Integrating Geo-spatial techniques for reflecting micro-nutrients and sulfur variations and spatial distribution to support farm management practices

Abstract

To understand the spatial dependency of available sulphur and micronutrients in an experimental farm, 83 soil samples (surface and subsurface) were taken from Agricultural College, Killikulamto characterize the spatial variability of available Sulphur and micronutrients. The geostatistics and geographic information system (GIS) techniques were applied. With the help of geostatistical analyst of ArcGIS software kriged map of different soil parameters were prepared. Available S, Fe, Cu and Zn were fitted with a spherical model and that available Mn was fitted with an exponential model. Soil available Cu had strong spatial dependence with a range of 3.62 km. Available Fe, Zn and Mn had moderate spatial dependence with a range of 9.47 km, 5.61 km and 2.70 km, respectively. Available sulphur had weak spatial dependence with a range of 6.86 km. The spatial distribution of the available sulphur and micronutrients were significantly correlated to the soil formation factors. Agricultural practices such as application of fertilizers and pesticides also had significant effects on the spatial distributions of the available micro-nutrients and sulfur.

Key words: spatial variability, soil micro-nutrients, farm management, soil formation

1. Introduction

"Soil is an important source of available micronutrients. Either shortage or surplus of available micronutrients in the soil would limit growth of crops. Understanding the spatial variabilities and distribution patterns of soil available micronutrients is essential for management of the soil. There are different techniques for evaluating soil spatial variability, including geostatistics and geographic information systems (GIS). These are very useful for the evaluation of soil variations and can reasonablycharacterize soil properties according to their spatial distribution. Such evaluations and interpretations are also applicable to neighbourhood areas" (Kumar et al., 2022)[5]. "Geostatistical tools are useful in the preparation of the maps based on the limited number of samples collected from agricultural land. Kriging interpolation technique predicts the values at unsampled locations by spatial correlation and reduces the variance of estimation error and investigation costs" (Rosemary et al., 2017; Tamburi et al., 2021) [13,16]."The evaluated soil properties can be mapped at different distances" (Rahul et al., 2019; Reza et al., 2017)[11,12]. Soil maps could help in correcting management of soil nutrients. These maps are required to understand the patterns and processes of soil spatial variability and nutrient distribution with different anthropogenic activities.

Several authors have shown that the spatial distribution maps generated serve as productive tools for site-specific nutrient management. There is minimum information available on the spatial distributions of soil available micronutrients in experimental farm. The objectives of this study were: (1) to analyse the spatial dependency and understand the variation of available sulphur and micronutrients in an experimental farm and (2) map the spatial distribution of available sulphur and micronutrients in the soil.

2. Materials and Methods

The spatial variability study was conducted in soils of experimental farm of Agricultural college and Research Institute, Killikulam, Tamil Nadu Agricultural university in Thoothukudi district (Fig. 1). Geographically the study area is located between 8°41' N to 8°43' N Latitude and 77°50' E to 77°53' E Longitudes. The annual rainfall of the region is 736.7 mm. The mean maximum and minimum temperatures are 38°C and 21°C, respectively. Thamirabarani is the main river flowing in the district from West to East direction.

