using ordinary kriging and indicator approach. J. Indian Soc. Remote Sens. 2013;41:319–29.
DOI: http://dx.doi.org/10.1007/s12524-012-0242-3
[61] Dharejo KA, Anuar AR, Khanif YM, Samsuri AW, . Junejo N. Spatial variability of Cu, Mn and Zn in marginal sandy beach ridges soil. African J. Agric. Res. 2011;6:3493–98.
[62] Gorai T, Ahmed N, Sahoo RN, Pradhan S, Datta SC, Sharma RK. Spatial variability mapping of soil properties at farm scale. J. Agric. Phys. 2015;15:29–37.
[63] Singh MV. Micronutrient deficiencies in Indian soils and field usable practices for their correction. in IFA International Conference on Micronutrients, Feb. 23-24, 2004;23–24.
[64] Wu J, Norvell WA, Welch RM. Kriging on highly skewed data for DTPA-extractable soil Zn with auxiliary information for pH and organic carbon. Geoderma. 2006;134(1–2):187–99.
DOI: http://dx.doi.org/10.1016/j.geoderma.2005.11.002