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RESEARCH ARTICLE Agricultural Science Digest

Spatial Analysis of Soil Texture using GIS based Geostatistics Models and Influence of Soil Texture on Soil Hydraulic Conductivity in Melur Block of Madurai District, Tamil Nadu

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ABSTRACT

Background: Soil texture is one of the important property constitute ultimate size particles. Proportions of these ultimate soil particles depend on the pedogenesis and mineralogical composition of parent material and also decide all other soil properties. Due to the imprudent crop selection and imperfect agricultural methods, the very fertile soil is becoming denser and low productive. Geostatistics is a set of Models and tools developed for statistical analysis of continuous data. A critical aspect of agriculture ecosystem and environment modeling is the accurate prediction for the spatial variability of soil properties.

Methods: In this study, Geostatistical modeling based Kriging techniques has been used to identify the textural variation of soil in the present scenario of Melur Block of Madurai district. Totally, 150 soil samples were collected across Melur block of Madurai district based on grid soil survey and geo coordinates.

Result: Geostatistical soil textural maps have been generated based on Kriging tools and these would be utilized for Land Use Pattern, precision agriculture, conservation practices, as well as land management in the research region. The characterization of the spatial variability and influence of soil texture on hydraulic conductivity is essential to accomplish a better understanding of intricate relations between soil properties and environmental factors.

Key words: Geostatistical tool, GIS, Ordinary kriging, Semi variograms, Soil texture.

INTRODUCTION

Spatial variability of soil properties is a well-known phenomenon that has been recognized for a long time (Burrough, 1993). In any landscape, pedogenic process and land use pattern influence soil properties. Over the past few decades, due to climate change and global warming, the important soil physical properties have changed a lot.

The soil ecosystem is complex and its composition yields different physical, chemical and biological properties (Akpan-Idiok *et al.,* 2012). These properties are modified by prevailing climate, topography, geology, biological and land use pattern. Soil texture is one of the basic soil physical properties which influence water movement related properties and thermal parameters (Adhikari *et al.,* 2009). Recently adopted farming techniques and land-use pattern significantly influence soil texture (Cotching *et al.,* 2013). Conventional mapping is a tiresome method due to its difficulty in collecting data on soil resources. Therefore, there is a need to develop and support various agricultural recent technologies and land use management approaches through more accurate quantification techniques. The potential for digital soil mapping has expanded due to its availability in spatially continuous covariates, the incorporation of remote sensing technologies, the development of improved quantitative methodologies and greater computing power, making it possible to produce high-resolution digital soil maps nationwide and even globally.

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Geostatistics is an effective technique to estimate the spatial variability using variogram models and predicted soil properties (Burgess and Webster 1980). Geostatistics is an improved technology to soil property values in non sampled or sparsely sampled areas (Yao *et al.* 2004). Kriging has been proven to be sufficiently enough for estimating values in un sampled locations based on the sampled data and has been used for many decades as a synonym for geostatistical interpolation. Among different methods of spatial interpolation of soil properties, ordinary kriging is most common (Franzen and Peck 1993). Geostatistics and Kriging methods are used in recent years to predict the soil properties in un sampled locations in soil resource inventory for better understanding of spatial variability. These have been widely applied over past three decades in soil classification, soil reclamation, soil productivity mapping and soil pollution investigations. The Melur block of Madurai District covers 681 km^2 including 657.8 km^2 of rural area. Agriculture is the main occupation with paddy and sugarcane being largely cultivated. Therefore this study was conducted to create an appropriate interpolation model using geostatistics and GIS to create precise soil texture maps.

MATERIALS AND METHODS

Description of the study area

Melur block of Madurai district, Tamil Nadu (Fig 1) lies between 10.03' N Latitude and 78.34' E longitude and located at 121 MSL is taken as study area. The geographical area is about 681 km^2 and agriculture is the main occupation. The gross cultivated area is about 11,289 ha including 7179 ha and 4110 ha of irrigated area and rain fed area respectively.

Soil sampling and analysis

Totally, 150 surface soil samples (0-20 cm) were collected throughout Melur block by grid sampling based on GPS coordinates. These samples were processed and analyzed for soil properties by adopting standard analytical procedure. Texture in the present experiment was determined by the International pipette method (Piper, 1966). The hydraulic conductivity was determined by using the procedure (Gupta, 2007).

