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Predictive Mapping of Soil Properties for Precision Agriculture Using Geographic Information System (GIS) Based Geostatistics Models

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Abstract

In precision Agriculture, geostatistical methods as a predictive tool have been extensively utilized. The approach estimates soil properties spatial variability and dependency. This study was carried out in Ovia north east Local Government Area of Edo State of Nigeria in order to map soil properties (Sand, Clay, pH, OC, P, N and CEC) and redict their spatial variability. Twenty-nine (29) soil samples were collected randomly from Typic Kandiudults soil type under three different land use, teak forest plantation, shrub, and arable farm. The soil samples were air-dried and passed through a 2 mm sieve before being analyzed for pH($CaCl_2$), SOC, Sand, Clay, Phosphorus, Nitrogen, and CEC. Generated data were statistically and geostatistically computed to explain the spatial variability of soil properties. The traditional method of soil analysis and interpretation are tedious, time-consuming with escalating budgets thus geostatical approach. Available phosphorus yielded large variability with CV=57.08% followed by clay content with CV=49.03%. Spherical, Gaussian, Hole Effect model, Stable, Exponential and Circular models were fitted for all the soil parameters. The result revealed that soil pH, Sand content, TN and CEC were moderate spatially autocorrelated with nugget/sill value of 0.32, 0.21, 0.49 and 0.30 respectively. SOC also gave a moderate spatially autocorrelated with nugget/sill value of 0.44. And Clay and Available phosphorus were strong spatially autocorrelated with nugget/sill value of 0.15 and 0.13 respectively. Cross-validation of the output maps using the semivariogram showed that the interpolation models are superior to assuming mean for any unsampled area. The output maps will help soil users within the area to proffer best management technology to improve crop, fiber and water production.

Keywords: precision agriculture, geostatistics, geographic information system, soil properties, ordinary kriging, landuse

1. Introduction

The soil ecosystem is a complex one which is formed from different weathering process of rock materials. It is composed of mineral and organic fractions, yielding specific physical, chemical, mineralogical and biological properties (Esu, 2005, Kingsley et al., 2019, Akpan-Idiok et al., 2012). These properties are also influenced by different environmental covariates such as micro-climatic, topography, geology, biological organisms and among others (Shukla, 2009; Jenny, 1941; Esu, 2005) leading to their spatial difference across the small land area (Townsend, Vitousek, & Trumbare, 1995). Therefore, soil mapping is essential. Soil mapping, on the other hand, is the process of gathering, describing, manipulating, classifying and predicting soil properties (Esu,2005). It also provides up-to-date information in terms of landforms, terraces, and vegetation (Denton et al., 2017; Brown et al., 1978). Importantly, these updated soil inventories are reliable in policy and decision making under precision agriculture (Denton et al., 2017).

In the past 20 years, so much have been achieved as regards to the approaches towards soil mapping (Goovaerts, 1999; Mcbratney et al., 2000 Pravat et al., 2016, Denton et al., 2017). Conventional soil mapping which happened to be a tedious method of gathering information about the soil resources by soil mappers have been improved with great advances in spatial science (Esu et al., 2005, Fasina et al., 2012)

In traditional soil mapping, a representative soil property from a given location is used to describe a soil unit, which is then vectorized using physiographic and landforms methods in the soil map. However, the soil mappers are fully aware that the spatial variability of the soil properties is not represented as they are distorted by boundaries (Heuvelink and Webster 2001). But in reality, the soil properties are spatially variable and shows a continuum, and for accurate prediction, this property should be considered. The traditional method of soil analysis and interpretation are tedious, time-consuming with escalating budgets. On the other hand, geostatistical methods are some packages in ArcGIS and other software alike are widely accepted as an important spatial interpolation method in land resource inventories (Pravat et al., 2016, Hengl et al., 2004; Bhunia et al., 2016). Geostatistics methods (Kriging, Inverse Distance Weighting, Spline) are widely employed as important spatial interpolation techniques in soil mapping. (Hengl et al., 2004; Bhunia et al., 2016, & Ofem et al., 2017). Although, Weller et al., 2002 reported a better interpolation result with Kriging than any other method. It is also commonly used as a predictive tool (Franzen & peck, 1995). Furthermore, the approach engages expert knowledge in making an accurate prediction of soil properties(Lin et al. 2005; Shibu et al. 2006).

Geostatistics techniques estimate the spatial variability using variogram models which predicts the values of soil properties at un-sampled locations (Pravat et al., 2016; Goovaerts, 1998 &1999; Denton et al., 2016; Gouri et al., 2018 and Ofem et al., 2017). These methods are widely used to assess spatial correlation in soils and ascertain the spatial variability in soil properties (physical, chemical and biological) as opined by Gouri et al., 2018. Kriging engages the mean of a known location to determine the property of value in the unsampled area, which will narrow the section of estimation to the highest degree (Penížek & Borůvka, 2006).

In Nigeria, all the soil maps available were prepared through conventional survey and very little effort have been made so far in modern spatial mapping techniques (Denton *et al.*, 2016 and Ofem *et al.*, 2017). The accurate prediction of soil properties variability (particle size distribution, pH organic carbon, CEC, ECEC, Available phosphorus among others) is essential in sustainable agriculture and it accounts as one of the fundamentals for soil users. Therefore, the objective of this study was to map soil properties (Sand, Clay, pH, OC, P, N and CEC) and predict their spatial variability using the geostatistical technique.

2. Materials and Methods

2.1 Study Area

The research was conducted in Odighi area of Ovia North East, Edo State in Nigeria stretching between 6°37'5.24''N- 6°36'46.97''N latitude and 5°45'53.88''E- 5°45'49.16''E longitude encompassing the area of 3 km^2 (Fig. 1). The vegetation of the study area is a multistoried high tropical rainforest characterized majorly by teak. The area is characterized by strongly undulating terrain with a gentle slope at the crest and valley slope. Geologically, the soils are derived from materials of tertiary coastal plain deposits and are made up of continental sand and sandstone with shale and are classified according USDA Soil Taxonomy classification as Typic kandiudlts (Imadojemu et al., 2018). Average annual rainfall pattern of the location varied between 1500-2500 mm in a bimodal form with two peaks in June and September and a peak fall referred to as August break (NIFOR, 2013). The monthly minimum and maximum temperature vary between 25˚C and 31℃, during the wet and dry period of the year. The relative humidity varies from 80 percent during the rains to about 60% in the dry season (NIFOR, 2013).

2.2 Field Sampling and Laboratory Analysis

A total of 29 samples were randomly collected from three selected land-use of the study location. These include 8 auger points from a shrub farm, 12 observation points from a teak forest and 9 auger points from an arable farm. Samples were collected at a depth of 0 – 20 cm for fertility purpose with the help of hand-held global positioning system (GPS).

Soil samples obtained were air-dried and pass through a 2-mm sieve and used for particle size analysis using Boyocouos hydrometer method (Bouyoucos, 1962; Van Reeuwijk, 1992). The pH of the soils was analyzed potentiometrically using a glass-calomel combination electrode (Van Reeuwijk, 1992); Organic carbon was determined by the Walkley and Black (1934) method. Available soil P was analyzed according to the standard procedure of Olsen *et al.* (1954) extraction method. Total N was analyzed using the Kjeldahl digestion, distillation, and titration method as described by Black (1965). Cation exchange capacity (CEC) was determined using flame photometer as described by (Chapman, 1965).

