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Geo-statistics and GIS technique to characterize spatial variability of soil available nutrients in an experimental farm

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Abstract
Mapping of soil properties using the Geographical Information System (GIS) is an important aspect as it plays a vital role in the knowledge about the soil properties and how it can be used sustainably. The study was carried out in an Agricultural College and Research Institute experimental farm, Killikulam, Thoothukudi district to map soil available nutrients and assess their variability. A grid pattern (200 x 200 m) was established at the experimental farm to collect soil samples at two sampling depths (0-15 & 15-30 cm). The soil samples were analyzed for available Nitrogen, Phosphorus, Potassium, pH, Electrical Conductivity (EC) and soil organic carbon (SOC). The location of the sampling points and field boundary were marked with a GPS. Descriptive statistics and geostatistical analysis were done. The results reveal that pH of surface soils varied from 6.08 to 8.73 with CV of 10.21 per cent. The EC exhibited very high variability in all the depths. The pH, available N, P, K exhibited moderate variability for both the depths. Geostatistics was used to estimate and map nutrients in unsampled areas. The spatial dependence classes were strong for EC and SOC, whereas all other soil properties exhibited moderate spatial dependence. Spatial distribution maps of soil available nutrients made using Arc GIS software. Most of the research area showed evidence of multinutrient deficiency. Critical nutrient deficiency zones were identified. The status of nutrient availability at the farm level was determined from the spatial variability maps. Farm managers can use the produced maps as a useful tool for site-specific nutrient management.

Keywords: Spatial variability, soil properties, farm level nutrient management

Introduction
Biodiversity and life depend on the soil, which is also crucial for the provision of vital ecosystem services that support human life. Food security, quality and availability are all impacted by soil through human interactions. The physical and chemical characterization of the soil is significant from this perspective. Unfortunately, because soil nutrients fluctuate over time and space in different types of soils, it is difficult to characterize soil nutrients (Goovaerts, 1998; Liu *et al.*, 2014) [7, 12]. The spatial variability of soil nutrients is related to factors such as climate, parent material, relief, organisms and time (Bogunovic *et al.*, 2017) [4]. In sustainable agriculture, precise soil management is a useful method for raising the productivity of crops (Yasrebi *et al.*, 2008) [25]. Understanding the spatial variation of soil nutrients help in the precise management of soil (Lagacherie and McBratney, 2007; Mulla, 2015) [10, 14]. The precise estimation of spatial variability is an important factor influencing land management practices (Chatterjee *et al.*, 2015) [6]. A number of factors, such as small agricultural land (less than two acres), being unable to handle advanced technological equipment due to financial constraints, and a lack of technical knowledge among farmers are contributing to a decline in awareness of sustainable and precision agriculture in many underdeveloped and developing countries, including India. In India, improper water management and fertilizer application rates leads to the decline in the fertility of topsoil. (Bhattacharyya *et al.*, 2015) [3].
Under these conditions, the initial preparation consists of mapping the soil nutrient's spatial variability for proper planning and practices for land management. In these circumstances,

measuring the spatial variability of soil nutrients in the experimental farm is the first step towards management of soil and also essential for application of fertilizers. It has been demonstrated that geostatistics is an effective technique for analyzing soil nutrient distributions (Shukla *et al.,* 2016) [20]. The ability of GIS to perform spatial operations on the data enables to prepare spatial distribution maps. Integration of geostatistics and GIS to map fertility properties of soil provide a helpful tool for application of inputs.

Understanding the spatial variability of soil nutrients in an experimental farm is important. In this concern, it is critical to assess the spatial variability of available soil nutrients nitrogen, phosphorus and potassium as they play a significant role in agriculture. However, the information on the spatial variability of soil nutrients in experimental farm of Agriculture College and Research Institute, Killikulam is lacking. Thus, the present study was carried out i) to analyse the spatial dependence and to explain the variation mechanism of available nutrients in farm soils, ii) to map the spatial distribution of available nutrients using geostatistics.

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.

Grid wise (200 x 200 m grids) soil samples were collected from 83 locations. Soil samples were collected from two sampling depth, surface (0-15 cm) and sub-surface (15-30 cm) at each grid point depth. A global positioning system (GPS) device was used to record the coordinates of each sampling point. Samples were air dried in shade and passed through 2 mm sieve and analyzed for physico-chemical properties. Soil pH and electrical conductivity was measured in soil-water suspension (1:2.5) using pH meter (Jackson, 1973) [8]. The soil organic carbon was determined by Walkley and Black method (1934) [24], available nitrogen was analysed by alkaline $KMnO_4$ method (Subbiah and Asija, 1956) [22]. Available phosphorus by Olsen method (1954), the available potassium was determined by NH_4OAC method (Stanford and English, 1949) [21].