Geostatistical methods

Geostatistics is a specific area of statistical analysis that focuses on spatial correlations between two or three-dimensional data. The ordinary Kriging method was used for prediction of the values of the unmeasured sites (un-sampled locations) x_0 by assuming the $z^*(x_0)$ equals the line sum of the known measured value (field measured value). Kriging process is represented as the following equation (Wang, 1999).

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i z(x_i)$$

Where

$z^*(x_0)$= Predicted value at position x_0.

$Z(x_i)$= Known value at sampling site x_i.

λ_i= Weighting coefficient of the measured site.

'n'= Number of sites within the neighbourhood searched for the interpolation. Semivariograms are the primary tool used to investigate the spatial distribution structure of soil properties. A semivariogram (Nielsen and Wendroth 2003) is expressed as:

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

Where

$\gamma(h)$= Semi variance,

h= Lag distance.

Z= Parameter of the soil property.

N(h)= Number of pairs of locations separated by a lag distance h.

$Z(x_i)$ and $Z(x_i+h)$= Values of Z at positions.

x_i and x_i+h= (Wang and Shao 2013).

The empirical semivariograms obtained from the data were fitted with theoretical semivariogram models to produce geostatistical parameters, including nugget variance (C_0), structured variance (C_1), sill variance (C_0+C_1) and distance parameter (k). The nugget/sill ratio, $C_0/(C_0+C_1)$, was calculated to characterize the spatial dependency of the values. A nugget/sill ratio of less than 25% and more than 75% indicates strong and weak spatial dependence respectively (Cambardella *et al.* 1994). Basic spatial characteristics such as nugget, nugget/sill ratio and range were determined by using the semi variograms model and serve as both structural indicators and in interpolation during Kriging. The range is the distance at which the graph becomes flat first. Locations far from the range are not spatially auto correlated while those closer are. The lag between measurements known as sill, is the point at which one value for a variable has no bearing on nearby readings. Nugget denotes fluctuation resulting from random elements like measurement inaccuracy (Lopez-Granados *et al.*, 2002).

Cross validation

The variograms parameters that are found for each fitted model were used to interpolate the value at the unsampled location by ordinary Kriging. The model was verified by analogizing the estimated mean value to the measured mean after the sample points were arbitrarily divided into two datasets. An error-based metric called the root mean square error (RMSE) is used to rate accuracy of interpolation methods.

$$RMSE = \sqrt{\frac{\sum_{i-1}^{N}(0_i - S_i)^2}{N}}$$

Where

0_i= Observed value.

S_i= Predicted value, N is the Number of samples.

Correlation analysis

The relationship between soil texture with water holding capacity was determined using correlation coefficient "r". The correlation co-efficient, r, between two variables, x and y is given by:

$$r = \frac{n(\sum x_i y_i) - (\sum x_i)(\sum y_i)}{\sqrt{(n\sum x_i^2 - (\sum x_i)^2)(n\sum y_i^2 - (\sum y_i)^2)}}$$

Where,

r= Correlation coefficient.

x_i= Values of the variable x.

y_i= Values of the variable y and n is the number of samples taken in the data set.

RESULTS AND DISCUSSION

Descriptive statistics

The soil textural data was analyzed using SPSS 22.0 software to obtain the maximum, minimum, mean, standard deviation (SD), coefficient of variation (CV), Skewness and Kurtosis. The statistical descriptors for the analyzed data set are listed in Table 1. A difference in the CV of these parameters was noted. Generally, coefficient of variation (CV) of 35% denoted as low, 15-35% as moderate and >35% as high variation (Ranjbar and Jalali 2016). The CV value for silt and hydraulic conductivity was found to be 36.52% and 49.87%, respectively, with high spatial variability. The CV for sand and clay were 25% and 18.05%, respectively classified as moderate. The CV despite not being enough to determine spatial variability is the most distinguishing element for describing variability of soil attribute than other factors (Xing-Yi *et al*., 2007). However, the geostatistical analysis is necessary to determine the spatial dependency of parameter in addition to the statistical analysis.