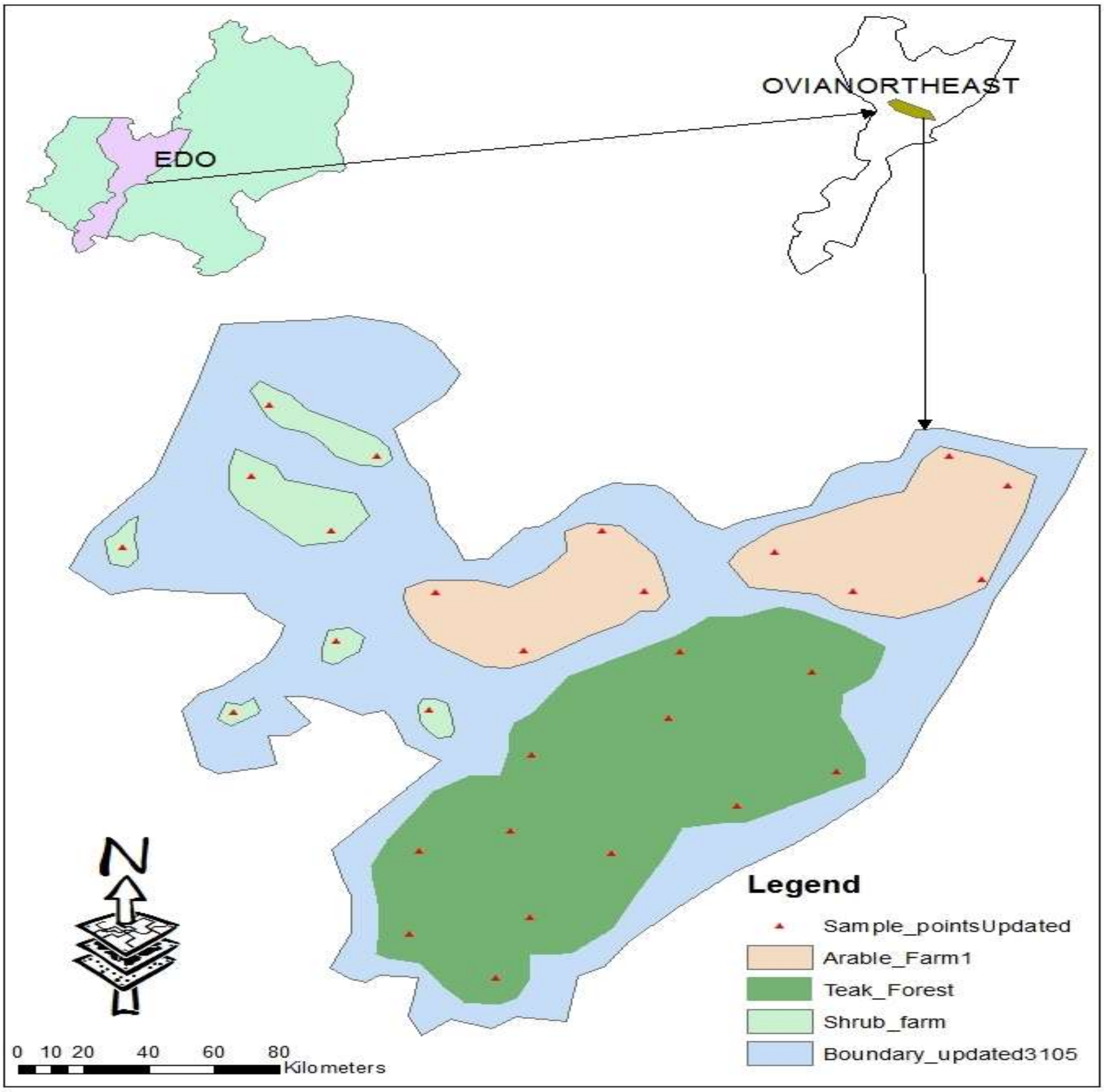

Figure 1. Location and sampling points map of the study area

2.3 Geostatistical Model in GIS

Soil spatial prediction and GIS approach were engaged to produce predictive maps of the soil properties under study. The software used for the research was ArcGIS 10.6 (ESRI Co, Redlands, US). The software package known as spatial analyst tool was activated to carry out the interpolation process, to predict spatial dependency and spatial variability of the soil properties under investigation. Meanwhile in the spatial tool analyst is the geostatistical model known as Ordinary kriging (OK), and was used in the study. "The model utilizes measured for prediction of the values of the unmeasured sites (un-samples locations) X_0 by assuming the $z^*(X_0)$ equals the line some of the known measured value (field measured value). The model can express spatial variation and allow a variety of map outputs, and at the same time minimize the errors of predicted values (González et al. 2014)".

Kriging models as follows (Wang et al. 2009):

$$z^*(X_0) = \sum_{i=1}^{n} \lambda_i z_i \quad (1)$$

Where $z^*(X_0)$ is the predicted value at position X_0, $Z(X_i)$ the known value at sampling site X_i, λ_i the weighting coefficient of the measured site and n is the number of sites within the neighborhood searched for the interpolation.

In kriging, a semivariogram model is also used to define the weights of the function as pointed out by Webster & Oliver (2001), and the semivariance is an autocorrelation statistic (Mabit & Bernard 2007). It is used as a basic tool to evaluate the spatial distribution structure of the soil properties with reference to regionalized variable theory and intrinsic hypotheses (Nielsen and Wendroth 2003), a semivariogram is expressed as:

$$\gamma(h) = \frac{1}{2N(h)}\sum_{i=1}^{n}[Z(X_i - Z(X_i + h)]^2 \quad (2)$$

where γ(h) is the semivariance, h the lag distance, Z the parameter of the soil property, N(h) the number of pairs of locations separated by a lag distance h, Z(xi), and Z(X_i+h) are values of Z at positions xi and xi + h (Wang and Shao 2013).

After the semivariogram computation, the models suitable were Gaussian, spherical, linear and exponential). The empirical semivariograms generated from the data were fitted by theoretical semivariogram models to yield geostatistical parameters, including nugget variance (C_0), variance (C_1), sill (C_0+C_1), and range (k). The nugget/sill ratio, C_0/(C_0/C_1), was computed to characterize the spatial dependency of the values. In addition, a nugget/sill ratio <25 %= strong spatial dependency, 25-75%=moderate spatial autocorrelation and >75 % shows weak spatial dependency; otherwise, the spatial dependency is moderate (Cambardella et al. 1994).

Accuracy assessment

2.4 Cross Validation

This “model validation technique is used in assessing how the results of the statistical analysis will generalize to an independent data set. Cross-validation technique was adopted for evaluating and comparing the performance of ordinary kriging interpolation method. The sample points were arbitrarily divided into two datasets, with one estimate mean value against measured mean were engaged in order to validate the model. The root means square error (RMSE) is error based measures to evaluate the accuracy of interpolation methods. RMSS must be close to 1 (Johnston, Hoef, Krivoruchko, & Lucas, 2001)”.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{\mathrm{i=1}}^{\mathrm{N}}(0_\mathrm{i} + \mathrm{Z_i})^2}{\mathrm{N}}} \quad (3)$$

3. Results

3.1 Descriptive Statistics of the Soil Properties

The summary of the descriptive statistical analysis of Soil pH, Soil organic carbon (SOC), Sand fractions, Clay content, Available phosphorus, Total nitrogen, and Cation exchange capacity is presented in Table 1.

Table 1. Descriptive statistical analysis for the soil properties under investigation

Variables	***Mean***	***Min***	***Max***	***Std.Dev.***	***Coef.Var.***	***Skewness***	***Kurtosis***	***Distribution Pattern***
Soil pH	4.0	3.2	4.7	0.42	10.52	0.002	-0.894	Normal
SOC	1.1	0.2	3.1	0.33	30.00	0.414	-1.088	Log
Sand	826.5	700	954	78.94	9.55	0.196	-0.992	Normal
Clay	154.3	34	280	75.66	49.03	-0.101	-1.083	Normal
Avail. P	9.1	2.8	19.8	5.20	57.08	0.576	-0.474	Normal
N	25.5	12.2	44.6	8.74	34.22	0.429	-0.350	Normal
CEC	1.5	1.0	2.3	0.36	23.55	0.305	-0.815	Normal

The means of the parameters were 4, 1.1, 826.5, 154.3, 9.1, 25.5 and 1.5 for pH, SOC, Sand, Clay, Available Phosphorus, Nitrogen and Cation exchange capacity respectively. The sand fractions gave the highest standard deviation (78.94 g/kg) while the soil organic carbon gave the lowest (0.33 g/kg). Soil organic carbon, Clay, Available phosphorus and total nitrogen gave the highest coefficient of variation of between 30-60%. The soil parameters gave a positive skewness except for clay fraction which was negatively skewed. The soil properties were normally distributed except for soil carbon which was log transformed to removed outliers. This was carried out to yield a more reliable output (Reza et al., 2015).

3.2 Geostatistics Models of the Soil Properties

Inasmuch as the descriptive analysis result gave a vital output of the soils under investigation but they could not describe the spatial variability and autocorrelation of the soil the property. Hence geostatistic modeling was adopted to interpret spatial variability pattern of the soils (Table 2). The results of the geostatistic interpolation of the soil properties are presented in Table 2, Fig. 1 and Fig.2. These result revealed the spatial variability of the soil properties.

Table 2. Geostatistical models for the soil properties

Variables	*Fitted model*	*Nugget*	*Sill*	*Range**	*Nugget/Nugget+Sill*	*Spatial class*	*RMSE***
Soil pH	Spherical	0.134	0.283	0.2	0.32	Moderate	1.082
SOC	Spherical	0.595	0.435	0.6	0.44	Moderate	1.025
Sand	Gaussian	1542.8	5912.7	0.1	0.21	Moderate	1.144
Clay	Hole Effect	742.8	4955.2	0.8	0.13	Strong	1.184
Available P	Stable	4.7	25.9	0.8	0.15	Strong	1.050
Nitrogen	Exponential	47.954	34.658	0.1	0.49	Strong	1.049
CEC	Circular	0.0494	0.116	0.1	0.30	Moderate	0.942

In the semivariogram model pH and soil organic carbon followed a **spherical model**; sand=**Gaussian model**, Clay=**Hole Effect Model**; Available phosphorus= **Stable model**; Nitrogen= **Exponential model** and CEC=**Circular model**. The nugget/sill ratio of soil pH, SOC, Sand, Clay, available P, nitrogen and CEC were 0.32, 0.44, 0.21, 0.13, 0.15, 0.49 and 0.30 respectively. The RMSE revealed the steadiness of the predicted values and the acceptable precision respectively, as it shows the suitability of the predicted models by ordinary kriging approach.