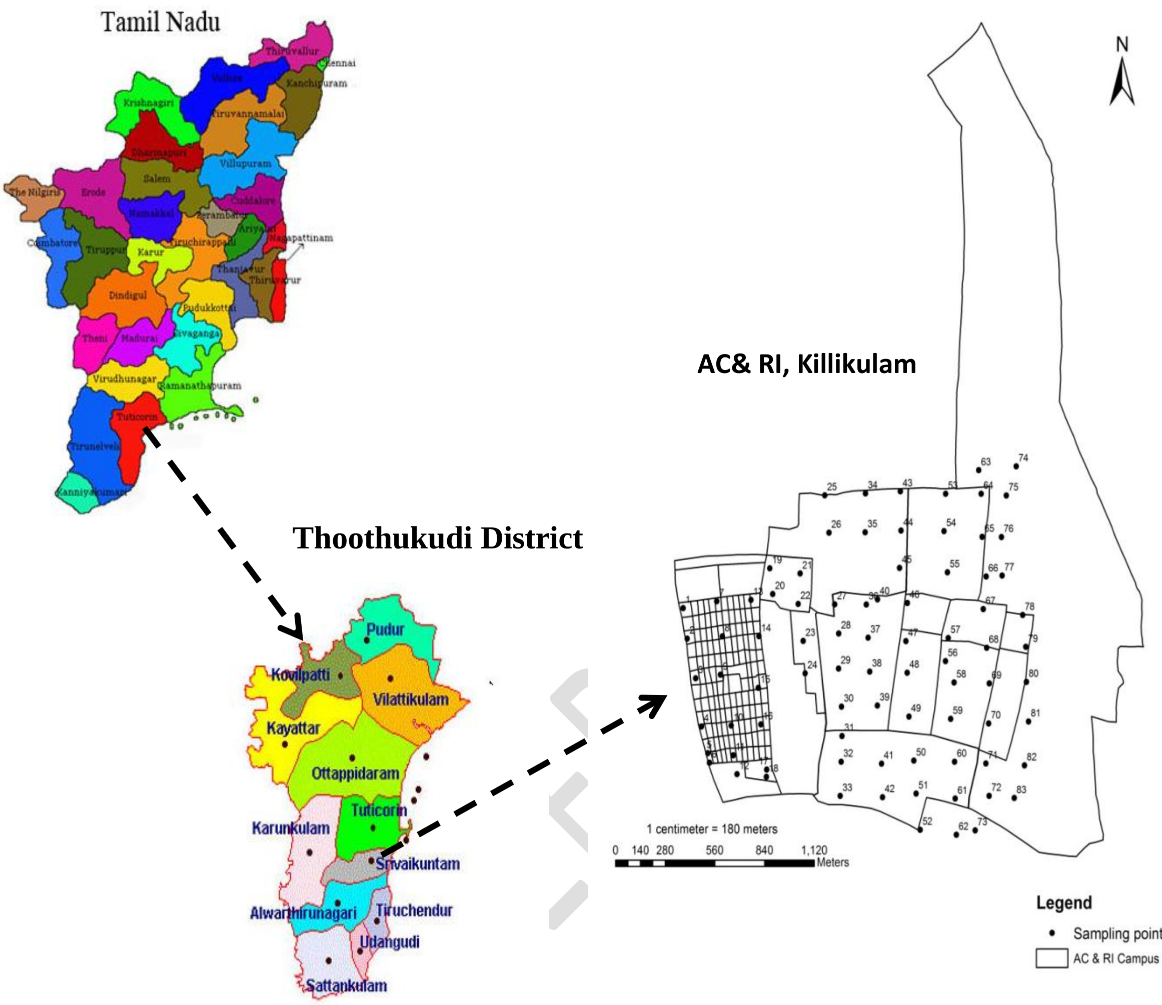


Fig.1. Study area located in AC & RI, Killikulamfarm ofThoothukudi District in Southern Tamil Nadu, India.

Grid wise (200 x 200 m grids) soil samples were collected from 83 locations. The total geographical area is 332 ha.Soil samples were collected from two sampling depth, surface (0-15 cm) and sub surface (15-30 cm) at each grid point. A global positioning system (GPS) device was used to record the coordinates of each sampling point. Samples were air dried in shade and passed through2 mm sieve and analyzed for available sulphur and micronutrients (Fe, Mn, Cu and Zn). The soil available sulphur was determined by $CaCl_2$ 0.15% extract (Williams and Steinbergs, 1959)[18]. The micronutrients (Fe, Mn, Cu and Zn) were extracted by diethylene triamine penta acetic acid (Lindsay and Norvell, 1978) [6].followed by analysis using atomic absorption spectrophotometer (Varian Spectr AA 55B).

Descriptive Statistics

The descriptive statistics namely minimum, maximum, standard deviation, mean, median, coefficient of variation, skewness, and kurtosis were calculated for each soil for each soil designated soil nutrient. The statistical analysis in the present study was done using the Statistical Product and Service Solution (SPSS 16.0) statistical package (Hejase&Hejase, 2013)[3].A correlation analysis was conducted to determine the relationship among surface soil properties under study.

Geostatistical Analysis

Geostatistical analysis of soil properties was performed to develop semivariogram model using Geostatistical analyst module of ArcGIS 9.1. The data were checked for skewness. The skewed soil properties were transformed using natural logarithm to a nearly normal distribution and back transformed using back transformation (Tripathi *et al.*, 2015)[17]. Different variogram models *viz,* Spherical, Gaussian and exponential were fitted. Using the fitted models, an ordinary kriging were performed to estimate properties at unmeasured points as interpolated values for mapping (Schepers *et al.*, 2004)[14].

3. Results and Discussion

Table 1 presented statistical results of the available sulphur and micronutrients for 83 soil samples. Available sulphur ranged from low to high in surface and subsurface soils. Available Feexhibited an average value of 9.77 mg/kg in the surface soil and 8.98 mg/kg in subsurface soil. The mean available Mn for both the surface and subsurface soil were 9.42 mg/kgand 8.33 mg/kg, respectively, The available Mn, Cu and Zn content ranged from low to high (Kumar et al.,2022)[5]in both the surface and subsurface soil depths. The mean values of soil available Fe, Mn, Cu and Zn were higher for the surface soils. The soil sulphur showed a reverse trend of having high sulphur in the subsurface soil.This may be due to the presence of more amount of clay that has resulted in retention of more amount of nutrients.