Geostatistical analysis

The variable characters developed for various properties using semivariogram model is presented in Table 2, where C_0 is nugget variance; C is structural variance and C_0+ C represents degree of spatial variability which is affected by both structural and stochastic factors (Fig 2). The value of <0.25, 0.25-0.75 and >0.75 can show strong, moderate and weak spatial auto correlation of soil properties respectively. The values of C_0/C_0+C for various properties are depicted in Table 2 as 0.45, 0.71 and 0.53 for sand, silt and clay respectively. The nugget/sill ratio is fallen between 25 and 75% for sand and clay, indicating moderate spatial correlation imprinted by intrinsic factor (soil forming process) and extrinsic factors (tillage operation and cultivation practices) (Cambardella *et al.,* 1994). The same line of work has already been done on moderate spatial dependence of soil physical properties by Iqbal *et al*., (2005) and Safari *et al*. (2013).

Spatial distribution map and cross-validation

Sand, silt and clay content values were estimated by using ordinary Kriging. According to Fig 3 (a), (b) and (c), the research region as a whole was distinguished by a moderate to high degree of sand content, with just a few locations being rich in clay. Although the distribution of higher sand content areas appears to be more toward the northern east quadrant and central part of the study area, clay rich patches appear around the central-east. The spatial variability of sand and clay content appears in sparser as also suggested by the natural behavior of our best fitted model. Moreover, clay content was also observed to be fairly distributed throughout the area but in lesser contents. The Pearson's correlation coefficients between soil texture fractions are presented in Table 3. As anticipated, a significant (P<0.01, two-tailed) negative correlation existed between sand with clay and sand with silt. From this, it is concluded that soil erosion or leaching may influence the locations with lesser clay contents due to erosion process.

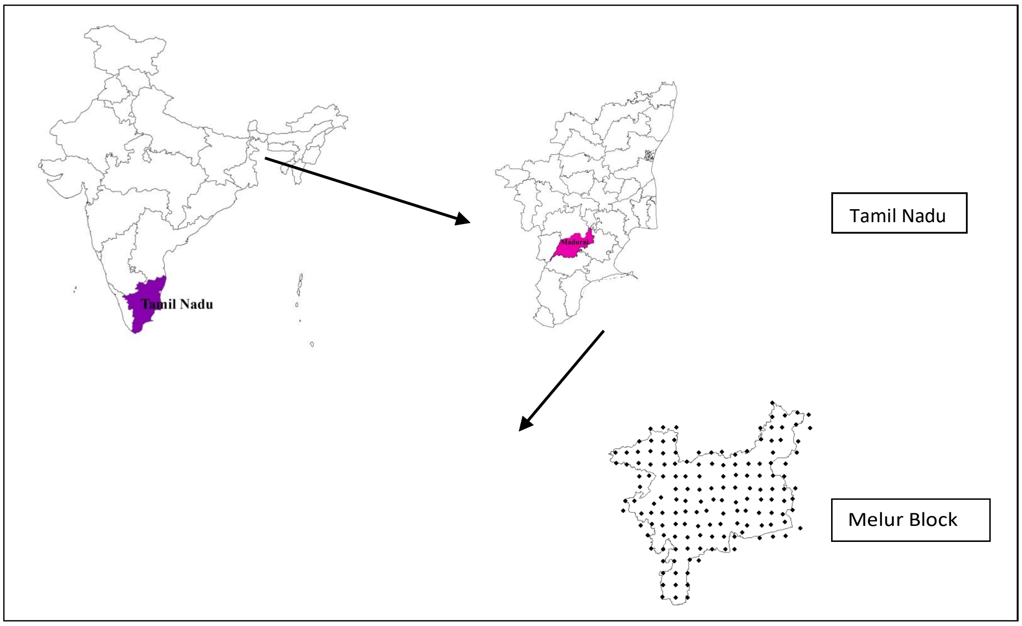

Fig 1: Map of study area.

Soil texture affects physical, chemical, hydrological, ecological processes biogeochemical cycling, retention of pollutants and soil bio diversity. Hence, precise determination and prediction of soil texture classes is critical for effective soil management. Textural data is used as input in a variety of models and pedotransfer functions to assess other soil properties and processes such as soil water holding capacity, soil organic carbon and nutrients, *etc*. For instance, with heavy textured soil the water movement properties are restricted, which in turn transport of bacteria, nutrients, sediment and pesticides from field to field and water bodies like rivers, lakes *etc*. It can also lead to soil leaching and increased erosion (Cole *et al*. 2017).

Relationship between soil texture and hydraulic conductivity of soil samples

According to the following workers (Gupta, 2007; Singanan, 1995) a good correlation is predicted if the linear regression

Table 1: Statistical desrciptors for sand, silt and clay.

