# SPATIAL VARIATION OF SOIL PHYSICAL AND BIOLOGICAL PROPERTIES UNDER *FAIDHERBIA ALBIDA* SYSTEM

BY

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## DECLARATION

I Patience Chanda hereby declare that the dissertation is my own original work, and has not been submitted for a degree award in this or any other University.

Patience Chanda                                                                                    Date

## CERTIFICATE OF APPROVAL

This dissertation by Patience Chanda was approved as a partial fulfilment of the requirement for the award of the Bachelor of Science degree in Agricultural Sciences at the University of Zambia.

## ABSTRACT

*Faidherbia albida* is a deciduous and indigenous tree species in the *Fabaceae* (legume family) native to much of Africa and the Arabian Peninsula to western Asia. It is used in agroforestry systems to stabilize and improve soil fertility as it is associated with nitrogen-fixing bacteria. *Faidherbia albida* (Del.) A.Chev. (Syn. Acacia albida Del.), is appreciated in many parts of Africa for its ability to provide shade in the hot season, good quality fodder, improve soil fertility through litter fall and nitrogen fixation. The tree has received little management and research attention over the years leading to over-exploitation by the local communities. Assessing the spatial variability of soil properties is crucial to efforts designed to introduce sustainable cropping systems. Soil properties vary spatially from a field to a larger regional scale as affected by both intrinsic (soil forming factors) and extrinsic factors (soil management practices). Therefore, knowledge of soil spatial variation is an important determinant of efficiency of farm inputs and yield, as well as in site specific farming and environmental modelling. The study was conducted to evaluate the degree of spatial variability of selected physical, chemical and biological properties under and outside the tree canopy. Spatial interpolation of soil properties was determined by using Ordinary Kriging. The results obtained indicate that soil texture (% sand, % silt and %clay) was highly variable within the sampled site. The spherical model is the best fitting model for predicting sand and microbial activity. Whilst soil reaction and organic matter were best described by both the spherical and exponential models. The best fit model for silt and clay was Gaussian and Exponential models respectively using the least sums of square error. The spatial distribution of soil properties provides basic and useful information relevant to soil management and agricultural production.



**Keywords** *Faidherbia albida,* soil, kriging, sand, silt, clay, soil reaction, organic matter, microbial activity

## DEDICATION

I dedicate this thesis to my family for their love, encouragement, sacrifice, prayers, and financial, spiritual and moral support and for always being there for me when I needed them.

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# CHAPTER ONE: INTRODUCTION

## 1.1 Background

In Zambia, soil nutrient mining has become a major threat to food security and of great concern to natural resource conservation. One of the major biophysical causes in the decline of food production is as a result of soil fertility depletion. This has been observed in most areas in Zambia especially among small scale farmers who experience low yields due to poor management. According to Morris (2007), Zambia is among the developing countries in sub-Saharan Africa that have experienced the lowest mineral fertilizer application rates and consequently, witnessed much lower crop yields than achieved in other developing countries. In Southern Africa, the decrease of soil fertility has been contributed to a corresponding decline in crop yields, an increase in food insecurity, food aid and environmental degradation (Mafongoya et al., 2006). Over the years, population pressure and lack of growth in other economic sectors in Zambia has increased pressure on land resources, resulting in declining soil fertility, productivity and general environmental degradation. Land degradation is the lowering of the land productive capacity through processes such as soil erosion, loss of soil fertility and soil salinity (Young, 1997a).

Soil fertility defined as the capacity of the soils to provide essential elements for plant growth is one of the major limiting factors in crop production (Foth and Ellis, 1997). Soil organic carbon is one of the major factors influencing fertility and productivity of soils (Kucharik et al., 2001; USDA, 2002). A significant decline in soil carbon on farms in Zambia due to continuous cultivation and low soil fertility replenishment has been widely reported. One of the major biophysical causes in the decline of food production is as a result of low soil fertility, poor crop husbandry and use of unimproved seeds among others have led to declining yields (Murithi et al., 1994). This has been observed in Zambian agriculture especially among small scale farmers who experience low yields due to poor management. Population pressure in most parts of Zambia has increased demand on food production forcing smallholder farmers to practice poor methods of farming such as limited crop rotation and clearing large areas of natural forests.

In order to address the problem of soil fertility, agroforestry systems have been proposed as an innovation especially suited to resource poor farming households. Fertilizer tree systems add biologically fixed nitrogen and other agriculturally important nutrients to the soils. This is done in a way that complements the crops grown in association with the trees (Akinnifesi *et al.*, 2010). *Faidherbia albida* is a leguminous tree which is capable of fixing nitrogen in the soil and recycling nutrients from underground to the surface due to its very deep root system. Incorporation of *Faidherbia albida* with annual crops is done to improve the fertility of soils. *Faidherbia albida* sheds off its leaves during the wet season and it resumes leaf growth during the dry season. Because of this unique characteristic, it is possible to grow crops under the tree canopy as there is light shading during early cropping season results in decrease in soil surface temperatures (ICRISAT, 1991).

Soil properties vary spatially from a field to a larger regional scale as a result of both intrinsic (soil forming factors) and extrinsic factors (soil management practices) (Cambardella and Karlen, 1999). This spatial variation is a gradual change and associated with soil properties as a function of landforms, geomorphic elements, soil forming factors and soil management (Buol *et al., 1997*). Some variability is as a result of management systems such as soil tillage, fertilizers and extreme irrigation often create unsuitable changes in soil quality.

Heterogeneity is an inherent quality of soil that typifies its distribution in space (J´unior et al., 2006). Soil characteristics can highly change by various forms and factors. Characterizing spatial variation of soil variables can provide important implications in water and nutrient management and fertilizer applications in agricultural production. Soil management systems play an important role in sustainable agriculture and environmental quality. Management practices have greater effect on the direction and degree of changes in soil properties. Conversion of an area from natural ecosystem to cultivated land associated with poor practices is attributed soil degradation and decrease in soil quality. Knowledge of soil spatial variation is therefore an important determinant of efficiency of farm inputs and yield, as well as in site specific farming and environmental modelling. Therefore, evaluation of soil spatial variability becomes an important issue in agricultural and environmental research and development. The variation of soil properties should be monitored and quantified in order to understand the effects of land use and management systems on soils. As the measurements are frequently not statistically independent, soil properties measured at nearby locations vary less than those measured far apart. Because spatial correlation impacts the results of classical statistics, the magnitude of spatial variability of soils is often analyzed using geostatistics. Geostatistics provides a means to characterize and quantify spatial variability. This information is often used for rational interpolation and to estimate the variance of the interpolated values. Variance estimation provides valuable information on the sampling density configuration which is necessary for estimating a property to a specified precision. Geostatistics is a technology for estimating the soil property values in non-sampled areas with sparse samplings (Yao *et al.* 2004). In other words, geostatistics offers a way of describing the spatial continuity of natural phenomena and provides adaptations of classical regression techniques to take advantage of this continuity. (Isaaks and Srivastava, 1989). Geostatistics deals equally well with spatially auto-correlated data. Autocorrelation is defined as the correlation between elements of a data series and others from the same series separated from them by a given interval (Oxford American Dictionary). The non-sampled areas can vary in space (in one, two, or three dimensions) from the sampled data. At present, soil science research largely relies on the use of geostatistics, which, together with classical statistics, constitutes an extraordinarily important tool for agronomy (Junior *et al.*, 2005). Recently, uncertainties associated with poor seasonal rainfall distribution have often made water availability a major limiting factor in crop production (Lobell *et al.*, 2009).