4. Discussion

There is so much variation in the clay, available phosphorus, and total nitrogen parameters and little variation in soil pH and sand content. The result obtained in this study is similar to the report by Denton et al., 2016 & Reza et al., 2015. But contradicts the Reza et al., 2015 in the sand content CV. Similarly, the high mean value obtained in the sand content may have been contributed by a large number of point data with high sand content, this also raised the standard deviation. This type of soil may encourage the leaching of basic cations especially in the period of high rainfall regime (Ofem *et al.,* 2017, Kingsley et al., 2019). Also, the low coefficient of variation for pH was influenced by land use, parent materials, climate among others (Denton et al., 2016, Akpan-Idiok et al., 2012, Ofem et al., 2017) and gave a spatial variability in the three different land use.

The continuous variability that exists in the soil ecosystem is influenced by several environmental covariates, mass movement, soil creep, hydrology, and landforms. In addition, soil properties under different land uses can also be influenced by micro-climate and litterfall in forest land; irrigation, fertilization, or drainage pattern in arable farms (Moasheri & Foroughifar, 2013). These factors have influences on the data distribution pattern.

The spatial interpolation of the soil properties, soil pH, SOC, sand, clay, available phosphorus, total nitrogen, and CEC was carried out using ordinary kriging method (Fig.1). This technique was adopted to transform point soil observations into continuum variables. The predictive maps of soil properties (pH, SOC, Sand, Clay, P, N, and CEC) revealed the concentration of high pH values in teak forest land and low pH value in the arable farm. This may be as a result of slow degradation of litterfall and yielding low organic matter turnover for teak forest and the application urea fertilizers for the arable farm. Although the general low pH (<5.0) value in all the land use may be a structural factor (parent material and climate). Soil organic carbon was high in the teak forest land use as expected. While the lowest SOC value was obtained in the shrub farm. This may be caused by a lack of organic matter turnover by excessive animal grazing in the region. High sand content was concentrated in the southern region (teak forest). This result collaborates with that of Akamigbo, 1984. High clay distribution was obtained in the northeastern (arable farm) part of the area under study. This may be attributed to the structural factor like land denudation (Kerry, 2012). Also, well-reflected changes were observed in the spatial distribution for Available P, Nitrogen, and CEC. Although high spatial distribution of phosphorus, nitrogen, and CEC was observed in the teak forest which is in the south direction of the area. The result obtained suggests the engagement of certain land management practices such as the use of biochar, minimum tillage, fallow system. This will, in turn, increase carbon in the other parts of the land.

Using the ordinary kriging, maps for each soil property was plotted based on the semivariogram fitness models of cross validation (Fig 3). The model with the best fit were fitted into all the parameters as thus:

$$\text{Soil pH}= (0.13417*\text{Nugget}+0.090542*\text{Spherical}(0.57836) \quad (4)$$

Soil organic carbon= (0.59574*Nugget+0.43453*Spherical(0.57836) (5)

Sand content= 1542.8*Nugget+5912.7*Gaussian(0.10928) (6)

Clay content= 742.8*Nugget+4955.2*Hole Effect(0.8) (7)

Available phosphorus= 4.7*Nugget+25.8*Stable(0.8) (8)

Nitrogen= 47.954*Nugget+34.658*Exponential(0.11462) (9)

CEC= 0.049451*Nugget+0.11583*Circular(0.11462) (10)

Fig. 2 showed the selected semivariogram models of fitness plots. The nugget effects are accredited to either laboratory measurement errors or spatial dependency errors at varying points smaller than the sampling ranges or both. Lag distance is a distance beyond which the samples do not affect each other or do not show enough dependence and the spatial points can be considered independently of each other.

The nugget/sill ratio may be low or high. High nugget/sill ratio reveals that the spatial distribution is influenced by stochastic factors such as cropping system, soil amendments usage and other human factors. While low nugget/sill ratio indicates structural dependency such as parent material, biological organism, relief and other natural factors that influence soil spatial variability. Soil pH gave moderate spatial autocorrelation (0.25-0.75) and SOC gave a weak spatial autocorrelation (>0.75). Sand content yielded a moderate spatial autocorrelation which collaborates with the results by (Reza et al., 2015, Safari et al., 2013). Clay content and Available phosphorus were strongly spatial autocorrelated (<0.25). But a high nugget effect was obtained in Nitrogen semivariogram plot contradicts the result by Denton et al., 2017. CEC yielded moderate spatial autocorrelation (0.25-0.75). Therefore, the strong spatial autocorrelation was obtained in clay and available phosphorus could be attributed to structural elements. While the moderate and weak spatial autocorrelation in other soil property (pH, SOC, Sand, nitrogen, and CEC) may have been developed from random factors such as poor land conservation approach, chemical fertilizer application, uncontrolled grazing amongs others. Furthermore, the decrease of the soil heterogeneity across the three different land use may have been influenced by human activities, drainage, fertilization among others, these reduce spatial correlation (Gouri et al., 2018).

5. Conclusion

In this study, 29 samples were collected from three different land use (teak forest, arable and shrub farms) and were used to evaluate soil spatial distribution. The geostatistics models in GIS which were adopted in this study proved essential for evaluation of different land use inventories in various status. The six (6) geostatistical interpolation models were fitted for seven (7) soil properties (Soil pH, SOC, Sand, Clay, Available Phosphorus, Total Nitrogen and CEC). The soil pH and sand content did not vary that much in all the three land uses as these were referenced to stochastic factors. The spatial distribution of SOC and total N, Phosphorus and CEC were greatly influenced by the land use. As per the transformation of forest land to arable or shrubs results to a reduction in biomass accumulation which affects organic matter content and in turn, SOC. The output from our study indicates the spatial distribution of soil parameters and the observation points distance in this research is adequate for predictive modeling. This approach is important for precision agriculture and environmental modeling.

The result from this study also showed that the soil properties in the three different land use are variable and heterogenous hence the spatial distribution and dependency within the same area under investigation. This also validates the relevance of GIS methods in predictive mapping. Cross validation of the semivariogram models generated the ordinary kriging geostatistical revealed that predictive mapping is superior to guessing the mean of the observed points at any unsampled location.

The result from this research puts a value on geostatistic interpolation as a useful guide for Soil Scientist within Southern Nigeria in improving soil maps resolution with detailed information. In addition, the result of this study can help profer suitable crop management technology to be adopted by small farm holders in increasing crop, fiber, and water production. Concluding, the enhancement of regional soil maps using this approach using more point data is strongly recommended.