Soil property	Mean	Minimum	Maximum	SD	CV (%)	Skewness	Kurtosis
sand (%)	47.30	10.2	73.48	11.82	25	-1.22	1.77
silt (%)	21.35	9.21	50.84	7.80	36.52	1.45	2.29
clay (%)	30.52	11.68	44.1	5.51	18.05	-0.01	1.21
Hydraulic conductivity (cm hr^{-1})	7.20	0.29	12.50	3.59	49.87	-0.56	-0.75

Table 2: Geo-statistical parameters of fitted semivariogram models for clay and cross-validation statistics.

Property	Fitted model	Nugget (C_0)	Sill (C_0+C)	Range (m)	Nugget/sill	RMSE
Sand	Circular	0.10	0.32	5119	0.45	11.79
Silt	Exponential	0.10	0.14	9051	0.71	7.69
Clay	Exponential	15.45	29.15	6436	0.53	5.12

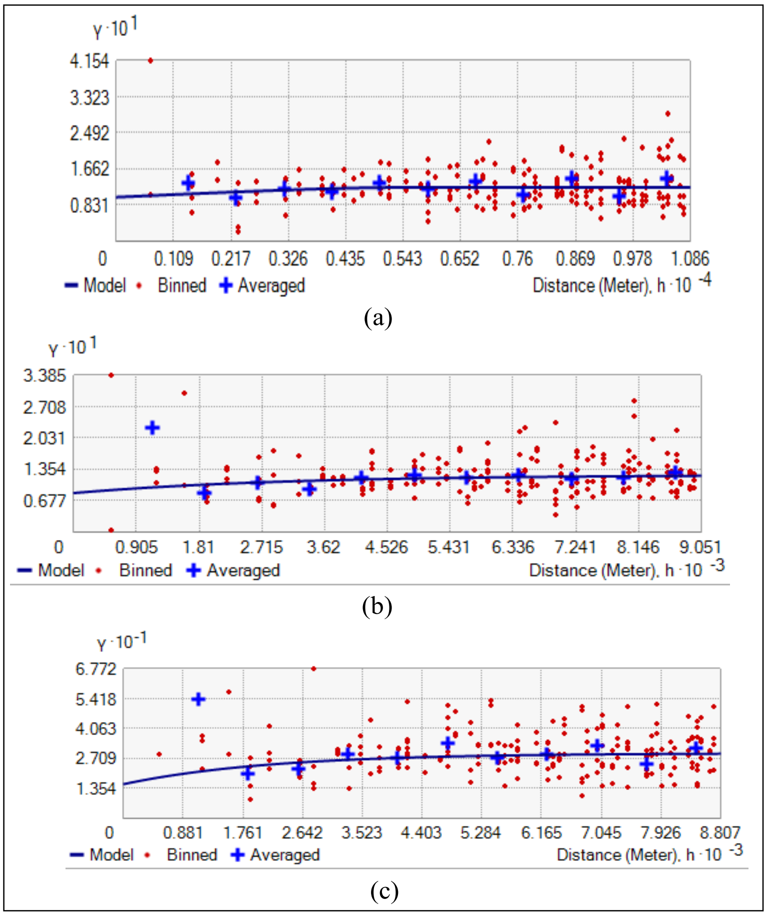

Fig 2: Semivariogram parameters of best-fitted theoretical model to predict sand (a), silt (b) and clay (c).

Table 3: Pearson correlation coefficients of the measured soil properties.

Parameters	Sand	Slit	Clay	Hydraulic conductivity
Sand	1			
Silt	-.924**	1		
clay	-.842**	.573**	1	
Hydraulic conductivity	.684**	0.178*	-.904**	1

**.Correlation is significant @0.01 level (2-tailed).

*.Correlation is significant at the 0.05 level (2-tailed).