As the measurements are frequently not statistically independent, soil properties measured at nearby locations vary less than those measured far apart. Again because spatial correlation impacts the results of classical statistics, the magnitude of spatial variability of soils is often analyzed using geostatistics.

The basic components of Geostatistics are; (Semivariogram analysis which is the characterization of spatial correlation, Kriging which is optimal interpolation and generates best linear unbiased estimate at each location. Kriging employs semivariogram model and stochastic simulation necessary for generation of multiple acquirable images of the variable; also employs semivariogram model. Geostatistical methods are often considered optimal when the data are normally distributed and stationary (mean and variance do not vary significantly in space). In other words, kriging is a recognized method among geostatistical methods for modelling complex spatial patterns of soil variability by treating as regionalized variables (Mcbratney, 2003). The kriging methods are based on the existence of a significant spatial autocorrelation among the values of a certain variable. In an ordinary kriging approach, the estimated value depends only on the neighbouring values. The integration of auxiliary variables is possible through the co-kriging approach; in which case the interpolation is based on cross-variogram. However, regression analysis attempts to link a dependent quantitative variable to one or several quantitative predictors by means of a linear or non-linear equation. The method is useful when the soil property displays significant correlations with terrain parameters for example slope.

Spatial correlation between samples can be expressed by semi-variance and semivariogram. Spatial dependency manifests itself in the variogram typically by a monotonic increase from the origin with increasing lag distance, which are further used to compute weighting coefficients for the sample points (Heuvelink, 2001). Independent sample validation was applied to the validation sample (not included in the elaboration of the models) and which implied the comparison of the real and the estimated values. For validation procedures the sum of square error (SSErr), represents the sum of square error of the residuals, as the selection criteria of the parameter for the best method. Statistical validation implies testing the statistical significance of quality parameters (correlation coefficients, partial regression coefficients, intercept), testing the residuals normality and computing standard errors. The first major applications of ordinary kriging in soil studies in the early 1980's (Burgess and Webster, 1980) were mainly at the field scale level, since then it has been extended to larger areas.

## 1.2 STATEMENT OF THE PROBLEM

Studies that have been done show that the organic matter content and nutrient contents are spatially correlated with agricultural practices, while generally the physical and biological properties are equally correlated to distance. Small scale farmers in Zambia experience low yields due to poor management practices as a result of high costs of fertilizers because of nutrients depletion through leaching and soil erosion. Although the great benefits of *Faidherbia albida* are known of improving soil fertility, very little information exists. The tree has received little management attention over the years resulting from over-exploitation by the local communities. This is attributed to the fact that the various environmental services provided by the tree are not well understood. Studies show that the presence of Faidherbia albida trees in a farming system increases organic matter and nutrient content of the soil; however, spatial variability of physical and biological properties of soils under *Faidherbia albida* has received little attention (Sileshi, 2016).

## 1.3 MAIN OBJECTIVE

The main objective of the study was to evaluate the degree of spatial variability of selected physical and biological properties under *Faidherbia albida* trees.

## 1.4 SPECIFIC OBJECTIVES

1. To characterize variability of selected soil physical and biological properties under *Faidherbia albida* trees; and
2. To compare the spherical, exponential and Gaussian models for best-fit spatial structure and variability.

## 1.5 HYPOTHESIS

The tested hypotheses included the following,

1. There are significant differences in spatial variability of selected soil physical and biological properties as a function of *Faidherbia albida* trees; and
2. Spatial structure and variability of selected soil physical and biological properties can be easily described by Spherical, Exponential and Gaussian models.

## 1.6 JUSTIFICATION

Soil attributes show considerable heterogeneity, therefore characterizing spatial variation of soil variables can provide important implications in water and nutrient management and fertilizer applications in agricultural production systems. This study was carried out in order to identify the spatial variation of selected soil physical and biological properties that are critical in designing land management practices. The knowledge of soil physical and biological properties and their spatial variability is of crucial relevance in understanding soil processes such as heat flow, water flow and solute transport, and in general land management.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 *Faidherbia albida*

*Faidherbia albida* is a fast growing indigenous and deciduous tree that can grow up to a height of 30 m and a diameter of 2 m. It has branches which can erect to a roundish crown with a greenish grey to whitish grey leaves. The flowers appear from March to September maturing into fruit from September to December. *Faidherbia albida* is one of the dominant tree species on farmlands in dryland ecosystems. It's considered a multipurpose tree as it provides fodder and fuelwood, prevent soil erosion and promote biodiversity among other benefits. *Faidherbia albida* is believed to have originated in the Sahara before desertification. It is a riverine tree of northern, eastern and southern Africa that was introduced through pastoralism and agriculture into western Africa, where it was only found on cultivated or previously cultivated land. Apart from its unique reverse phenology of shedding leaves during the rainy season, it adds organic matter to the soil which have a high specific surface area and high cation exchange capacity (CEC). CEC is the total number of negative charges on the colloids which helps organic matter to act as a cementing agent hence the soil structure is improved, stabilized and permeability increases due to greater pore spaces. Adamu (2012) reported that due to unique reverse phenology of *Faidherbia albida* provides microenvironment favourable for crops, for instance the leaves during rainy season acts as mulch which prevents soil water loss due to evaporation. Owing to its phenology, the tree provides shade during dry season which protects the soil from direct sunlight hence prevent soil degradation. *Faidherbia albida* has a remarkable capacity for recycling nutrient from underground to the surface due to its very deep root system (Le Houerou, 1980). The tree does not compete with crops for soil nutrients as it enters a period of physiological rest during the normal crop-growing season (ICRAF, 1989). The tree has been used to stabilize sand dunes and prevents soil erosion (Dancetta and Paulain, 1969). Despite the fact that *Faidherbia albida* is an important component of the traditional farming systems in arid and semi-arid zones of Africa, its establishment in these areas is often difficult.