Descriptive Statistics

Using SPSS 9.2, descriptive statistics such as mean, standard deviation (SD), minimum, maximum, coefficient of variation (CV), skewness, and kurtosis were computed for each value. 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) [23]. 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) [18].

Results and Discussions

Exploratory data analysis

Soil pH were slightly acidic to alkaline in reaction in both the sampling depths. The EC was non-saline in the surface and subsurface soils. The SOC content ranged from low to medium with average value of 3.86 g/kg in surface soil and 1.87 g/kg in subsurface soil. The available nitrogen content was found to be low in both the depths. The available phosphorus content varied from low to medium in all the depths. The available potassium content ranged from low too high in both the surface and subsurface soil depths. The mean pH value was higher at the sampling depth of 15-30 cm when compared to 0-15 cm. The mean values of soil available N and K were higher for the surface soils except soil P having reverse trend of having high P 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.

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 pH were found to have low variability in all the depths as shown in Table 1. Electrical conductivity exhibited very high variability in the surface and subsurface soils. The SOC showed moderate variability in surface soils and high variability in subsurface soils. The addition of manures and application of fertilizers might be attributed to the variability in organic carbon. The available N, P and K were observed to have moderate variability in both the depths. This was in line with Ameer *et al.,* (2022) [1]. The variation in the mineral composition of the soil might have been the reason for relatively higher variation of P when compared to K. The findings corroborate those of Reddy *et al*. (1996) [16] and Satyavathi and Reddy (2004) [17], who noted that the soil EC, and SOC ranged widely. This can be attributed to different soil types, climate, and different farming techniques.

All the soil properties at both sampling depths had positive skewness, except soil available P in the subsurface soils. pH, EC, available N, P and K had highly skewed distribution due to large variation within the field. SOC had a similar value of skewed distribution for both sampling depths.

Correlation between soil properties

Table 2 shows the degree of correlation between soil properties. Almost all of the variables except few were significantly correlated among each other. Correlation coefficient values of pH were negatively correlated with available K. Soil available N were positively correlated with SOC, in which SOC was an important portion of the soil which affected soil chemical, physical and biological properties influencing soil nutrients' availability (Behera *et al.,* 2018) [2]. The correlation of pH and EC with available N was negative.

Geostatistical parameters of soil properties

Geostatistical analysis was done and semivariograms were generated to determine the spatial variation of soil properties. The semivariogram of surface soil properties *viz.,* pH, available N and K and subsurface soil properties pH, EC, SOC and available P were well defined by spherical model

(Table 3). Surface Soil properties such as EC and available Mn and subsurface soil properties like available N and K were well fitted by exponential model. The surface soil organic carbon and available P were fitted by gaussian model. A number of researchers reported that spherical models were the most effective for modeling most soil parameters. (Lopez Granados *et al*., 2002 and Jiang *et al*. 2012) [13, 9]. The findings revealed that human-induced factors, including farming systems, fertilizer application, and methods of managing crops on the soil, were responsible for the spatial autocorrelation of soil attributes in the research area.

The ranges of influence from semivariogram for all the parameters were < 1000 m except for SOC in both the depths, available P in the surface soil and available K in the subsurface soil (Table 3). The SOC having ranges > 1000 m at both depths, surface available P showed 1551 m and subsurface available K ranged 1124 m (Fig 2 & 3). Low variation were observed in pH, available N, P and K. High variation were observed in SOC in both the depths. The nugget to sill ratio can be used to determine the spatial dependence of a soil property. High spatial dependency of a parameter is indicated by a low nugget to sill ratio, and vice versa. Nugget to sill ratio < 25% represents high spatial dependence, 25-75% indicates moderate spatial dependence, > 75 indicates weak spatial dependence (Cambardella *et al*. 1994) [5]. The results showed that strong spatial dependency for SOC in both the depths and EC in surface soil with the nugget to sill ratio of <25%. Spatial dependence was moderate for soil pH, available N, P and K (nugget to sill ratio between 25 and 75%). Strongly spatially dependent features may be regulated by inherent variation in soil qualities such as texture and mineralogy, which was found by Cambardella *et al*., (1994) [5]. The soil property map that might be produced by kriging would be more accurate if the soil property exhibit stronger the spatial correlation. All the soil properties exhibited moderate spatial dependency except EC and SOC. These imply that as a result of cultivation, external variables like fertilizer, ploughing, and other soil management techniques diminished their spatial correlation.