Table 1. Descriptive statistics of soil properties in study area

Soil Properties	Min	Max	Mean	SD	CV (%)	Kurtosis	Skewness
Surface soil (0-15cm)							
Available S (mg/kg)	3.17	17.58	10.42	3.61	34.64	-0.98	0.08
Available Fe (mg/kg)	1.10	24.00	9.77	7.02	71.88	-0.97	0.67
Available Mn (mg/kg)	1.12	25.10	9.42	6.55	69.55	-0.47	0.94
Available Cu (mg/kg)	0.38	5.27	2.44	1.12	45.85	-0.31	0.24
Available Zn (mg/kg)	0.05	4.90	1.16	0.99	84.92	2.46	1.45
Subsurface soil (15-30 cm)							
Available S (mg/kg)	2.83	15.89	11.10	3.64	32.76	-0.53	-0.85
Available Fe (mg/kg)	0.26	25.31	8.98	7.20	80.17	-0.11	1.02
Available Mn (mg/kg)	0.26	25.76	8.33	5.95	71.41	1.40	1.36
Available Cu (mg/kg)	0.09	4.79	1.78	1.07	60.32	-0.07	0.65
Available Zn (mg/kg)	0.09	4.19	1.02	0.89	87.47	2.01	1.45

The overall variability in soil properties can be assessed by the coefficient of variation (CVs). The CVs less than 15 indicated the low variation; CV ranging from 15-50% reveals moderate variability and CV > 50% represents high variability for the collected soil parameters. Descriptive statistics showed low to high variation in soil properties. Soil sulphurwere found to have moderate variability in all the depths as shown in Table 1. Available Zn exhibited very high variability in the surface and subsurface soils. The available Cu showed moderate variability in surface soils and high variability in subsurface soils. The addition of copper fungicides manures and application of fertilizers might be attributed to the variability in available Cu. The available Fe, Mn and Zn were observed to have high variability in both the depths. This variation in S and micronutrient concentration in the experimental farm is primarily because ofred soil derived from granitic gneiss parent material, types of crops grown and amount and type of fertilizers applied Weathering of the parent material determines the natural supply of S and micronutrients. Both the microorganisms' and the crop residue's organic acids' release promotes the weathering of soil minerals and the subsequent release of nutrients. The available S > available Fe > available Mn > available Cu > available Zn was the sequence in which the mean concentrations of available nutrients were found.

All the soil properties at both sampling depths had positive skewness, except soil available sulphur in the subsurface soils. Available Fe, Mn and Cu had highly skewed distribution due to large variation within the field. Available Zn had a similar value of skewed distribution for both sampling depths.

Correlation between soil properties

Table 2 shows the degree of correlation between soil propertiesfor 83 soil samples. “Almost all of the variables except few were significantly correlated among each other. Available Fe, Cu and Zn were in positive correlation with the pH. The available Mn were, however, in negative correlation with pH. In addition, the soil available Fe, Mn and Cu were in positive correlation with organic matter. Available copper was relatively high which was due to higher contents of organic matter and clay, because soil available Cu was in positive correlation with organicmatter” (Liu et al. 2004)[8].

Table 2. Correlation matrix for soil properties in study area**.**

	pH	**OC**	**Available S**	**Available Fe**	**Available Mn**	**Available Cu**	**Available Zn**
pH	1						
OC	0.251*	1					
Available S	0.126	0.191	1				
Available Fe	0.338**	0.331**	0.145	1			
Available Mn	-0.170	0.246*	0.283**	-0.038	1		
Available Cu	0.276*	0.331**	0.266*	0.265*	0.038	1	
Available Zn	0.150*	0.154	0.098	0.206	-0.035	0.579**	1

**. Correlation is significant at the 0.01 level *. Correlation is significant at the 0.05 level

Exploratory data analysis

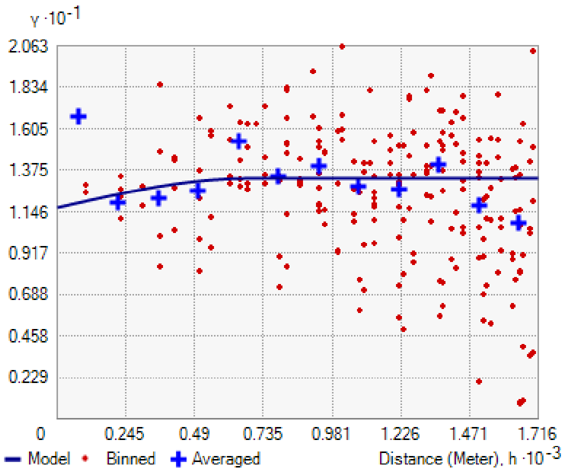
Figure 2 and 3 presented the semivariogram and fitted models for each available S and micronutrient for surface and subsurface soils. The attributes of the semivariograms for each soil available micronutrient are summarised in Table 3. The semivariogram of surface soil properties *viz.*, available S, Fe, Cu and Zn and subsurface soil properties available Fe, Mn, Cu and Zn were well defined by spherical model (Table 3). Surface Soil properties such as available Mn and subsurface soil properties like available S were well fitted by exponential model. A number of researchers reported that spherical models were the most effective for modeling most soil parameters. (Lopez Granados et al., 2002; Metwally et al., 2018and Tamburi et al., 2021)[9,10,16].