Therefore, planting of fast growing, drought tolerant, nitrogen fixing tree species is an important soil conservation and fertility restoration strategy. Increase in yield from intercropping has been attributed to increased fertility due to nitrogen fixation, dung from stock browsing and fallen leaves and pods (Radwanski and Wickens, 1967). It is among the most preferred species because of its nitrogen fixing, shade abilities and fodder providing roles.

### 2.2 Soil Reaction

Soil pH is the degree of the soil acidity or alkalinity of the soil. It is caused by a particular chemical, mineralogical and biological environment. It affects nutrient availability, toxicity, and microbial activity and root growth. In strongly acid soils Aluminium $Al^{+3}$ becomes soluble while in alkaline soils exchangeable bases tend to occupy the exchange sites of the soils by replacing exchangeable H+ and Al+3 ions (Miller and Donahue, 1995). Soil having low pH leads to high Aluminium and Manganese toxicity which hinder root growth and formation. Soil pH also influence plant growth through its effect on microbial activity an important component of decomposition of organic matter. Low pH leads to accumulation of organic matter and nutrient bounding, particularly nitrogen, that are held in the organic matter. Soils with higher clay content have a well buffered pH and high cation exchange capacity. *Faidherbia albida* has been observed to buffer pH through accumulated organic matter (Haynes and Mokolobate, 2001). Observations on mature *Faidherbia albida* in Zambia have shown that maize under continuously fertilized fields had a lower pH than the maize grown under *Faidherbia albida* (Chintu et al., 2004). This was attributed to the build-up or incorporation of soil organic matter and hence mitigate soil acidity.

### 2.3 Soil organic matter and microbial activity

Soil organic carbon is a name for carbon held within the soil, primarily in association with its organic content. Size of the carbon pool is influenced by human activities (Baldock and Skjemstad, 1999). The presence of soil organic matter is vital as it improves the soil physical properties and the chemical characteristics. Studies have shown that organic matter, organic nitrogen, available phosphorus and exchangeable bases were higher in soils under *Faidherbia albida* tree (Depommier et al., 1992). The presence of *Faidherbia albida* strongly influences organic matter status. Under the faidherbia *albida* tree, higher percentage of soil carbon and nitrogen, and higher microbial activity was observed (Poulain 1984). Most soil microbes respond to soil management induced changes in soil physical, and chemical environment. Soil management practices impact soil microbes and biological processes through changes in the quality and quantity of plant residues, seasonal and spatial distribution and changes in nutrient inputs (Kandeler et al., 1999). Other studies carried out in Nigeria also showed that the organic carbon was greater in the topsoil under the canopy as compared to that outside the canopy (Kidd *et al.*, 1992).

### 2.4 **Soil physical properties**

Fertilizer trees improve soil physical properties through the addition of litter fall, root biomass, root activity, biological activities and roots leaving macro pores in the soil after decomposition. *Faidherbia albida* also improve soil aggregation, thereby enhancing water filtration which reduces runoff and soil erosion relative to production systems (Chirwa *et al.*, 2007). Soil water and soil texture, the relative proportions of sand, silt and clay are the most important soil physical properties which govern almost all the attributes of the soils. Soils vary spatially due to differences in soil management and soil formation factors (Hulugalle *et al.*, 1997).

### **2.5 Geostatics and spartial variability**

Geostatistics is a subset of statistics specialized in analysis and interpretation of geographically referenced data (Goovaerts, 1997; Webster and Oliver, 2001; Nielsen and

Wendroth, 2003). In other words, geostatistics comprises statistical techniques that are adjusted to spatial data. One of the main uses of geostatistics is to predict values of a sampled variable over the whole area of interest, which is referred to as spatial prediction or spatial interpolation. Assuming that the samples are representative, unbiased and consistent, values of the target variable at some new location s0 can be derived using a spatial prediction model. It defines inputs, outputs and the computational procedure to derive outputs based on the given inputs:

$$Z_{(SO)} = E\{(Z|z(Si), qk(So), (h), s2A)\}$$

Where z $(Si)$ is the input point dataset, qk $(So)$ is the list of deterministic predictors and (h) is the covariance model defining the spatial autocorrelation structure

In the case of statistical models, coefficients/rules used to derive outputs are derived in an objective way following the theory of probability. Kriging has for many decades been used as a synonym for geostatistical interpolation. It originated in the mining industry in the early 1950's as a means of improving ore reserve estimation. The original idea came from the mining engineers D. G. Krige and the statistician H. S. Sichel. The technique was first published in Krige (1951), but it took almost a decade until a French Mathematician G. Matheron derived the formulas and basically established the whole field of linear geostatistics10 (Cressie, 1990; Webster and Oliver, 2001; Zhou et al., 2007).

A standard version of kriging is called ordinary kriging (OK). Here the predictions are based on the model:

$$Z_{(S)} = E\{\mu + "o(s)\}$$

Where μ is the constant stationary function (global mean) and "0(s) is the spatially correlated stochastic part of variation. The predictions are made as in Equation:

$$\hat{Z}_{ok}(s_o) = \sum_{i=1}^{n} w_i(s_o) \,.\, z(s_i) = \lambda_o{}^T \,.\, Z$$

Where $\lambda_0$ is the vector of kriging weights (wi), z is the vector of n observations at primary locations. In a way, kriging can be seen as a sophistication of the inverse distance interpolation. The key problem of inverse distance interpolation is to determine how much importance should be given to each neighbour. Intuitively thinking, there should be a way to estimate the weights in an objective way, so the weights reflect the true spatial autocorrelation structure. The novelty that Matheron (1962) and Gandin (1963) introduced to the analysis of point data is the derivation and plotting of the so-called semivariances differences between the neighbouring values:

$$\gamma(h) = \frac{1}{2} E\{z(s_i) - z(s_i + h)^2\}$$

where z(si) is the value of target variable at some sampled location and $z(s_i + h)^2$is the value of the neighbour at distance si +h. Suppose that there are n point observations, this yields n·(n−1)/2 pairs for which a semivariance can be calculated. Where all semivariances versus their distances can be plotted, which produce a variogram cloud. Such clouds are not easy to describe visually, so the values are commonly averaged for standard distance called the lag. If such averaged data is displayed, then a standard experimental variogram can be obtained. What is usually expected to be observed is that semivariances are smaller at shorter distance and then they stabilize at some distance. For the sake of kriging there is need to replace the empirical semivariogram with an acceptable semivariogram model. Part of the reason for this is that the kriging algorithm will need access to semivariogram values for lag distances other than those used in the empirical semivariogram. More importantly, the semivariogram models used in the kriging process need to obey certain numerical properties in order for the kriging equations to be solvable. The semivariogram model needs to be non-negative definite, in order the system of kriging equations to be non-singular. Therefore, geostatisticians choose from a palette of acceptable or licit semivariogram models.