Ordinary kriging was used to construct spatial variability maps (Fig 4 & 5) of surface and subsurface soil for different soil attributes based on the semivariogram parameters and the best suited theoretical models. The soil available nitrogen was low in the experimental farm because of the tropical climatic condition. The soil available phosphorus content ranged from low to medium. The soil available potassium content of the experimental farm varied from medium to high. The spatial distribution map of SOC was almost the same to distribution pattern of available Nitrogen.

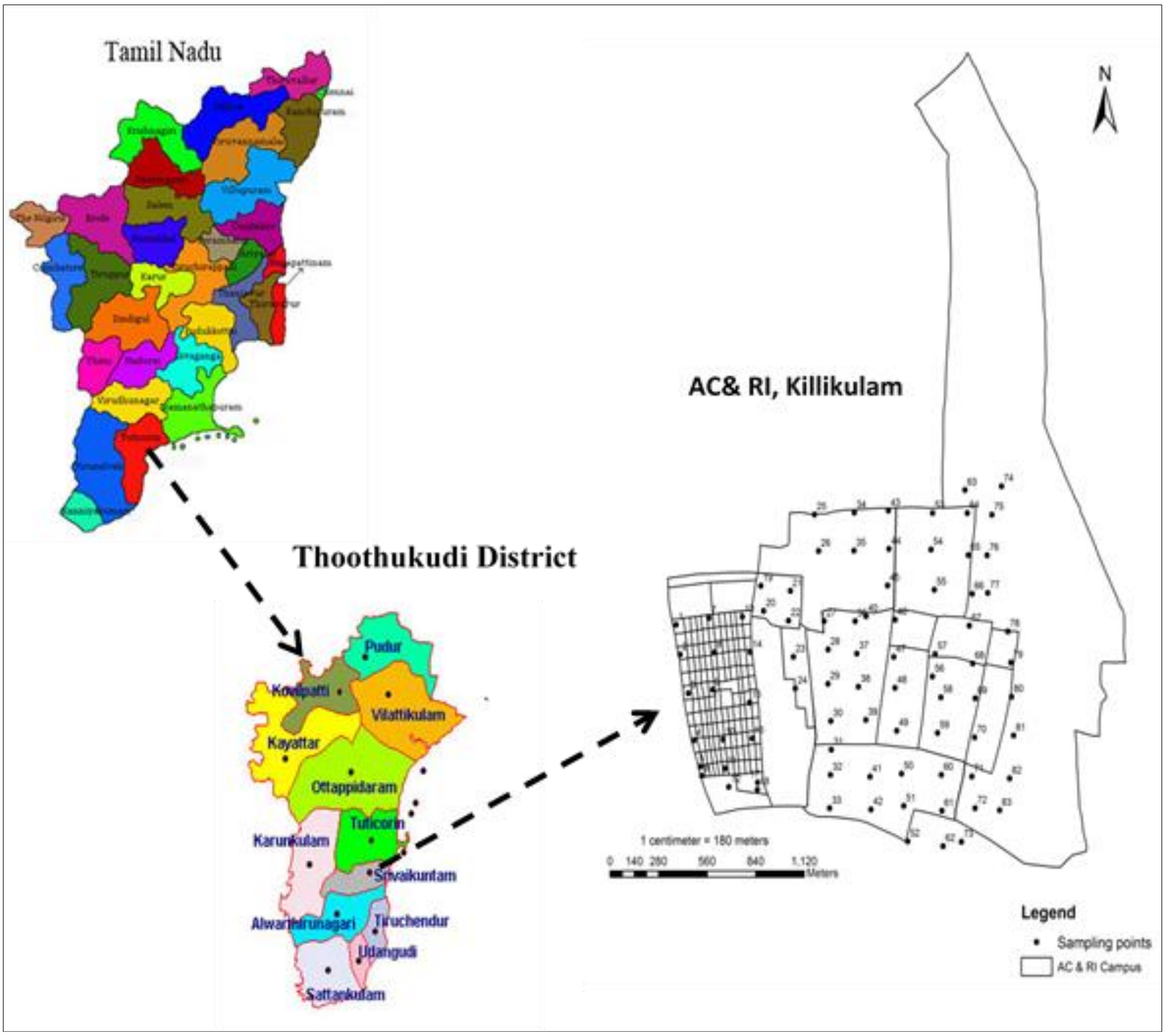


Fig 1: Study area located in AC & RI, Killikulam farm of Thoothukudi District in Southern Tamil Nadu, India and soil-sampling points