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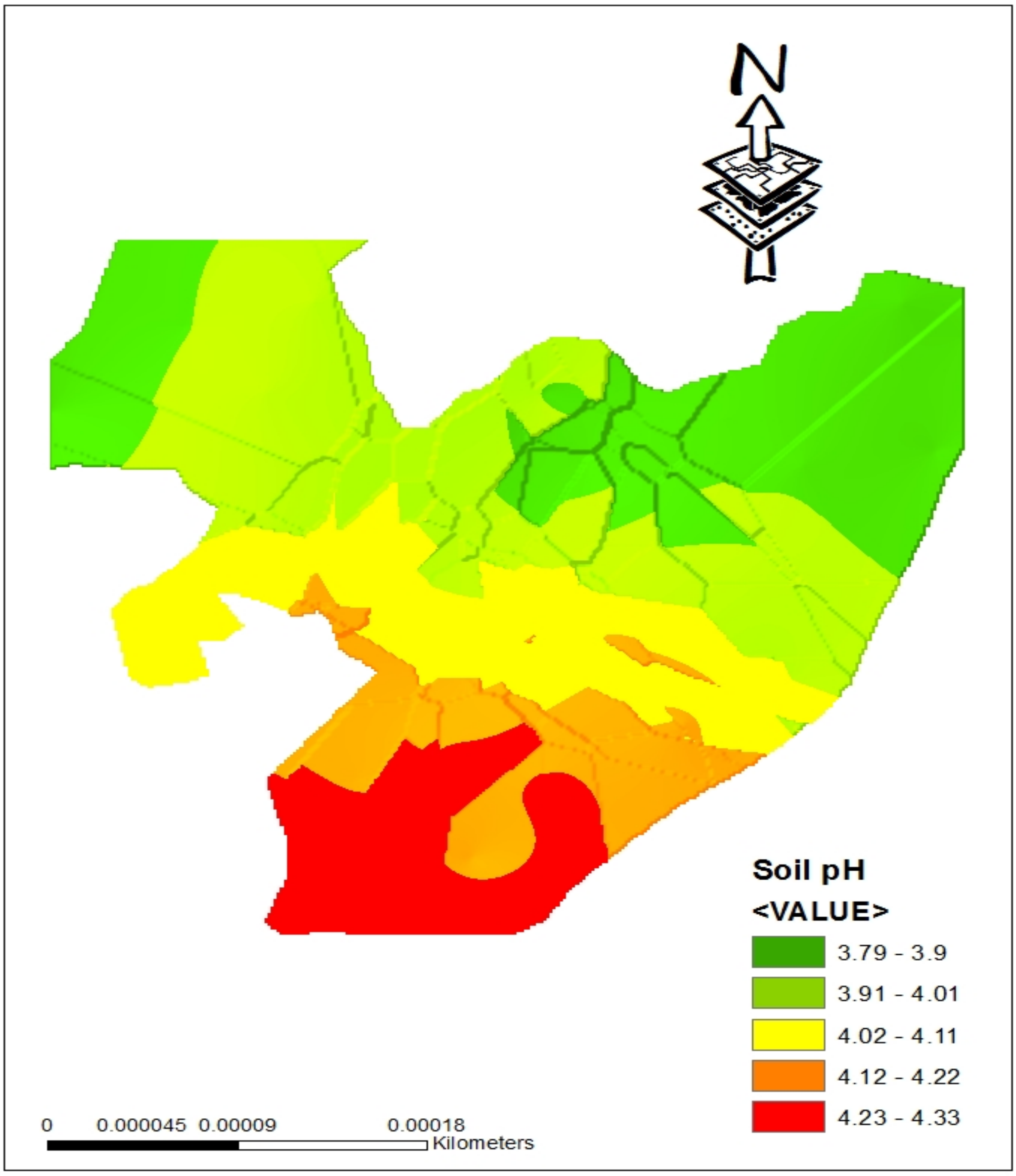
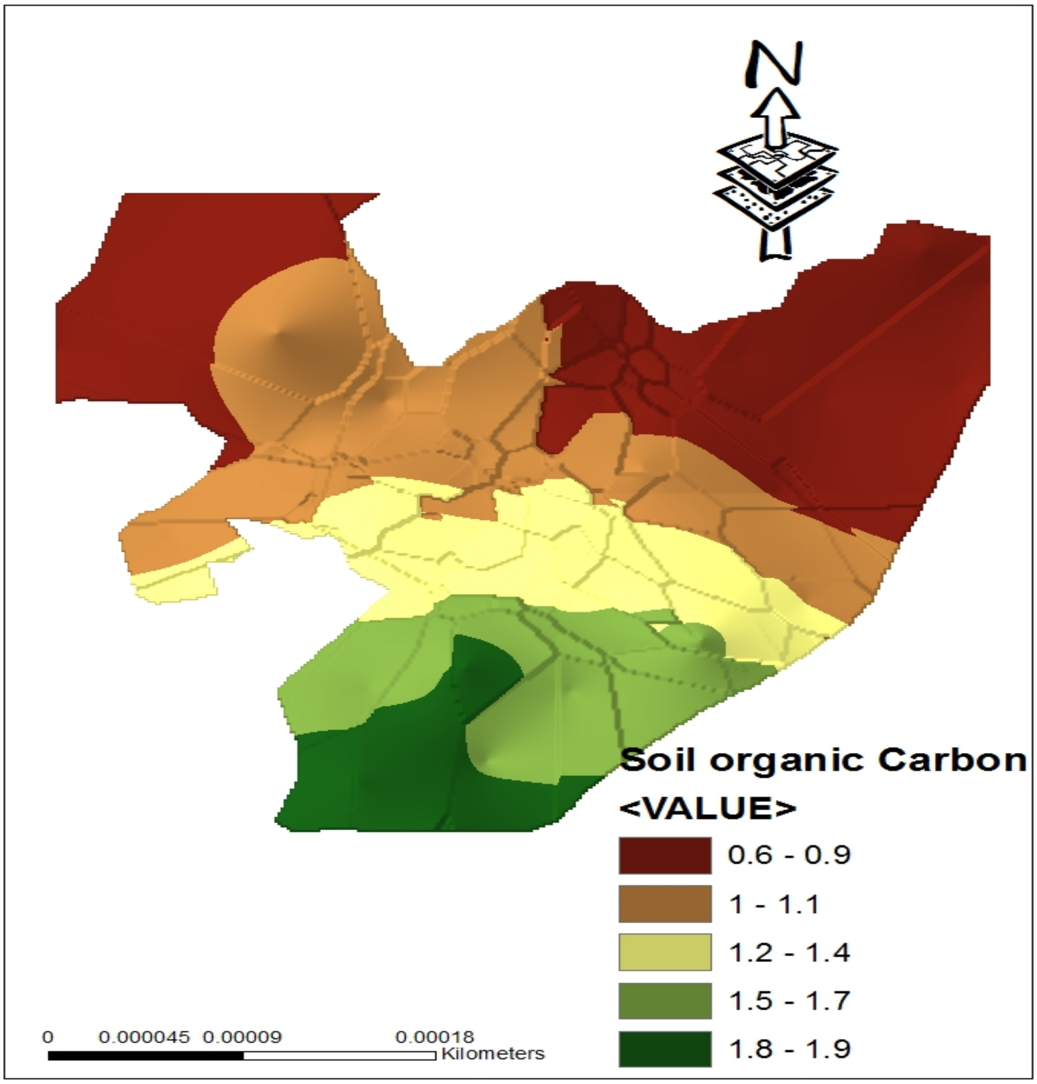
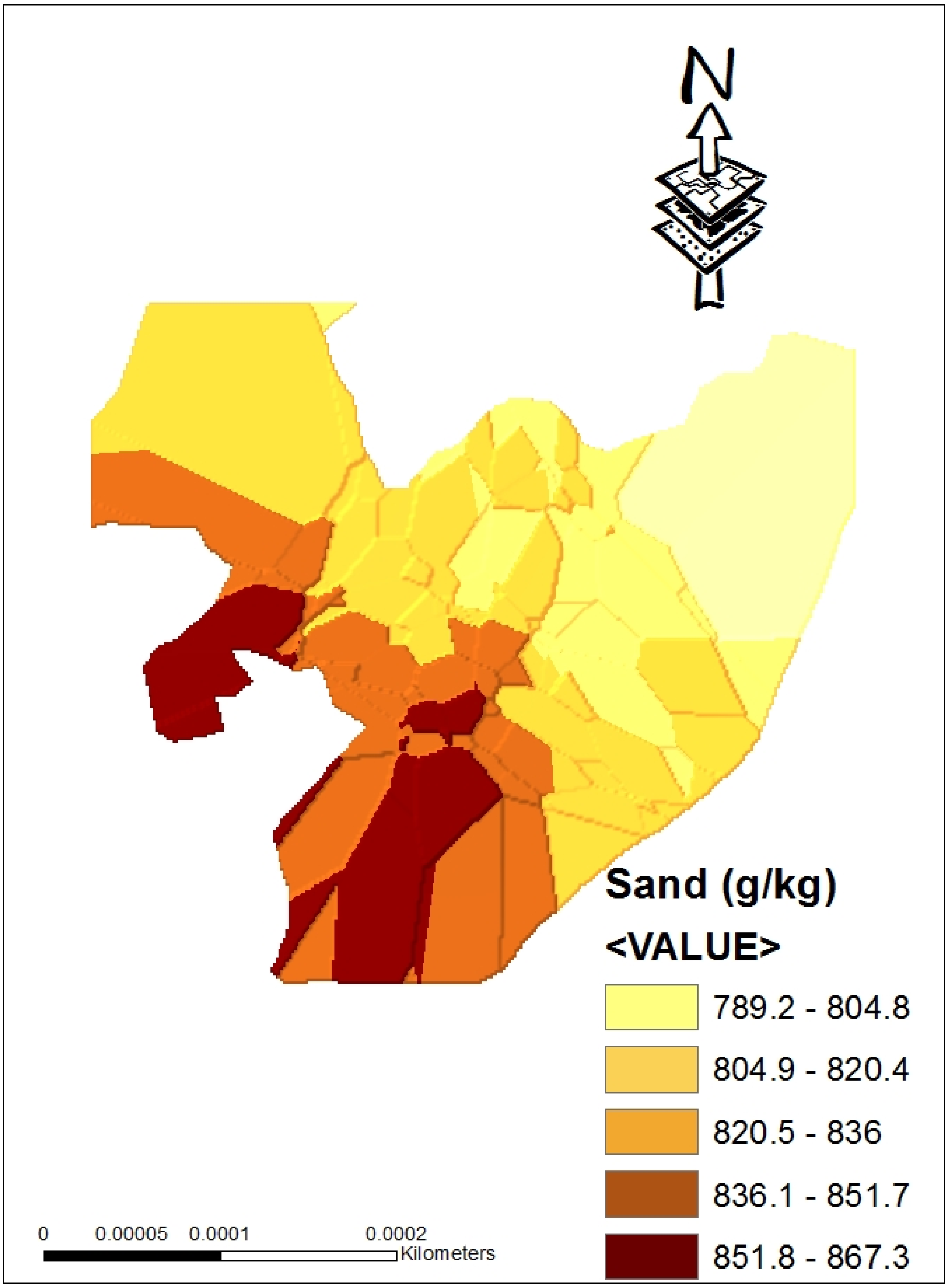