Table 3. Semivariogram models for soil properties in the study area.

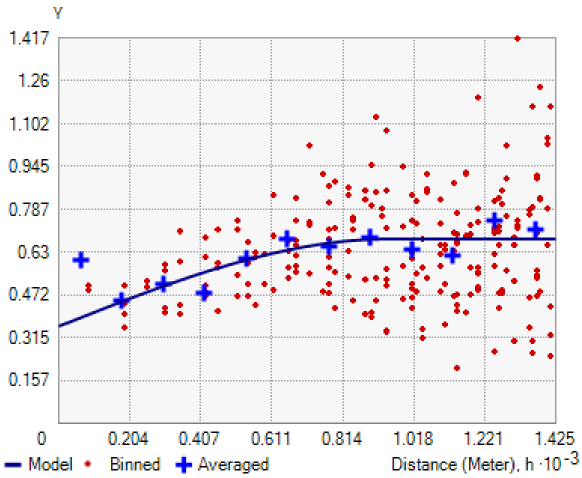
Soil property	Model	Sill	Nugget	Range	Nugget (%)	Spatial Dependence class
Surface soil (0-15 cm)						
Available S (mg/kg)	Spherical	1.59	11.70	686	88.04	Weak
Available Fe (mg/kg)	Spherical	0.32	0.35	947	52.24	Moderate
Available Mn (mg/kg)	Exponential	0.31	0.15	270	32.24	Moderate
Available Cu (mg/kg)	Spherical	0.97	0.01	363	1.32	Strong
Available Zn (mg/kg)	Spherical	0.35	0.54	561	60.18	Moderate
Sub surface soil (15-30 cm)						
Available S (mg/kg)	Exponential	3.03	10.62	590	77.80	Weak
Available Fe (mg/kg)	Spherical	0.26	0.57	1404	68.60	Moderate
Available Mn (mg/kg)	Spherical	0.57	0.10	270	14.20	Strong
Available Cu (mg/kg)	Spherical	0.35	0.13	284	26.91	Moderate
Available Zn (mg/kg)	Spherical	0.19	0.63	374	76.86	Weak

The field variation and experimental error within the smallest possible sampling spacing are represented by the nugget variance. One criterion to categorize the geographical dependency of soil parameters is the nugget/sill ratio. The variable exhibits severe spatial dependency if the ratio is less than 25%; moderate geographic reliance is seen if the ratio is between 25% and 75%; and weak spatial dependence is shown if the ratio is larger than 75%. Extrinsic (soil management techniques, such fertilization) and intrinsic (soil formation factors, like soil parent materials) factors can influence the spatial variability of soil parameters. Generally speaking, extrinsic variables are responsible for mild spatial dependence and intrinsic factors for substantial spatial reliance of soil parameters.

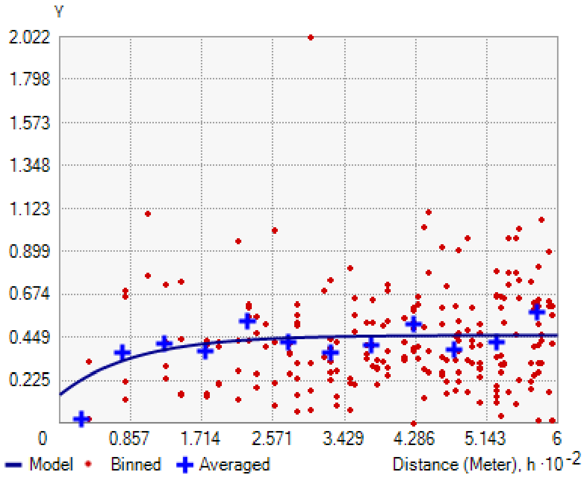
The results showed that strong spatial dependency for available Cu in the surface soil and available Mn in the subsurface soil with the nugget to sill ratio of <25 %, their spatial variabilities were mainly controlled by intrinsic factors such as the red soils derived from granitic gneiss, relief and soil types. Spatial dependence was moderate for available Fe, Mn and Zn in the surface soil (nugget to sill ratio between 25 and 75 %) (Cambardella et al. 1994)[1].Spatial dependence was moderate for available Fe in surface and subsurface soil. Weak spatial dependence was exhibited by available Sulphur in both the surface and subsurface soil. Strongly spatially dependent features may be regulated by inherent variation in soil qualities such as texture and mineralogy, which was found by Shukla et al., (2020)[15].The ranges for available Mn and Cu were 2.7 km and 3.6 km, respectively. Available Fe has a range of 9.47 km (Desta et al., 2021)[2].