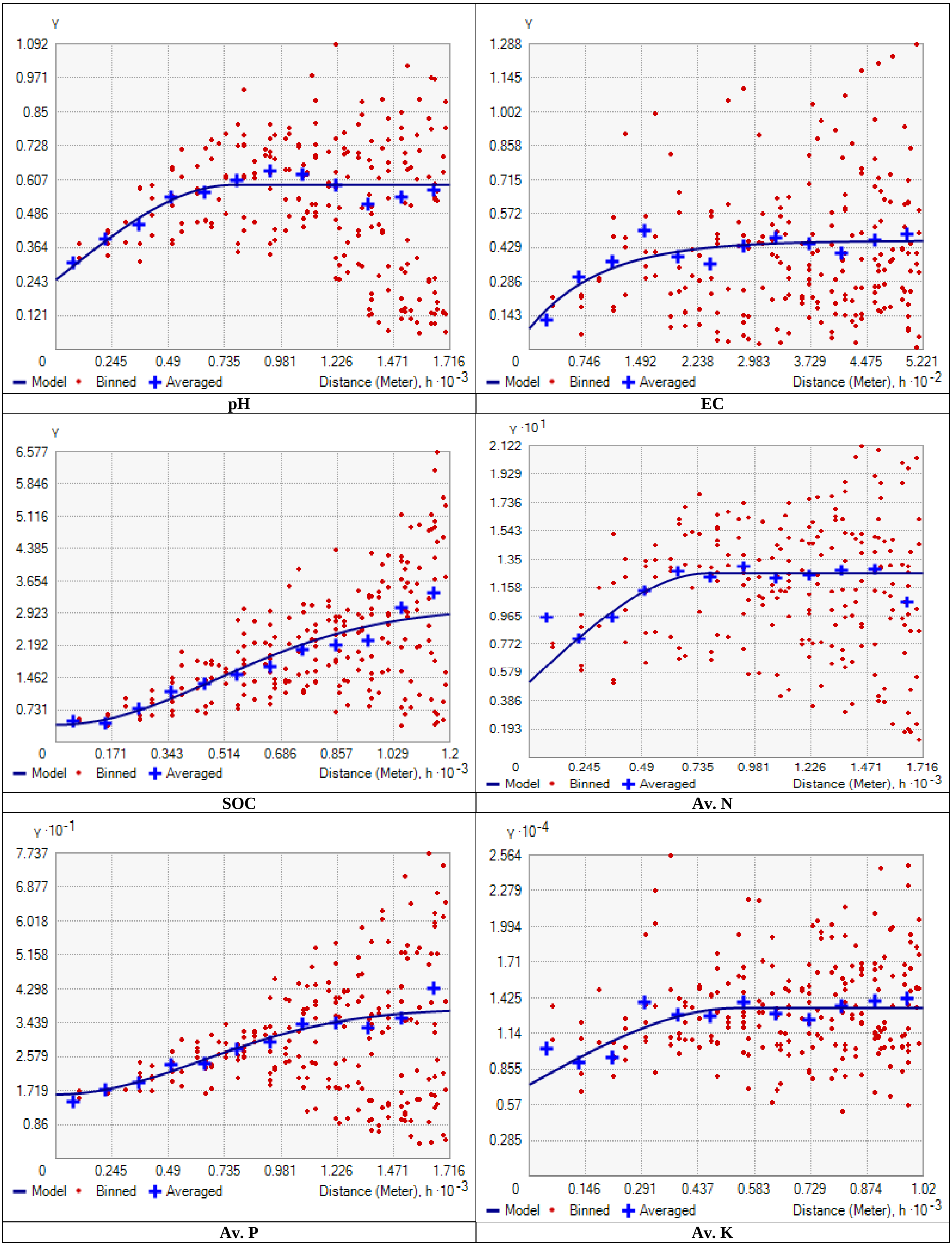


Fig 2: Semi variograms and fitted models of surface soil properties