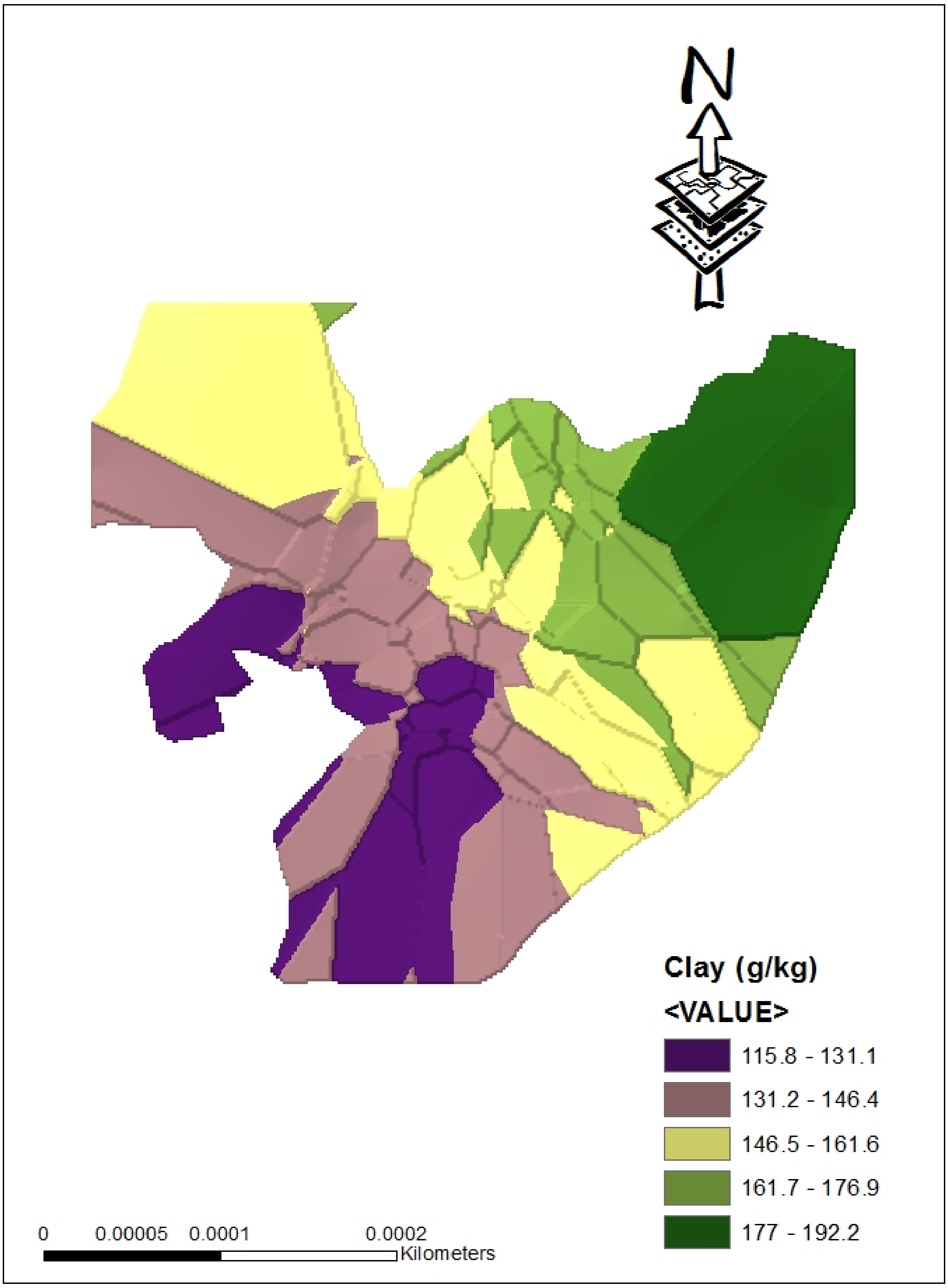
a. Soil pH



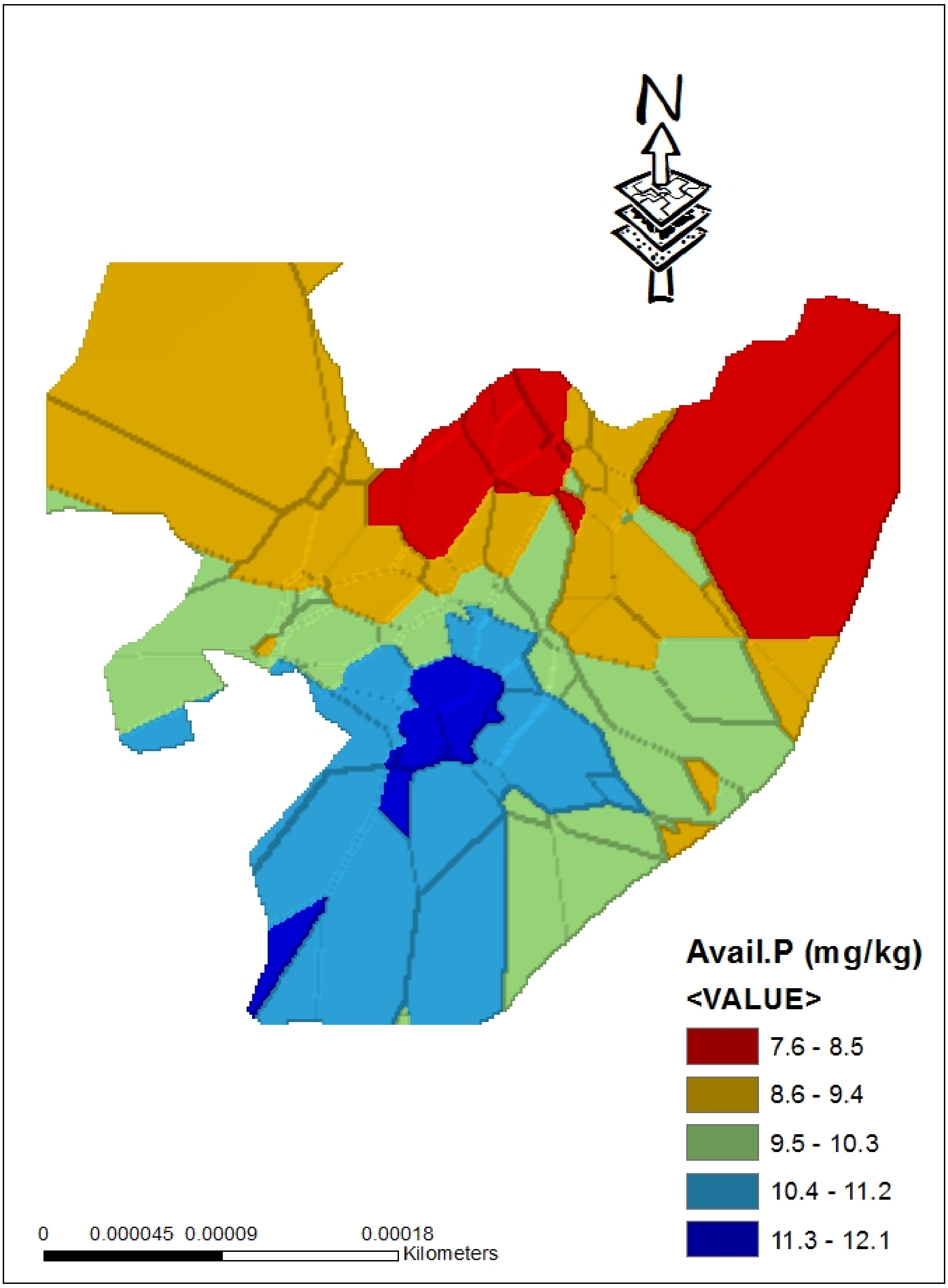
b. Soil organic carbon


N
Sand (g/kg)
<VALUE>
789.2 - 804.8
804.9 - 820.4
820.5 - 836
836.1 - 851.7
851.8 - 867.3
0 0.00005 0.0001 0.0002
Kilometers