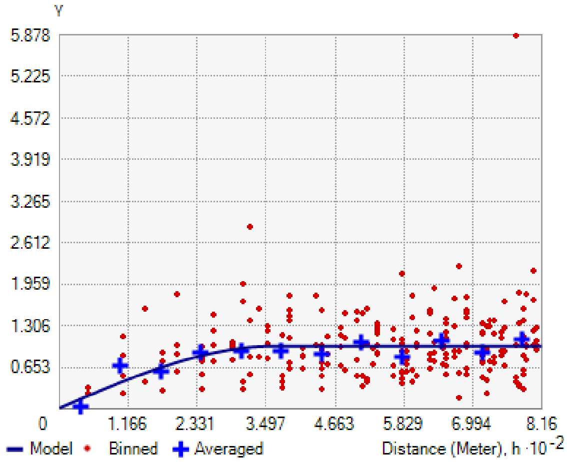
Available S



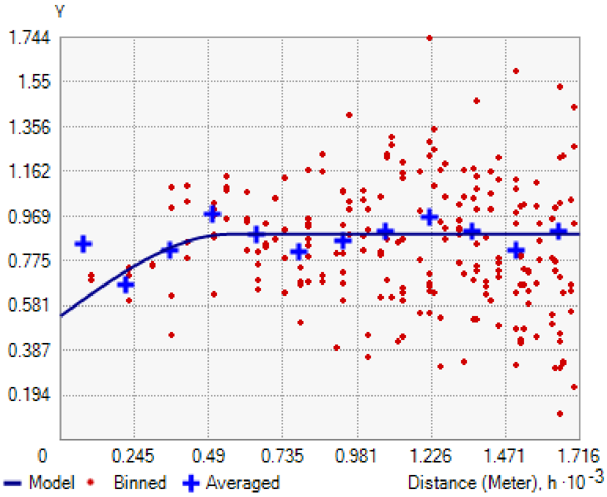
Available Fe



Available Mn



Available Cu



Available Zn

Fig.2. Semi variograms and fitted models of surface soil properties

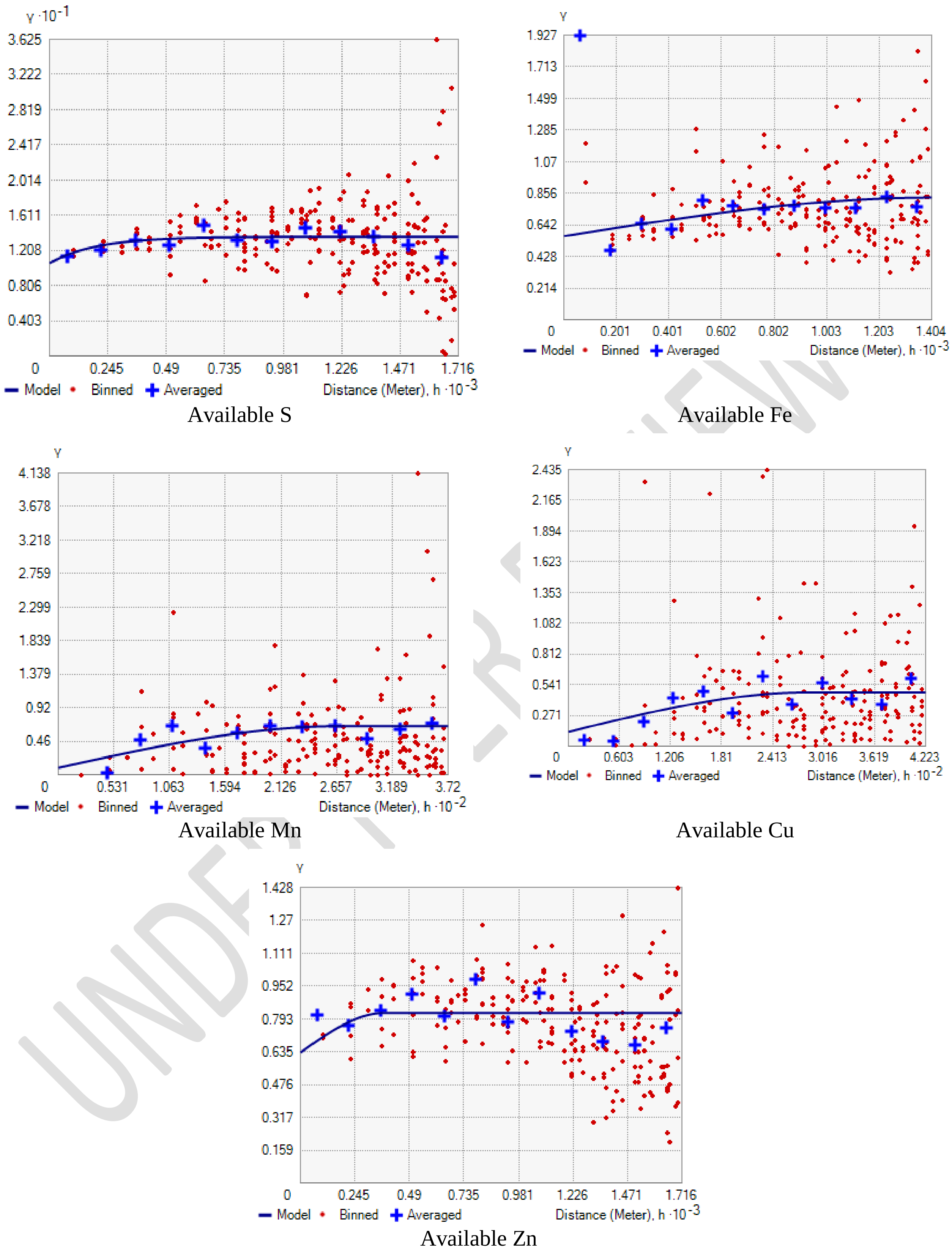
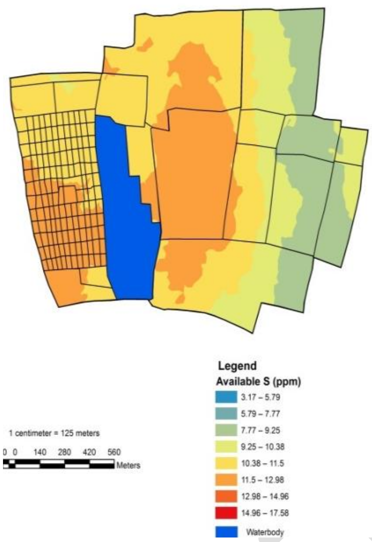