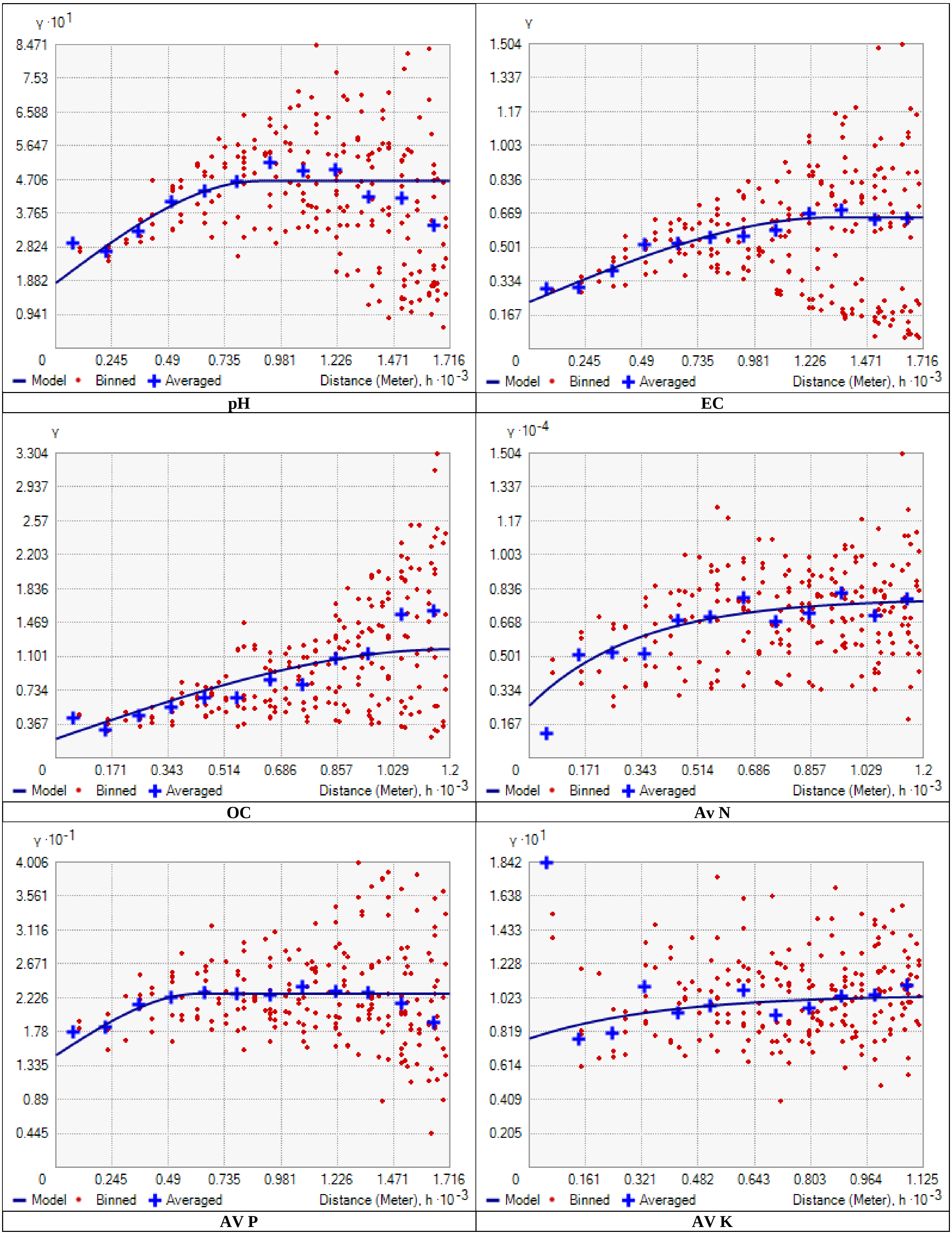


Fig 3: Semi variograms and fitted models of sub surface