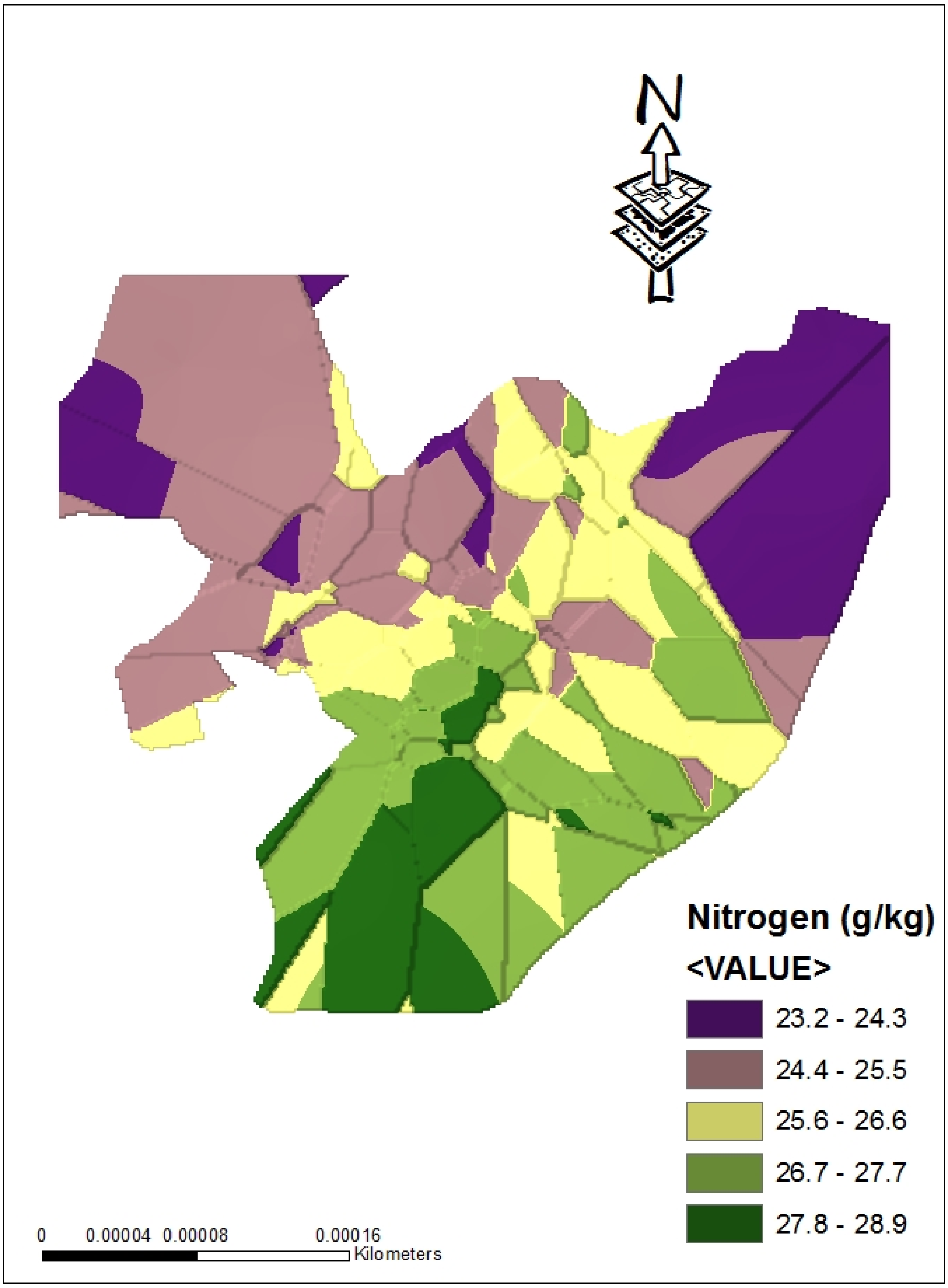
c. Sand


N
Clay (g/kg)
<VALUE>
115.8 - 131.1
131.2 - 146.4
146.5 - 161.6
161.7 - 176.9
177 - 192.2
0 0.00005 0.0001 0.0002
Kilometers

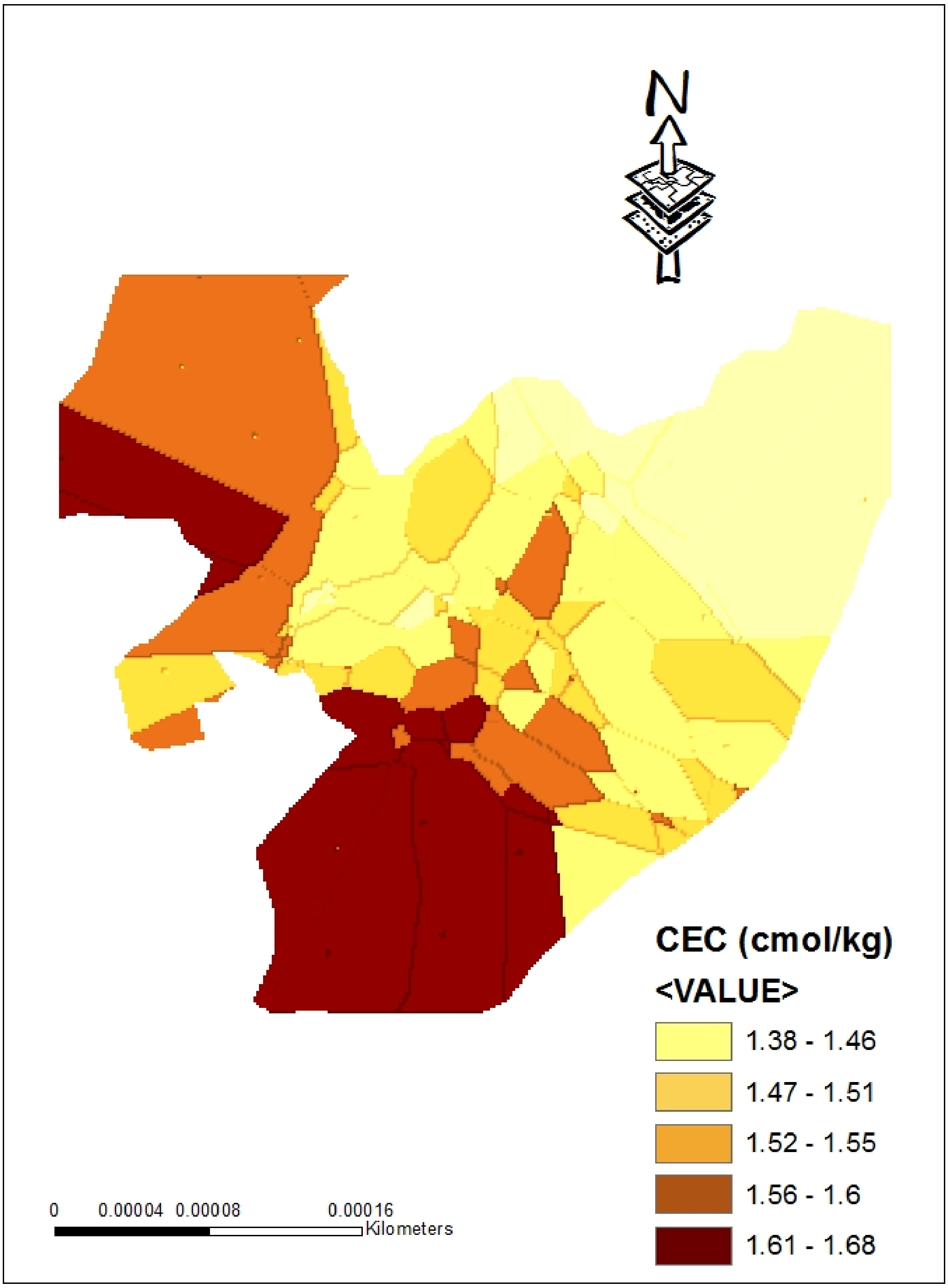
d. Clay


N
Avail.P (mg/kg)
<VALUE>
7.6 - 8.5
8.6 - 9.4
9.5 - 10.3
10.4 - 11.2
11.3 - 12.1
0 0.000045 0.00009 0.00018
Kilometers