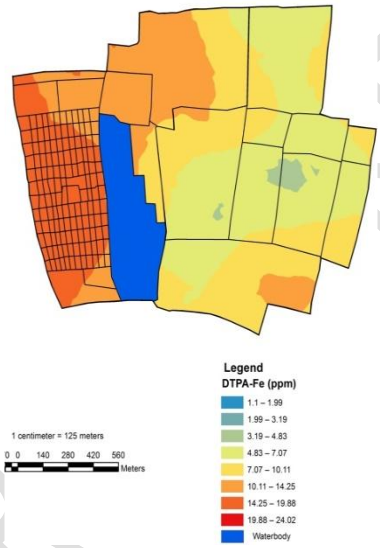
Fig. 3. Semi variograms and fitted models of sub surface soil properties

"South east and northeast zone of the farm were lowin available Zn; the soil available Zn in the zones was lessthan 1 mg/kg, and lower than the mean available Zn as shown in Figure 4. In contrast, the north west zone of the farm has a high available Zn; the soil available Zn in the zone was high ranging from 1.80 mg/kgto 4.9 mg/kg. The soil pH value in north west of the farm was between 6.0–6.9. High soil pH usually results in low available Zn, as the available micronutrients decrease with increasing pH"(Kumar et al 2022) [5].

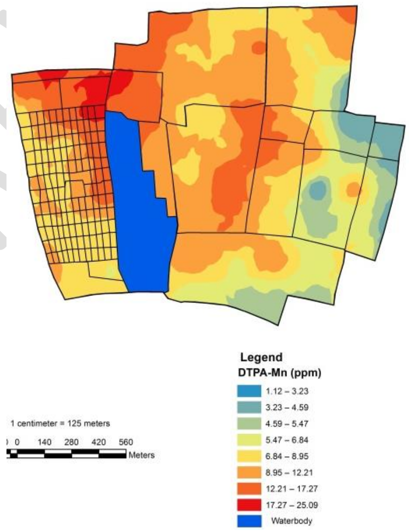
"The soil available Fe had distinct geographical distribution, was high in Central experimental farm including the north and west area, and the lowest in southeast of the farm, which was comparable with pH and organic matter". [19] The soil available sulphur was high in the central part of experimental farm and low in the south west of the experimental farm. From the maps shown in Figure 4 and Figure 5 of soil available sulphur and micronutrients, information about their spatial distribution over long distances could be clearly achieved.