soil properties

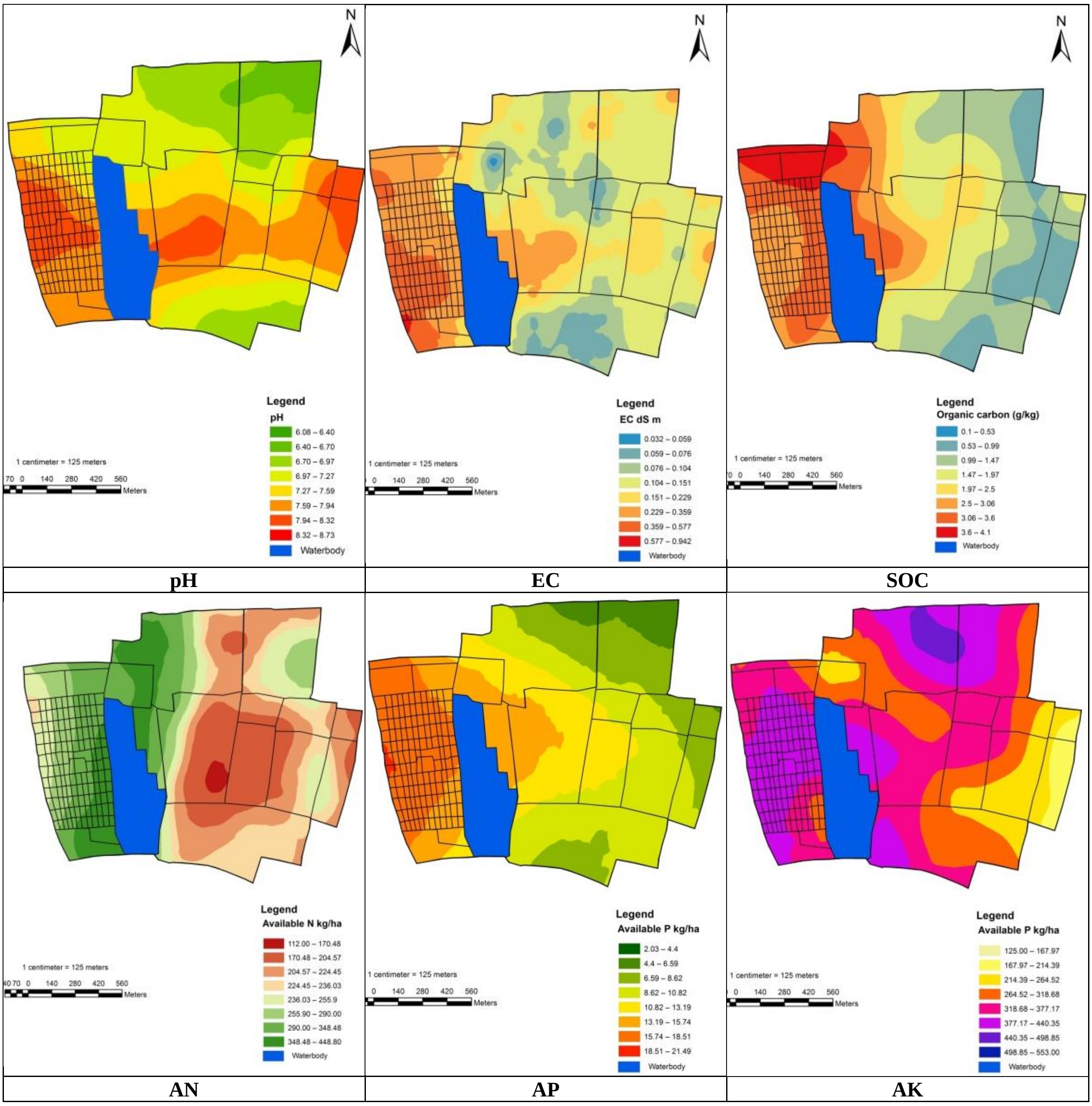
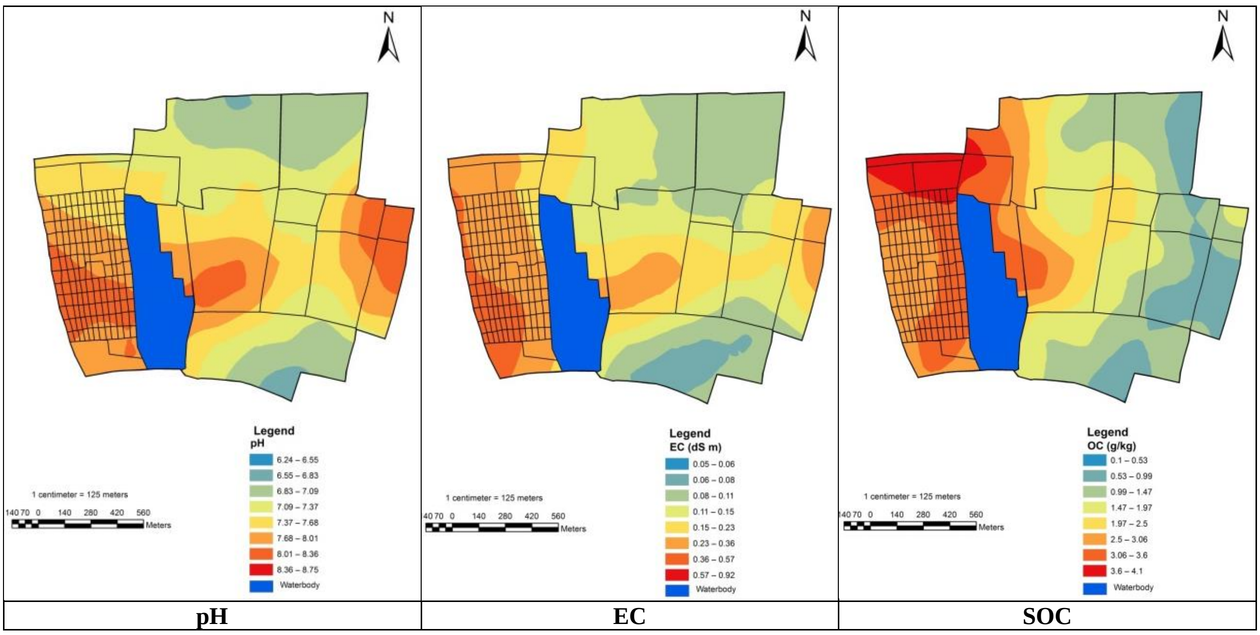