Using *h* to represent lag distance, *a*, to represent (practical) range is (the distance where the model first flattens out), and *c* to represent sill (the value that the semivariogram model attains at the range the value on the y-axis), the models that were used included: The Geostatistical models included:

1. Exponential Model

Exponential models exhibit linear behaviour from the origin, appropriate for representing properties with a higher level of short-range variability. The exponential model approaches the sill asymptotically, with a representing the practical range, the distance at which the semivariance reaches 95% of the sill value.

$$\gamma(h) = C_0 + C_1\left[1 - exp\left\{-\frac{h}{a}\right\}\right] \text{ For } h\geq 0$$

2. Spherical Model

The spherical model actually reaches the specified sill value, c, at the specified range, a. The spherical model exhibit linear behavior the origin, appropriate for representing properties with a higher level of short-range variability.

$$\gamma(\mathrm{h}) = \mathrm{C_0} + \mathrm{C_1}\left[1.5\frac{\mathrm{h}}{\mathrm{a}} - 0.5\left(\frac{\mathrm{h}}{\mathrm{a}}\right)^3\right], \quad 0 \leq$$

$\mathrm{h} \leq \mathrm{a} = \mathrm{C_0} + \mathrm{C_1}$

3. Gaussian Model

The Gaussian model, with its parabolic behaviour at the origin, represents very smoothly varying properties. However, using the Gaussian model alone without a nugget effect can lead to numerical instabilities in the kriging process. Gaussian approach the sill asymptotically, with a representing the practical range, the distance at which the semivariance reaches 95% of the sill value.

$$\gamma(\mathrm{h}) = c_o + c\left[\left[1 - exp\left[{-h^2}/{a^2}\right]\right]\right] \quad \text{For}$$

h≥0

Nugget model

Theoretically, at zero separation distance lag = 0, the semivariogram value is 0. However, at an infinitesimally small separation distance, the semivariogram often exhibits a nugget effect, which is some value greater than 0.

The nugget effect can be attributed to measurement errors or spatial sources of variation at distances smaller than the sampling interval or both.

The nugget model represents the discontinuity at the origin due to small-scale variation. On its own it would represent a purely random variable, with no spatial correlation.

Where ....

$(h)$ is the semi-variogram, semi-variance as a function of lag.

$C_1$ is structural component of semi-variogram model

$C_o$ as the nugget

$h$ is the lag distance

$C_o + C_1$ is the sill

Characteristics of the Semivariogram

The figure presents a typical variogram Figure 1 which indicates its structural components. Sill is the semivariance value at which the variogram levels off. Also used to refer to the "amplitude" of a certain component of the semivariogram. Range is the lag distance at which the semivariogram (or semivariogram component) reaches the sill value. Presumably, autocorrelation is essentially zero beyond the range.

Nugget: In theory the semivariogram value at the origin (0 lag) should be zero. If it is significantly different from zero for lags very close to zero, then this semivariogram value is referred to as the nugget. The nugget represents variability at distances smaller than the typical sample spacing, including measurement error.

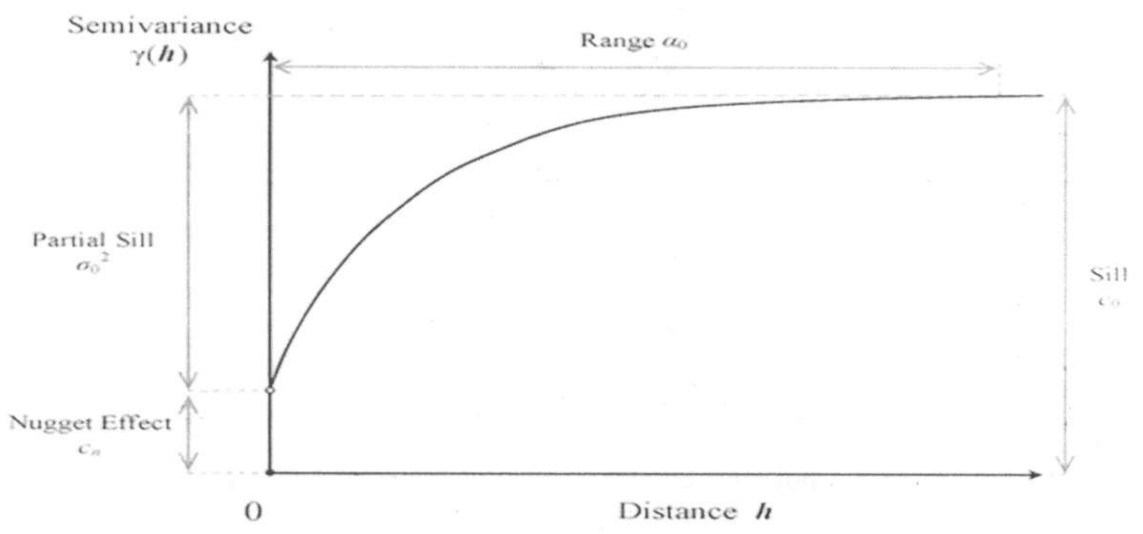



Figure 2: Example of a theoretical Semivariogram of Spherical Model and its characteristics/ parameters (Banerjee, Carlin, and Gelfand; 2004).

# CHAPTER 3: MATERIALS AND METHODS

## 3.1 Study site

The study was carried out at Kasisi Agricultural Training Centre in Lusaka located at latitude (15° 24'00" S) and longitude (28° 48'00" E). This site falls under Agro-ecological Region II of Zambia and receives rainfall of between 800 to 1200 mm per annum. The rainfall pattern and potential evapotranspiration rate is as indicated in Figure 3. The site has a well-established mature *Faidherbia albida* trees (>20 years old) planted in rows, predominantly planted a hedges. Climate classification according to Koeppen climate class is warm temperate climate with dry winter and hot summer (Cwa) and a climatic net primary production potential of 1329g dry matter/$m^2$/year limited by precipitation. The frequency of frost is 6 occurring in June and July. The rainy days are 85 occurring from October to April. The aridity index is 0.58 representing a dry sub-humid environment. The length of the growing season is 140days beginning on November 11$^{th}$ and ending on 30$^{th}$ March.