e. Available

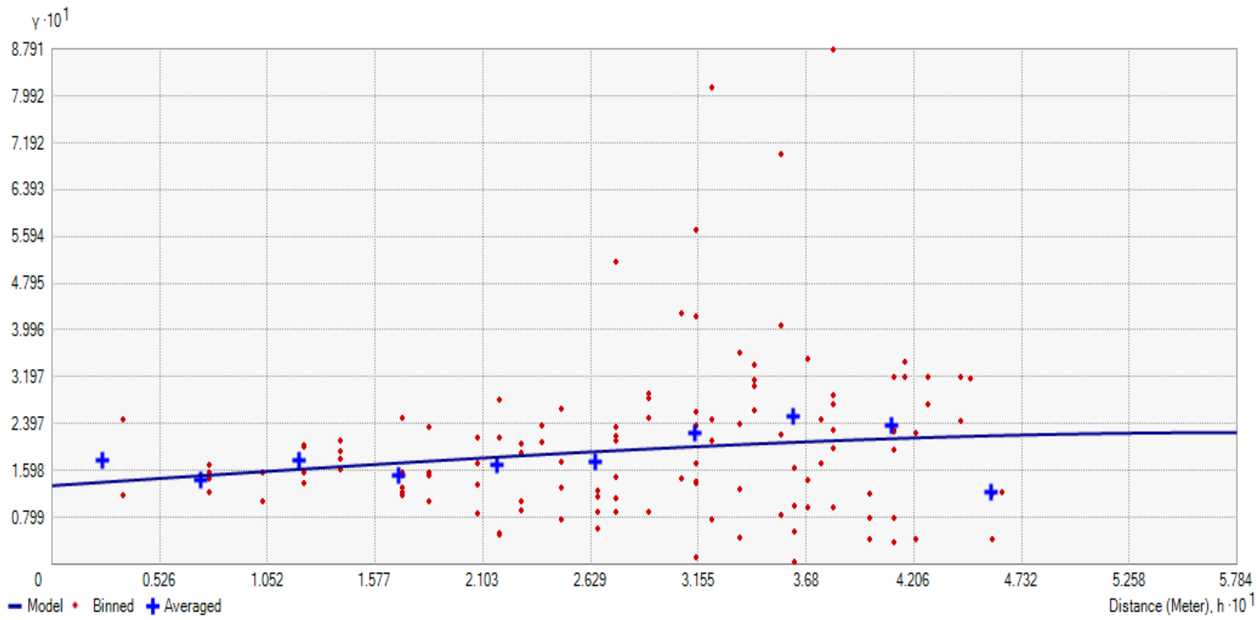

N
Nitrogen (g/kg)
<VALUE>
23.2 - 24.3
24.4 - 25.5
25.6 - 26.6
26.7 - 27.7
27.8 - 28.9
0 0.00004 0.00008 0.00016
Kilometers

f. Nitrogen

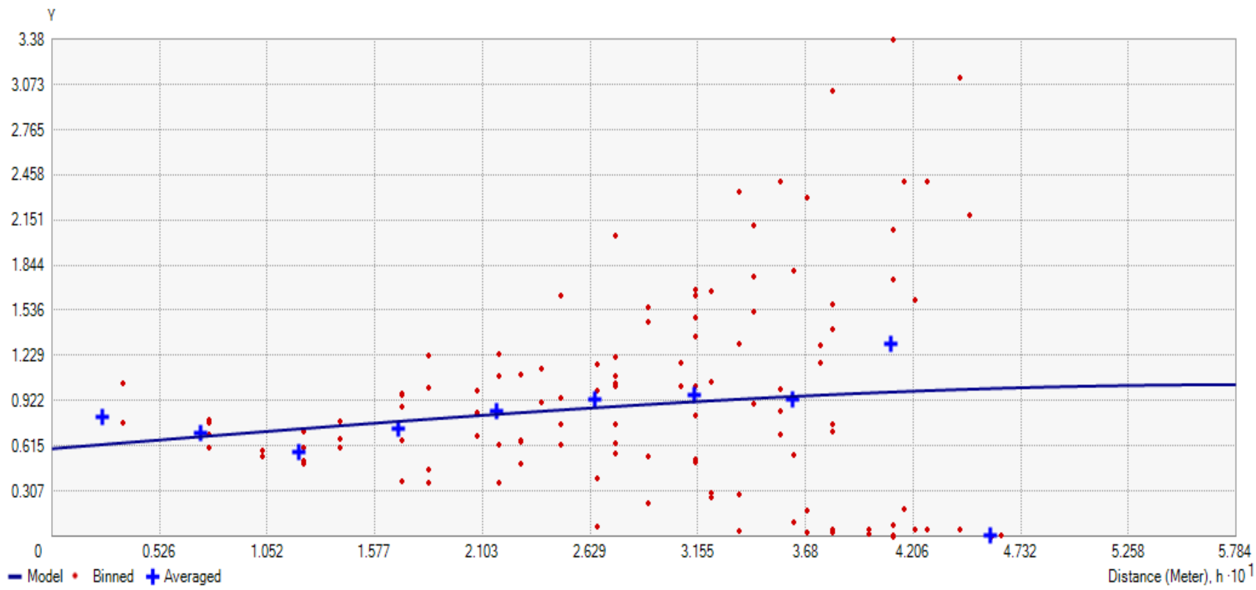


g. Cation exchange capacity

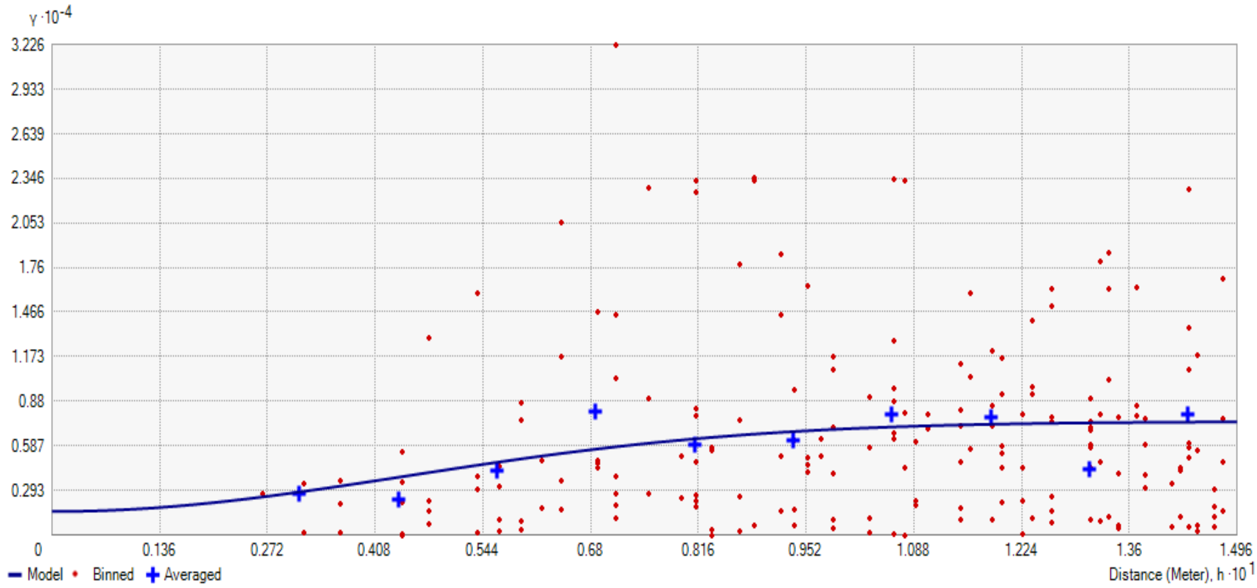
Figure 1.