Fig 4: Map of spatial distribution for surface soil properties in the study area. EC: soil electrical conductivity; AN: available nitrogen; AK: available potassium: AP: available phosphorous; SOC: Soil organic carbon in soil



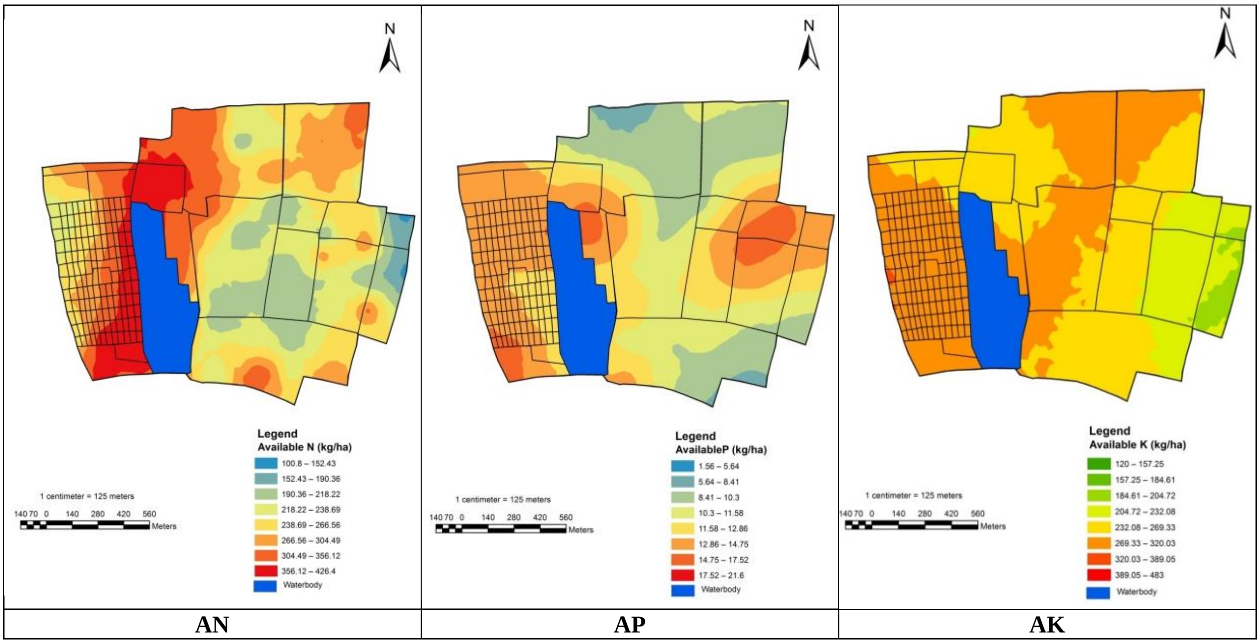


Fig 5: Map of spatial distribution for sub surface soil properties in the study area. EC: soil electrical conductivity; AN: available nitrogen; AK: available potassium: AP: available phosphorous; SOC: Soil organic carbon in soil