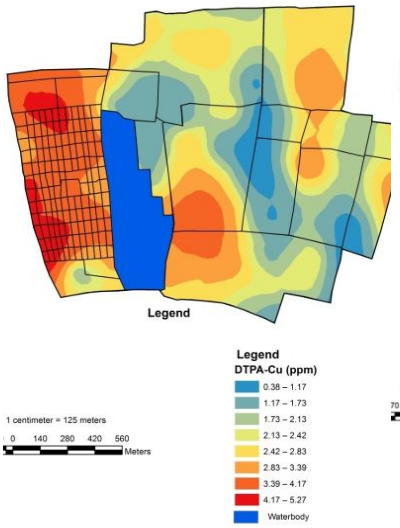
Available S



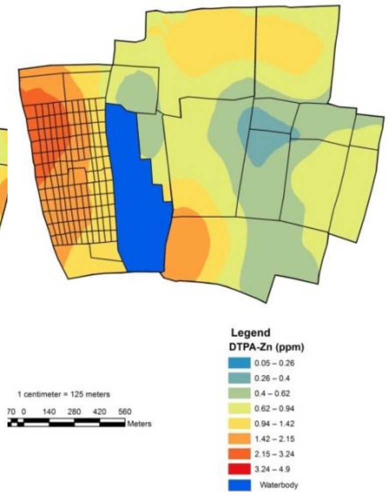
Available Fe



Available Mn

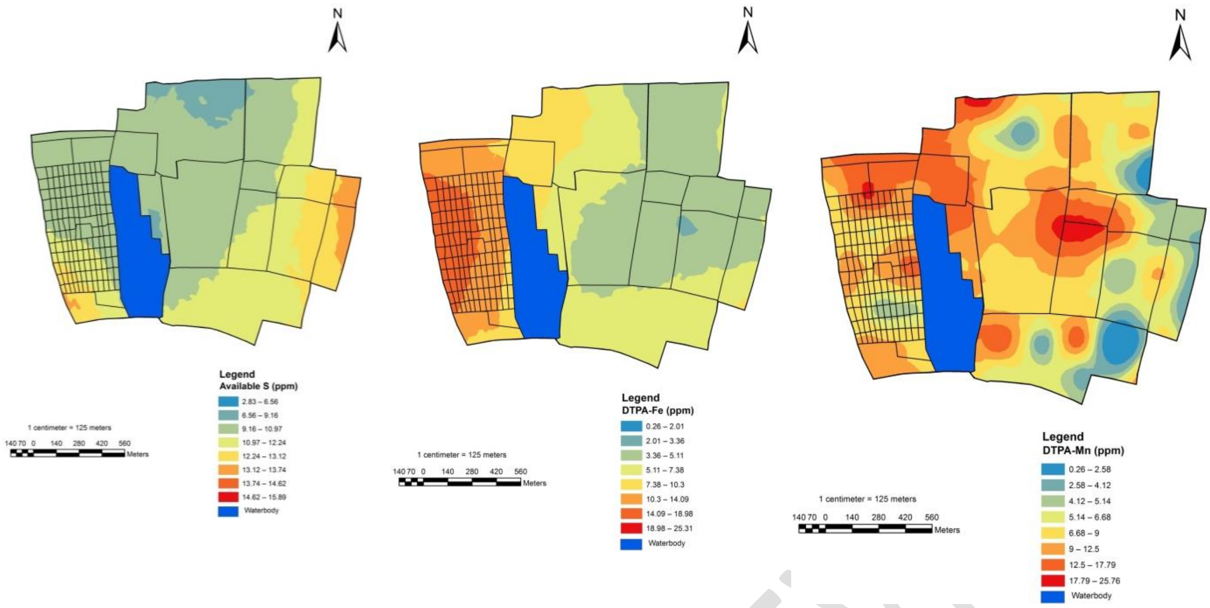


Available Cu

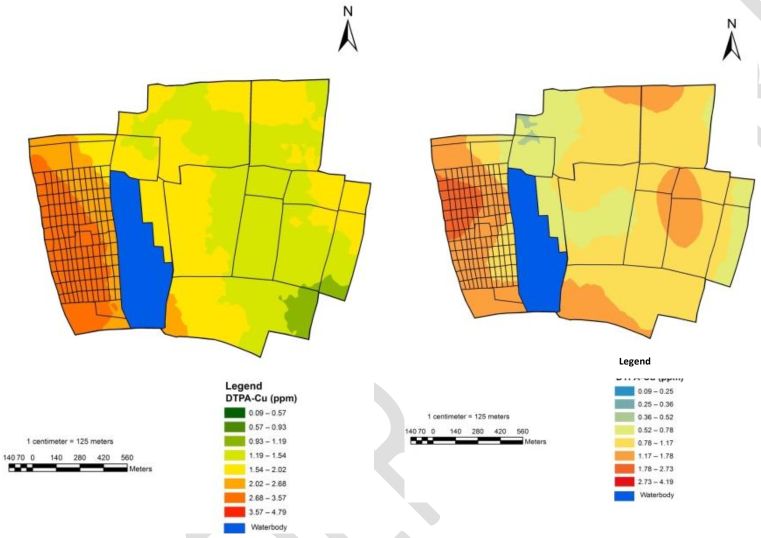


Available Zn

Fig. 4. Soil map of spatial distribution of nutrients for surface soil in the study area.



Available S Available Fe Available Mn



Available Cu Available Zn

Fig. 5. Soil map of spatial distribution of nutrients for sub surface soil in the study area.

4. Conclusions

The CV valuesfor the available sulphur and micronutrients decreased in theorder of available Zn> Fe > Mn >Cu>S. Geostatistical analysisindicated that the semivariograms for available S, Fe, Cu and Znwere fitted with aspherical model and thatavailable Mn was fitted with anexponential model. The available sulphur and micronutrients had different degrees of variability; soilavailable Cu had strong spatial dependencewith a range of 3.62 km.Available Fe, Mn and Zn had moderate spatial dependence with arange of 9.47 km, 2.70 km and 5.61 km, respectively. Available sulphur had weak spatial dependence with a range of 6.86 km. Integrating geostatistics and GIS to study spatial variability and map soil available sulphur and micronutrients provides an opportunity to assess variability in the distribution of native micronutrients. These results incorporated with the soil maps provide a basis of information for managing experimental farm in a rationally site-specific and precise way in alleviating the micronutrient deficiency.