γ ·10^1
8.791
7.992
7.192
6.393
5.594
4.795
3.996
3.197
2.397
1.598
0.799
0
0.526
1.052
1.577
2.103
2.629
3.155
3.68
4.206
4.732
5.258
5.784
Model
Binned
Averaged
Distance (Meter), h ·10^1

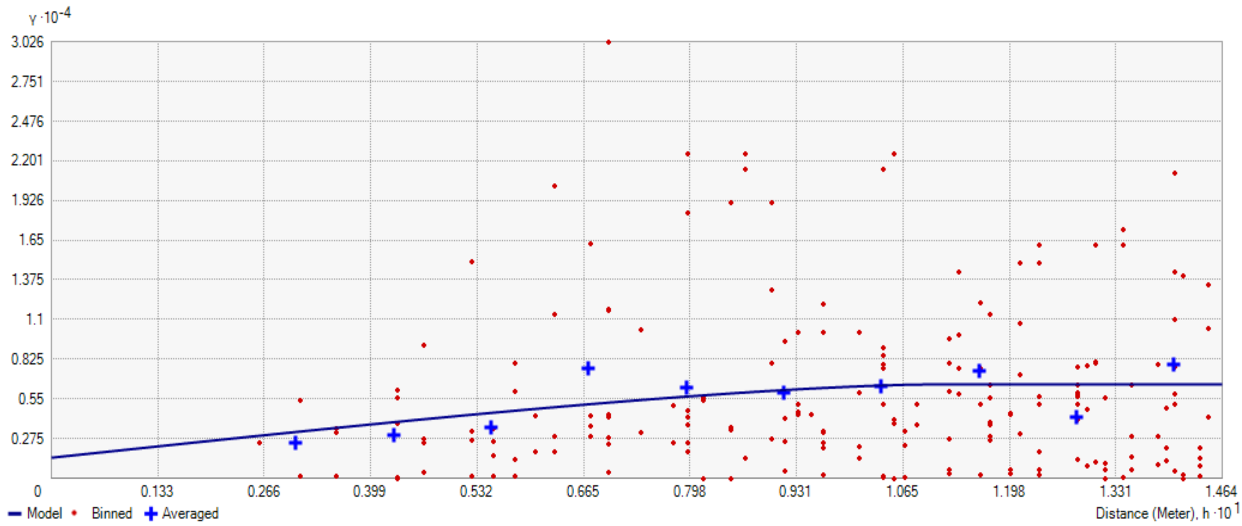
a. pH


γ
3.38
3.073
2.765
2.458
2.151
1.844
1.536
1.229
0.922
0.615
0.307
0
0.526
1.052
1.577
2.103
2.629
3.155
3.68
4.206
4.732
5.258
5.784
Model
Binned
Averaged
Distance (Meter), h ·10^1

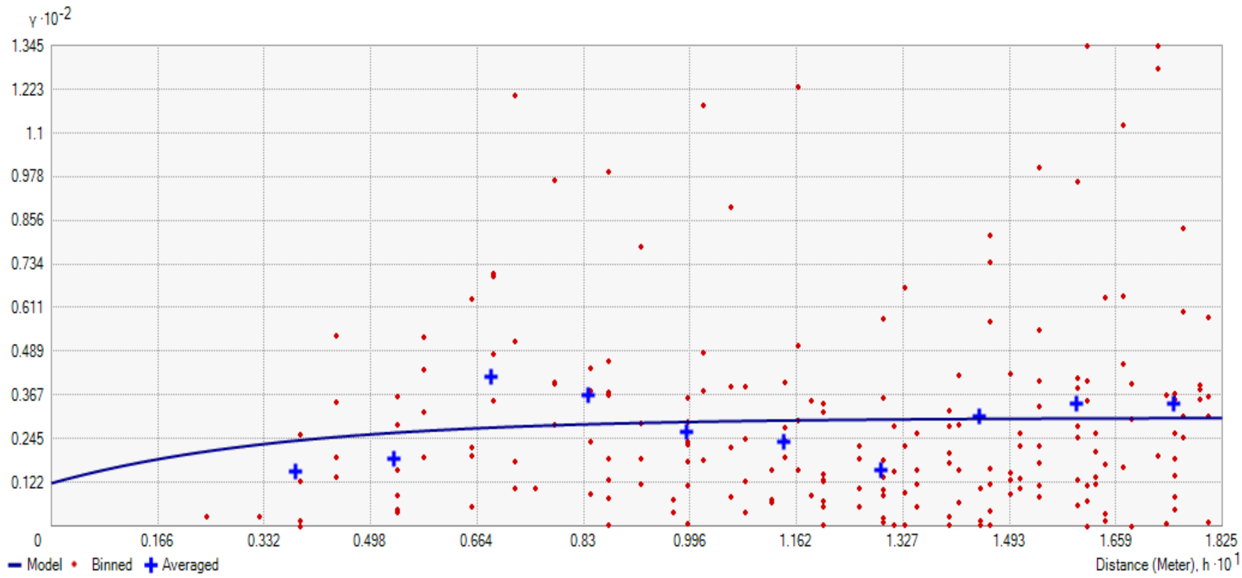
b. SOC



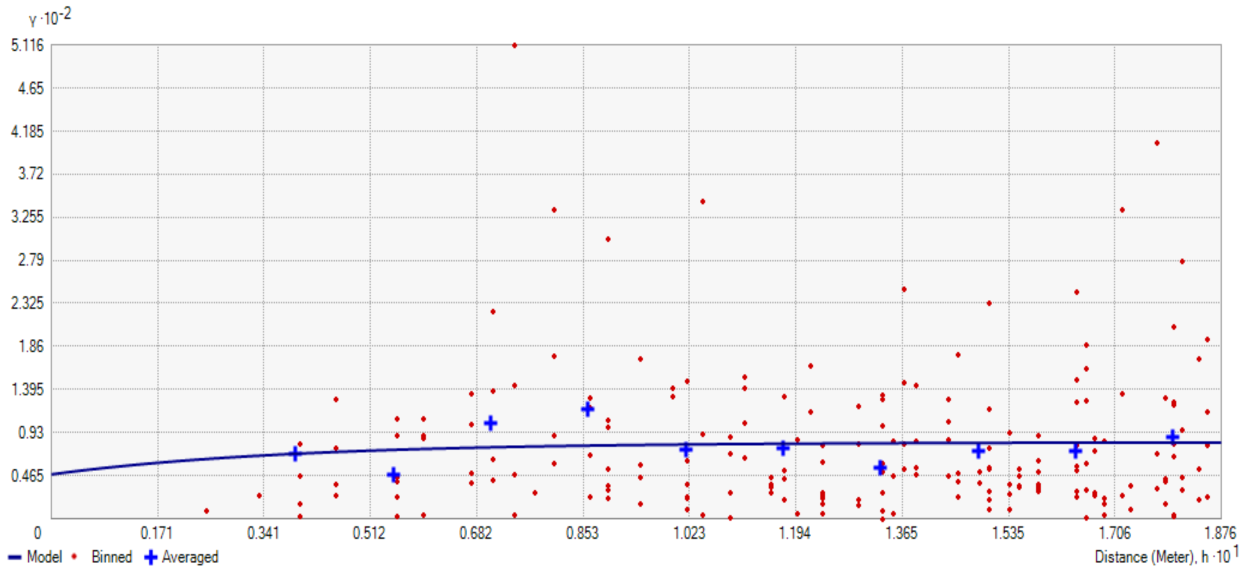
c. Sand



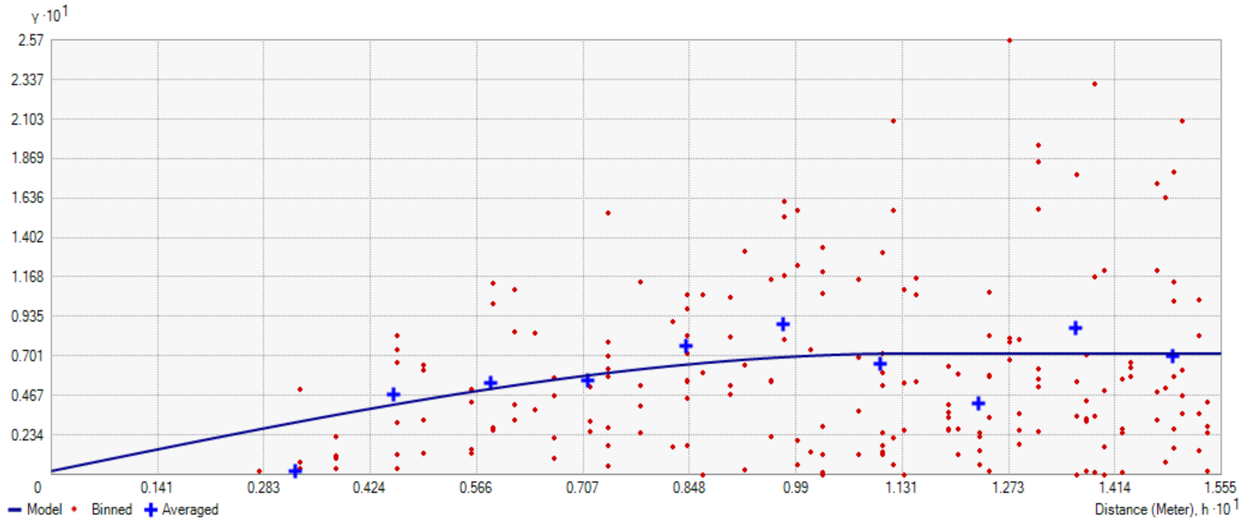
d. Clay



e. Available phosphorus



f. Total Nitrogen



g. CEC

Figure 2. semivariograms for soil pH, SOC, Sand, Clay, Available Phosphorus, Total Nitrogen and CEC