Table 1: Descriptive statistics of soil properties in study area

Soil Properties	Min	Max	Mean	SD	CV (%)	Kurtosis	Skewness
Surface soil (0-15 cm)							
pH	6.08	8.73	7.36	0.75	10.21	-1.01	0.33
EC (dS m^{-1})	0.03	0.94	0.20	0.19	94.00	5.61	2.29
SOC (g/kg)	0.18	7.30	3.86	1.70	44.00	-0.76	0.31
AN (Kg ha^{-1})	112.00	280.00	207.21	90.88	35.39	-0.43	0.79
AP (Kg ha^{-1})	2.03	21.49	11.00	5.56	50.50	-1.18	0.32
AK (Kg ha^{-1})	125.00	553.00	324.90	121.27	37.33	-1.27	0.17
Subsurface soil (15-30 cm)							
pH	6.24	8.75	7.48	0.66	8.78	-0.95	0.26
EC (dS m^{-1})	0.05	0.92	0.19	0.16	84.78	4.54	1.91
SOC (g/kg)	0.10	4.10	1.87	1.14	60.83	-1.11	0.35
AN (Kg ha^{-1})	100.80	280.00	196.92	86.36	32.85	-0.79	0.40
AP (Kg ha^{-1})	1.56	21.60	11.58	4.71	40.71	-0.47	-0.07
AK (Kg ha^{-1})	120.00	483.00	258.21	91.51	35.44	-0.22	0.92

EC: electrical conductivity; AN: available nitrogen; AP: available phosphorous; AK: available potassium

Table 2: Correlation matrix for soil properties in study area

	pH	EC (dS m^{-1})	SOC (g/kg)	AN (Kg ha^{-1})	AP (Kg ha^{-1})	AK (Kg ha^{-1})
pH	1					
EC (dS m^{-1})	0.286^{**}	1				
SOC (g/kg)	0.251^{*}	0.298^{**}	1			
AN (Kg ha^{-1})	-0.047	-0.021	0.427^{**}	1		
AP (Kg ha^{-1})	0.387^{**}	0.326^{**}	0.570^{**}	0.142	1	
AK (Kg ha^{-1})	-0.088	0.127	0.203	0.052	0.127	1

EC: Electrical conductivity; AK: available potassium; AP: available phosphorous; AN: available nitrogen in soil respectively.
**. Correlation is significant at the 0.01 level.
*. Correlation is significant at the 0.05 level.

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)						
pH	Spherical	0.34	0.25	770	42.25	Moderate
EC (dS m^{-1})	Exponential	0.37	0.09	284	19.00	Strong
SOC (g/kg)	Gaussian	3.07	0.41	1356	11.78	Strong
AN (Kg ha^{-1})	Spherical	0.07	0.05	776	41.13	Moderate
AP (Kg ha^{-1})	Gaussian	21.75	16.22	1551	42.71	Moderate
AK (Kg ha^{-1})	Spherical	6127.00	7297.00	538	54.36	Moderate
Sub surface soil (15-30 cm)						
pH	Spherical	0.29	0.18	890	38.84	Moderate
EC (dS m^{-1})	Spherical	0.40	0.19	978	32.26	Moderate
SOC (g/kg)	Spherical	0.97	0.21	1200	17.66	Strong

AN (Kg ha^{-1})	Exponential	5303	2572	991	32.66	Moderate
AP (Kg ha^{-1})	Spherical	8.08	14.72	628	64.55	Moderate
AK (Kg ha^{-1})	Exponential	0.03	0.08	1124	74.40	Moderate

EC: electrical conductivity; AN: available nitrogen; AP: available phosphorous; AK: available potassium

Conclusion

The main objective of the study were to identify the spatial dependence of soil properties using geostatistics and prepare spatial variability maps using GIS. The results of the study showed that low (10.21%) to high variation (94%) of soil properties requiring variable rate of inputs to improve crop productivity. Geostatistical analysis showed the spatial dependence of soil properties at both sampling depths. The range of influence from semivariogram can be helpful in planning future soil sampling to reduce time and analysis costs. Soil EC and SOC showed strong spatial dependence (nugget: sill ratio <25%) since it was induced by structural factors. All the properties (pH, available N, P, K) exhibited moderate spatial dependence (nugget: sill ratio 25-75%) since these properties were largely influenced by both internal and external factors.

The spatial variability maps show the soil nutrient status of the experimental farm which could be useful for site specific nutrient management. The farm managers can utilize the maps for site specific application of fertilizer. Additionally, it would aid in lowering the quantity of inorganic (fertilizer) inputs provided to the soil as supplements in order to prevent overburdening the soil, which could result in pollution and the degradation of the land. The study also shows that geostatistics and GIS is an effective tool for regionalized nutrient management.

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