References

1. Cambardella CA, Moorman TB, Novak JM, Parkin TB, Karlen DL, Tureo RF, Knnopka AK. Field scale variability of soil properties in central Iowa soils. Soil Science Societyof America Journal.1994;58:1501-1511.
2. Desta MK, Broadley MR, McGrath SP, Hernandez-Allica J, Hassall KL, Gameda S, Amede T Haefele SM. (2021). Plant Available Zinc Is Influenced by Landscape Position in the Amhara Region, Ethiopia. Plants, 2021; 10(2), 254-
3. Hejase AJ, Hejase H.J. Research methods: A practical approach for business students. Masadir Incorporated 2013.
4. Jiang H, Liu G, Wang X, Song W, Zhang R, Zhang R, Hu H, Li L. Delineation of site-specific management zones based on soil properties for a hillside field in central China. Archieves in Agronomy and Soil Science. 2012; 58:1075–1090.
5. Kumar P, Kumar P, Sharma M. Spatial variability of soil nutrients in apple orchards and agricultural areas in Kinnaur region of cold desert, Trans-Himalaya, India. Environment Monitoring and Assessment, 2022; 194: 290
6. Lindsay WL, Norvell WA. Development of a DTPA soil test for zinc, iron, manganese and copper. Soil Science Society of America Journal. 1978; 42, 421-448.
7. Liu XM, Xu JM, Zhang MK, Huang JH, Shi JC, Yu XF. Application of geostatistics and GIS technique to characterize spatial variabilities of bioavailable micronutrients in paddy soils. Environmental Geology. 2004;46:189-194.
8. Liu Z, Zhou W, Shen J, He P, 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.
9. Lopez-Granados LF, Exposito MJ, Atenciano S, Ferrer AG, Orden MS, Torres LG. Spatial variability of agricultural soil parameters in Southern Spain. Plant and Soil. 2002;246:97-105.
10. Metwally M S, Shaddad S M, Liu M, Yao R, Abdo A I, Li P, Jiao J, Chen, X. 2018. Soil Properties Spatial Variability and Delineation of Site-Specific Management Zones Based on Soil Fertility Using Fuzzy Clustering in a Hilly Field in Jianyang, Sichuan, China. Sustainability, 2018; 11(24): 7084.

11. Rahul T, Kumar N A, Biswaranjan D, Mohammad S, Banwari L, Priyanka G, Sangita M, Bihari P B, Rabi N S Shukla A K . Assessing soil spatial variability and delineating site-specific management zones for a coastal saline land in eastern India, Archives of Agronomy and Soil Science, 2019; DOI: 10.1080/03650340.2019.1578345

12. Reza, S. K, Nayak, DC, Mukhopadhyay, S, Chattopadhyay, T, Singh, SK. Characterizing spatial variability of soil properties in alluvial soils of India using

geostatistics and geographical information system. Archives of Agronomy and Soil Science. 2017; 63(11), 1489–1498.

13. Rosemary F, Vitharana UWA, Indraratne S P, Weerasooriya R, Mishra U. Exploring the spatial variability of soil properties in an Alfisol soil. catena. Catena. 2017; 150, 53–61.

14. Schepers JF, Shanahan MA, Liebig JS, Schepers S, Johnson A, Luchiari. Delineation of management zones that characterize spatial variability of soil properties and corn yields across years. Agronomy Journal. 2004;96:195–203.

15. Shukla AK, Behera SK, Singh VK, Prakash C, Sachan AK, Dhaliwal SS. Premonsoon spatial distribution of available micronutrients and sulphur in surface soils and their management zones in Indian Indo-Gangetic Plain. 2020. PLoS ONE. 2020; 15(6): e0234053.

16. Tamburi V, Shetty A Shrihari, S. Spatial variability of vertisols nutrients in the Deccan plateau region of north Karnataka, India. Environment Development and Sustainability, 2021; 23, 2910–2923.

17. Tripathi R, Nayak AK, Shahid M, Lal B, Gautam P, Raja R, Mohanty S, Kumar A, Panda BB, Sahoo RN. Delineation of soil management zones for a rice cultivated area in eastern India using fuzzy clustering. Catena. 2015; 133:128-36.

18. William CH, Steinbergs A. 1959. Soil sulfur fractions as chemical indices of available sulphur in some Australian Soils. Australian Journal of Agricultural Research. 1959; 10: 340–352.

19. Liu XM, Xu JM, Zhang MK, Huang JH, Shi JC, Yu XF. Application of geostatistics and GIS technique to characterize spatial variabilities of bioavailable micronutrients in paddy soils. Environmental geology. 2004 Aug;46:189-94.