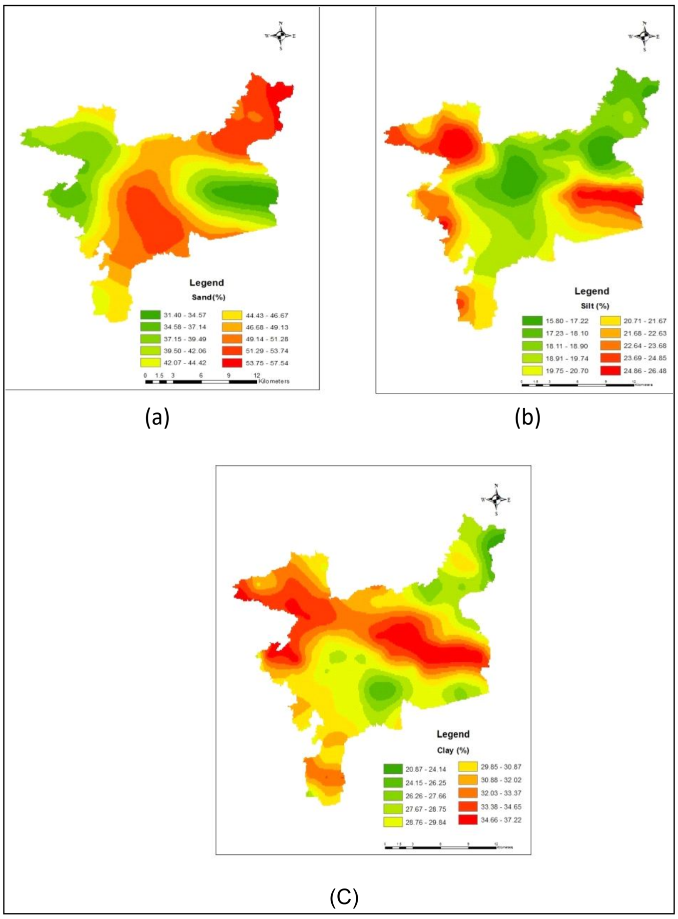

Fig 3: Predicted maps of sand (a), silt (b) and clay (c).

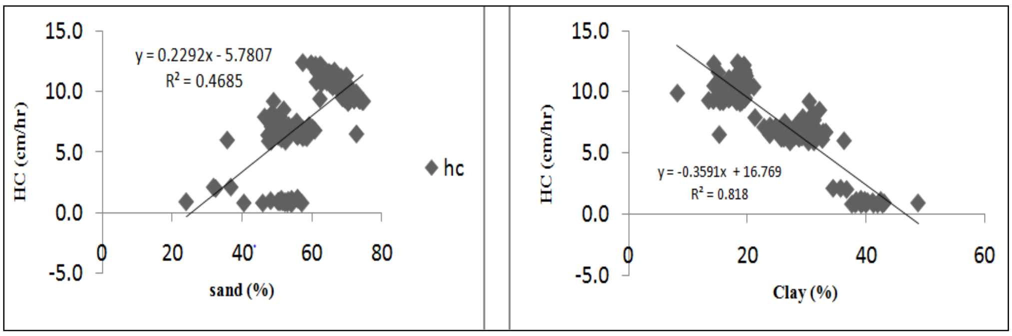

Fig 4: Linear correlation between hydraulic conductivity and a) Sand and b) Clay.

co-efficient " r " is > 0.7. The simple correlation coefficient between soil texture and hydraulic conductivity of soil samples are given in Table 3. It was observed that the hydraulic conductivity is dependent on texture of the soil. As the clay content of the soil sample increases the hydraulic conductivity decreases and as the sand content increases the hydraulic conductivity increases. Since sand particles are loosely bound and water molecules could pass through them easily and rapidly, sandy soils have high values of hydraulic conductivity. On the other hand, high clay content decreases hydraulic conductivity as the clay has a strong affinity towards water. Soils dominated by large sand particles tend to have relatively large pore spaces and thus large values of saturated hydraulic conductivity. Soils dominated by small clay particles tend to have relatively small pores spaces and small values of saturated hydraulic conductivity. Wang *et al*. (2009) also recorded an increase in HC with decreasing clay. It was observed that a strong negative correlation (r= -0.90) existed between clay content and hydraulic conductivity and positive correlation (r= 0.68) between sand content and hydraulic conductivity (Fig 4).

CONCLUSION

Based on the study, soil texture map was prepared for Melur Block, Madurai district using GIS based geostatistical technology with kriging. The desired predicted textural map could be used for Land Use planning, precision farming, irrigation management and soil and water conservation studies by the scientist and department officials. These predicted maps may be validated further with other model and information derived will be useful for other parameters and studies. Also, it was found that a strong relationship exists between soil texture and soil hydraulic conductivity.

Conflict of interest: None.

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