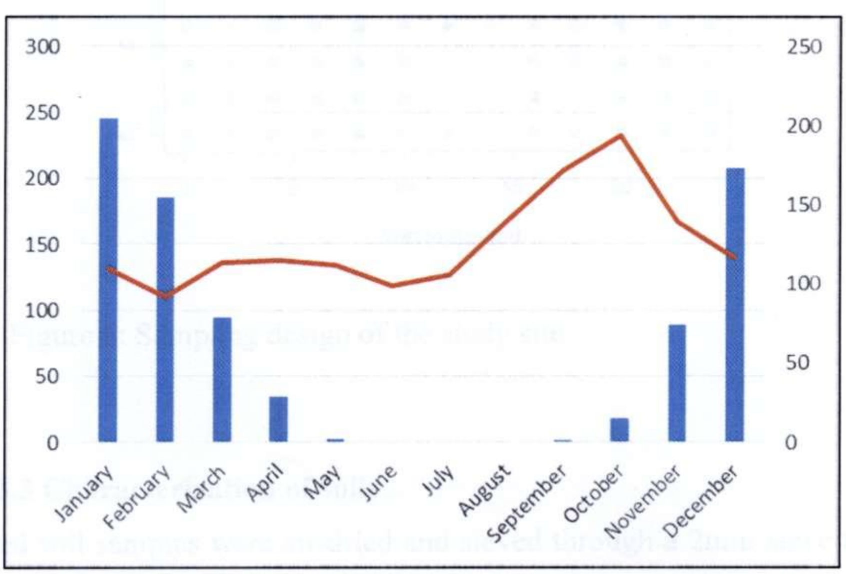



Figure 4: Rainfall distribution and potential evapotranspiration

## 3.2 Soil sampling

Soil samples were collected using a grid system of 2 m by 2 m in an area of 24 by 24 m leading to 169 soil samples. The soil sampling design is presented in Figure 5 with positions of the trees indicated by the black dots. Soil samples were systematically collected at fixed distances from 0-15cm soil depth as undisturbed soil samples. The collected samples were packed in air tight polythene bags and subsequently taken to the laboratory for soil analysis. The soil properties analyzed include: physical (soil particle size distribution), chemical (pH and organic matter) and biological (microbial activity)

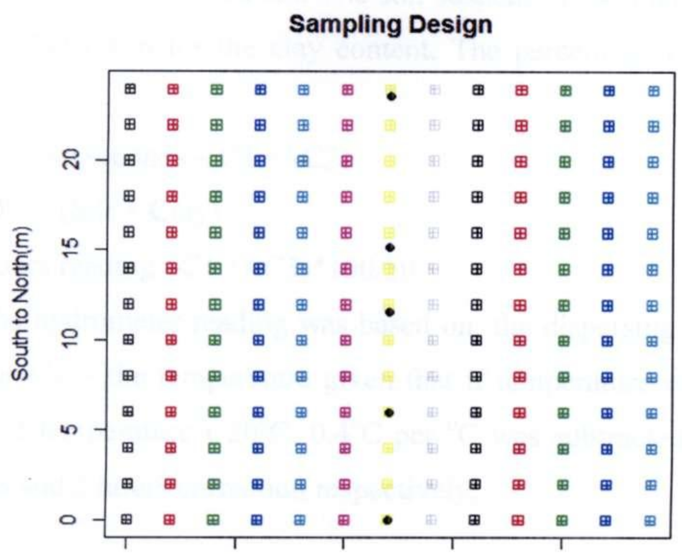



Figure 6: Sampling design of the study site

### 3.3 Characterization of soils

The disturbed soil samples were air-dried and sieved through a 2mm sieve to retain the fine earth fraction. The sieved soil samples were used for the physical and chemical analysis whilst the soils for the analysis of biological properties were refrigerated.

### 3.4 Determination of particle size analysis

Particle size distribution was determined by the hydrometer method (Day, 1965). In this method a 50 g air dry soil was weighed into a dispersing cup to which 50 ml of the dispersing agent Sodium hexametaphosphate was added. The dispersing cup was then half filled with tap water and stirred continuously stirred using the hydrometer kit for 5 minutes. The suspension was transferred to the cylinder using a stream of tap water in order to qualitatively transfer the soil to the cylinder and to fill the liquid up to 1 $dm^3$ mark. The temperature of the suspension was measured using a thermometer. A plunger was inserted and moved up and down in order to stir the suspension thoroughly. Immediately after stirring the suspension the hydrometer was lowered into the soil suspension the first density reading was noted at 20 seconds and the other at 40 seconds to determine the sand and silt content. The soil suspension was left for 2 hours and the density reading was taken for the clay content. The percentage of clay, silt and sand were calculated as:

%( Silt + Clay) = (40 seconds – C1 +/-C2)

%( Sand) = 100% - (Silt + Clay)

% (Clay) = (2hours reading –C1 +/-C3)*100/50

Correction to the hydrometer reading was based on; the dispersing agent reading of the correction factor *C1* = the temperature given that if temperature was $>20^{o}C$ 0.4 per $^{o}C$ was added and if temperature $< 20^{o}C$, $0.4^{o}C$ per $^{o}C$ was subtracted. Where *C2* and *C3* were 40 seconds and 2 hours correction respectively.

### 3.5 Determination of soil reaction

Soil reaction was determined in water using a pH meter. A subsample of 10g soil was weighed into a 50 ml plastic container to which 25 ml of water was added. Suspension in a 1:2.5 soil solution ratio using an electrode (Van Reewijk, 1992). The mixture was shaken on a mechanical shaker for 30 minutes. Calibration of the pH meter was done using buffer solutions at pH 4 and 7. After which the pH readings were taken using a pH meter of the supernatant solution.

### 3.6 Determination of soil organic matter

Soil organic matter was determined using the Walkley and Black method (1934). Air dried soil of 1 g was weighed and transferred into a 250 ml conical flask and 10 ml of 1N of $K_2Cr_2O_7$ was added to the sample using a pipette and a stream of 20 ml concentrated $H_2SO_4$ was rapidly added. The flask was swirled gently until the soil and solution had mixed followed by a more vigorous swirling. The samples were stored in the fume hood for 30 minutes then 150 ml of distilled water and 10 ml of concentrated $H_3PO_4$ was added. Few drops of diphenylamine indicator were added to the suspension before titrating with iron (II) sulphate ($FeSO_4$). The colour change from the initial yellow brown to blue and finally green indicated the end point of the titration process. The volume of FeSO4 was recorded. The percentage of organic carbon was calculated.

% Organic carbon = (a-b)*0.4

Where $a$ = volume of blank and $b$ = volume of sample

### 3.7 Soil microbial activity

Soil microbial activity was determined using the soil respiration method (Dubey et al., 2002). The soil microbial activity was determined by weighing 50g of soil which was not fumigated. The soil samples were put into plastic containers and moistened with distilled water. Small bottles containing 5 ml of potassium hydroxide were put in the same plastic containers, covered and incubated for 7 days in a dark cupboard at room temperature.

After 7 days of incubation, potassium hydroxide in the small bottles which reacted with carbon dioxide microbial activity was determined by titration with HCl. This was achieved by adding two drops of phenolphthalein indicator and KOH and then back titrated with 0.1 M HCL until the red colour of the indicator disappeared, and the volume noted. After the red color, 2 drops of methyl orange were added until the yellow colour of the second indicator had turned pink. The amount of HCL consumed between the colour shifts corresponded to the amount of carbon dioxide which was produced during the incubation period and trapped the KOH.

### 3.8 Statistical analysis

Data was analyzed using descriptive analysis and geostatistics in order to describe the spatial distribution of soil properties. The semivariogram depicts the spatial autocorrelation of the measured sample points. Once each pair of locations is plotted, a model is fit through them. There are certain characteristics that are commonly used to describe these models.

# CHAPTER 4 RESULTS AND DISCUSSION

4.1 Characterizing variability of selected soil physical, chemical and biological properties under and outside *Faidherbia albida* tree canopies

## 4.2 Descriptive statistics of soil physical, chemical and biological properties

The selected soil physical, chemical, biological properties such as particle size distribution (% sand, silt and clay), organic matter, soil reaction and microbial activity were measured in the laboratory for 169 soil samples collected at 0-20cm soil depth in spatially well distributed areas inside and under the *Faidherbia albida* canopies. Descriptive statistics for the measured variables was analyzed using Genstat Software to obtain the minimum, maximum, mean, standard deviation, coefficient of variation, skewness, and kurtosis.

Results on descriptive statistics of measured soil properties are presented in Table 1. The measured properties were particle size distribution (sand, silt and clay fractions), soil organic matter, soil reaction and microbial activity for the layers 0-20cm depth. The soil was high in sand fraction (>72%) while the silt and clay fractions was low (<3%, <6%) respectively, giving it a sandy loam textural class. The pH of the soil ranged from 4.52-6.05 (ranging from very strongly acidic to slightly acidic level) with an average of 5.21. Soil organic matter had values ranging from 1.12-3.52 with an average of 2.22%. The levels of soil organic carbon in all soils were above the critical limit of 1.5% for good crop productivity (Fairhurst, 2012). The microbial activity measured as carbon dioxide evolved varied from 0.15-7.61 with an average of 2.88mg/day. In terms of the normal distribution of the measured parameters sand and clay were negatively skewed, whilst silt, soil reaction, organic matter and microbial activity were positively skewed. The normal distribution as reflected by the frequency distribution is presented in Figure 7.

**Table 2: Descriptive statistics of the measured soil properties**

| Variable | N | Mean | SD | Median | Min | Max | Range | Skew | Kurtosis | SE |
|---|---|---|---|---|---|---|---|---|---|---|
| Sand (%) | 169 | 80.94 | 2.24 | 80.80 | 72.93 | 85.80 | 12.87 | -0.16 | -0.04 | 0.17 |
| Silt (%) | 169 | 7.58 | 1.67 | 7.20 | 3.80 | 12.67 | 8.87 | 0.49 | -0.07 | 0.13 |
| Clay (%) | 169 | 11.47 | 2.28 | 11.73 | 6.40 | 16.40 | 10.00 | -0.24 | -0.74 | 0.18 |
| pH($H_2O$) | 169 | 5.21 | 0.41 | 5.07 | 4.52 | 6.05 | 1.53 | 0.47 | -1.18 | 0.03 |
| OM (%) | 169 | 2.22 | 0.38 | 2.24 | 1.12 | 3.52 | 2.4 | 0.22 | 0.85 | 0.03 |
| MA ($CO_2$-C mg/d) | 169 | 2.88 | 1.36 | 2.68 | 0.15 | 7.61 | 7.46 | 0.83 | 0.60 | 0.10 |

Where; n is the number of observations, SD is the standard deviation, Min is the minimum, Max is the maximum, SE is the standard error, pH is soil reaction, OM is organic matter content and MA is the microbial activity

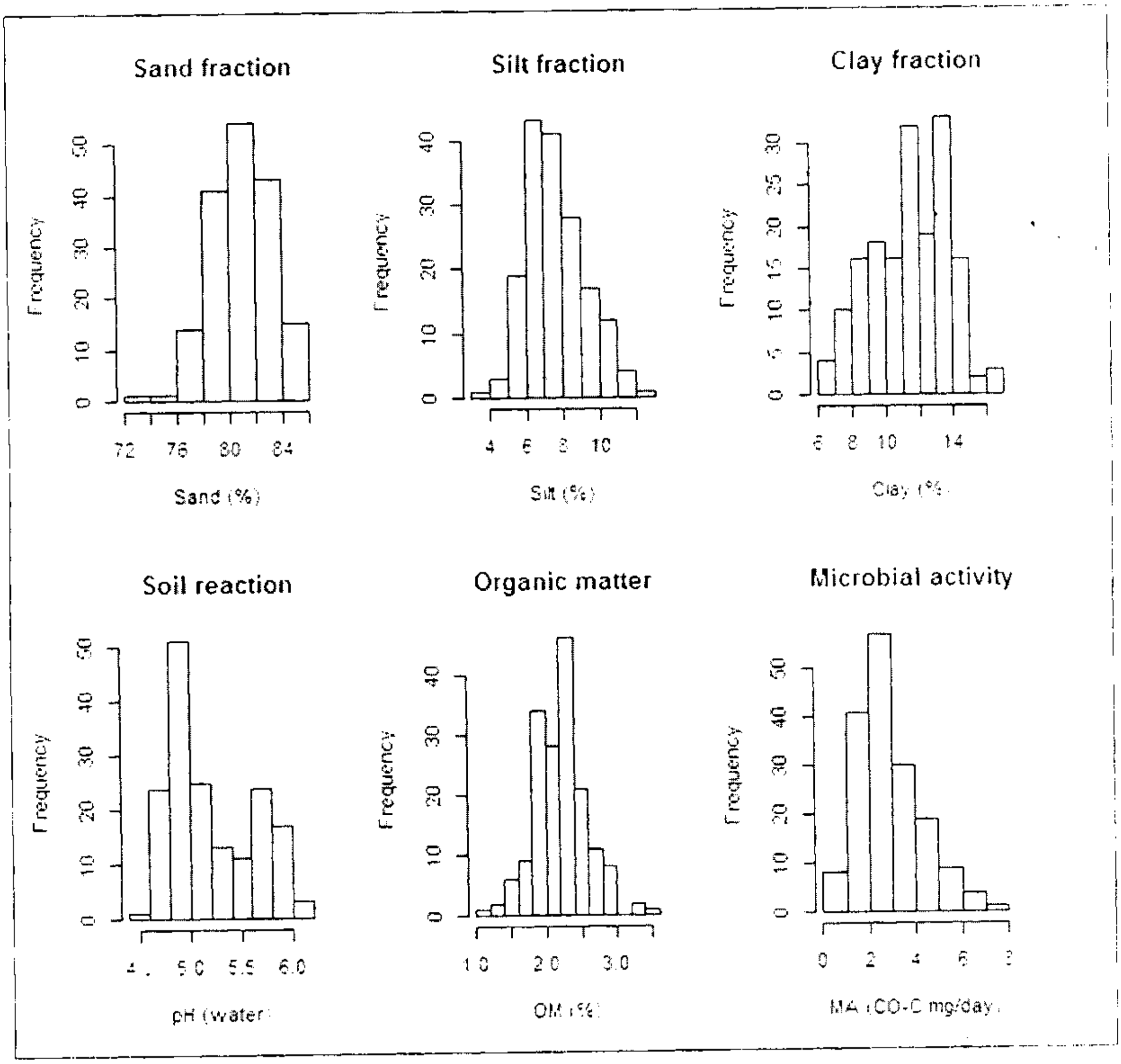



Figure 8: Histograms for sand, silt and clay fractions, soil reaction, soil organic matter and microbial activity

### 4.3 Effect of the *Faidherbia albida* on the measured soil parameters

The results on the trend of measured parameters across and parallel the tree line are presented in Figure 9 and Figure 10 . Basing on the figures, a stronger trend is observed in soil particle size distribution across than parallel to the tree line showing that the tree may have an influence on distribution. For sand fractions, the mean values seem to be the similar across the tree lines, while silt fraction increases towards the tree line. Clay fraction increases in the North-west and decreases in the South-east direction, this could be attributed to the type of parent material in the soil forming process. The amounts of clay are not influenced by the presence of the trees (Sail, 1992). A stronger trend is also observed in soil reaction, soil organic matter and microbial activity across than parallel to the tree line. This proves that *Faidherbia albida* increases both organic matter and microbial activity (Fredrik, 2005). Soil reaction was higher as the distance from the tree increased (Figure 11), this could because most of the leaves shed drop around the tree trunk, this increases the acidity of the soil during organic matter decomposition and nitrification processes due to release of hydrogen ions. Organic matter mineralization results in the formation of organic and inorganic acids, accumulation of organic acids from microbial metabolism or from the production of fulvic and humic acids during decomposition produce hydrogen ions which lower the soil pH, Albarell *et.al.* (1988), Chan and Griffiths (1988), Jones *et al.*, (2002). Carbon dioxide from decomposing organic matter and root respiration dissolving in soil water to form a weak organic acid and formation of strong organic and inorganic acids, such as nitric and sulfuric acid, from decaying organic matter leads to changes in pH. Strongly acid soils are usually the result of the action of these strong organic and inorganic acids. Organic matter accumulation is inversely related to lag while soil reaction is directly proportional to lag. The lower pH trend observed around the tree trunk could be attributed to the inherent soil pH as a result of the parent material being either weatherable as the soil type was more of a sandy loam whose parent material may have been a sandstone. The low soil reaction may have been attributed to higher uptake of cations by the trees leading to the lowering of pH in soils (Haynes, 1983). According to Atiyeh et.al (2000), earthworms reduced the pH, this is evident due to microbial activity. And leaching due to rainfall in the area would have had an effect on the soil reaction of the field. The pH values would have also been affected by the age of the tree which affected the canopy size. According to Christenensen et al, (1994) reported a higher susceptibility for leaching of bases when management practices such as tillage increase this results into lowering of the soil pH. The tolerance of different microorganisms for pH may vary; some slightly acidic to slightly alkaline ranging from 4.5 to 8.0 (Gupta, 1998).

The tree was seen to have an effect on microbial activity and organic matter as these seem to increase. Microbial activity would have increased as a result of the presence of the roots of the tree and organic matter arising from litter fall and decomposition of the roots leading to high populations of the organisms. Microorganisms are responsible for the mineralization and immobilization of N, P and S through the decomposition of organic matter (Duxbury, Smith and Doran, 1989). Thus, they contribute to the gradual and continuous liberation of plant nutrients. Available nutrients that are not taken up by the plants are retained by soil organisms. In organic-matter depleted soils, these nutrients would be lost from the system through leaching and runoff. Soil respiration rates respond to management measures such as plant residues, reduced tillage and legume - cereal crop rotations. A high soil respiration rate is an indicator of high biological activity, soil fertility and a good sign of rapid decomposition of organic residues into nutrients available for plant growth and improved crop productivity (USDA, 1998). Franzluebbers et al (1999) illustrated the amount of soil organic matter increases or decreases as a result of the changes in the carbon inputs to the soil, the microbial pool also increases and decreases.

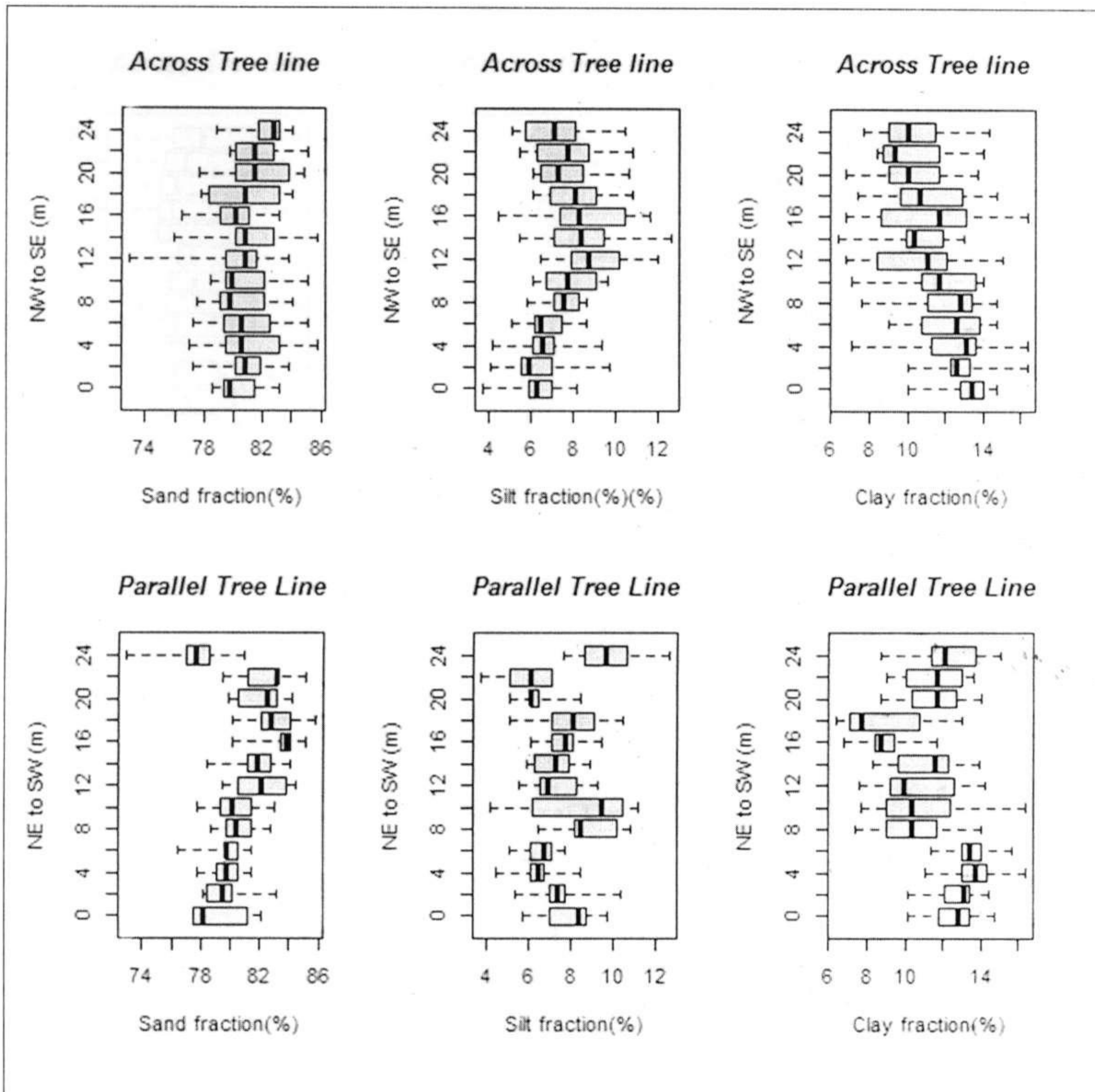



Figure 12: Boxplots for Sand, Silt and Clay fractions across and parallel the tree line

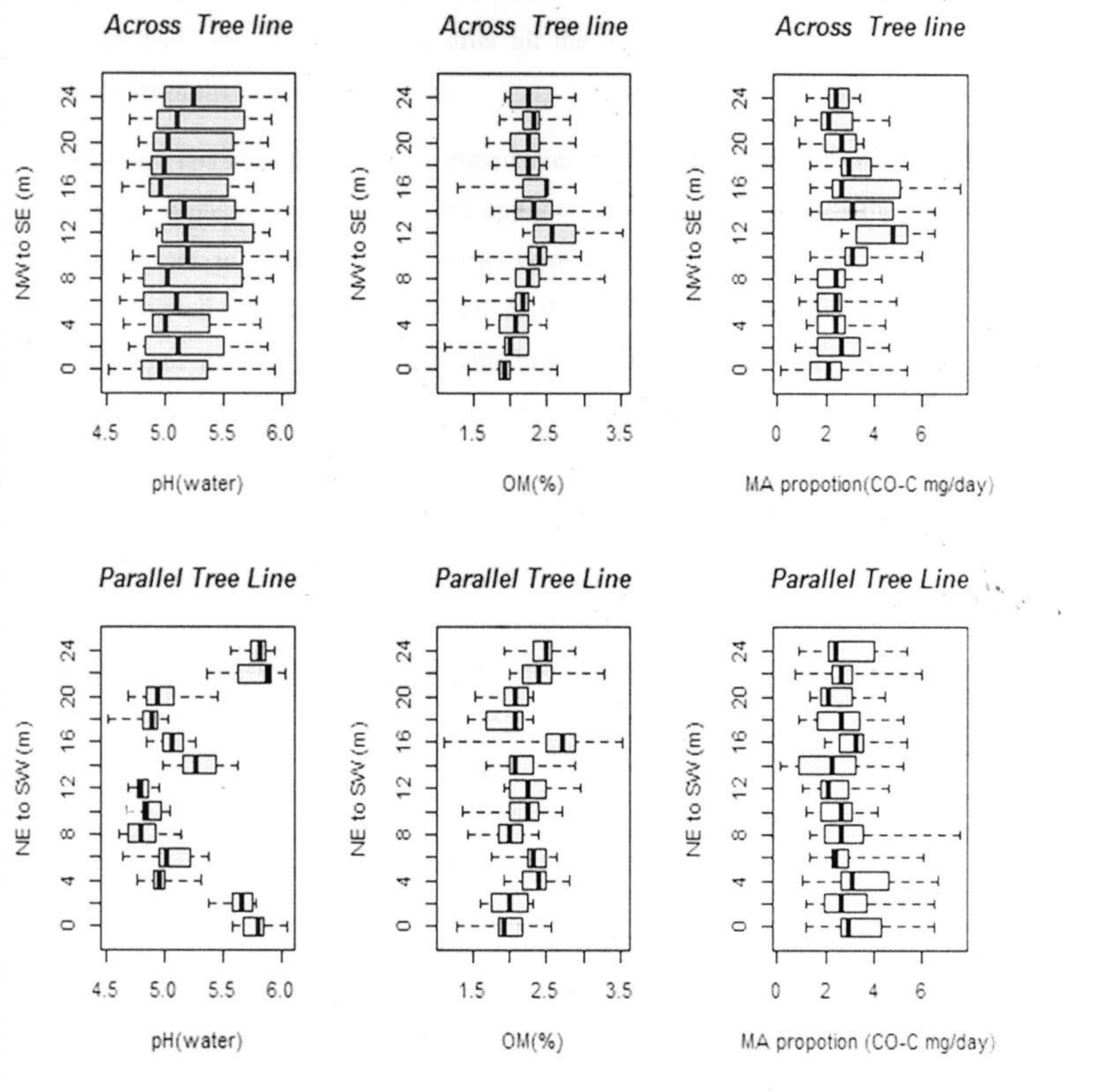



Figure 13: Boxplots for soil reaction (pH), organic matter content and microbial activity across and parallel the tree

### 4.4 Plot of Residuals versus Corresponding Fitted Values

The results on the effects of residuals on fitted values are presented in Figure 14 and Figure 15 The plot of the residuals versus the fitted values produced a distribution of points scattered randomly about 0 with no proper pattern, regardless of the size of the fitted value as shown in the figures. This was done to check for increasing residuals as the size of fitted values increased. Residuals are estimates of experimental error obtained by subtracting the observed responses from the fitted values. The fitted values were calculated from the chosen model, after all the unknown model parameters had been estimated from the experimental data.

Residuals are elements of variation unexplained by the fitted model. Since this is a form of error, the same general assumptions apply to the group of residuals that are typically used for errors in general hence these were (roughly) normal and (approximately) independently distributed with a mean of 0 and some constant variance. Hence the residuals were normally distributed and kriging works better when the residuals are normally distributed and the data did not require any transformation as the frequency of the residuals was normally distributed. Tendency of good plotting the data should be normally distributed for example soil reaction (pH) the residuals were binormally distributed and randomly scattered with no pattern observed whilst the residuals of sand seem to be negatively skewed. However, the data was normally distributed.The analysis of variance (ANOVA) of the residuals are shown in the Appendices.

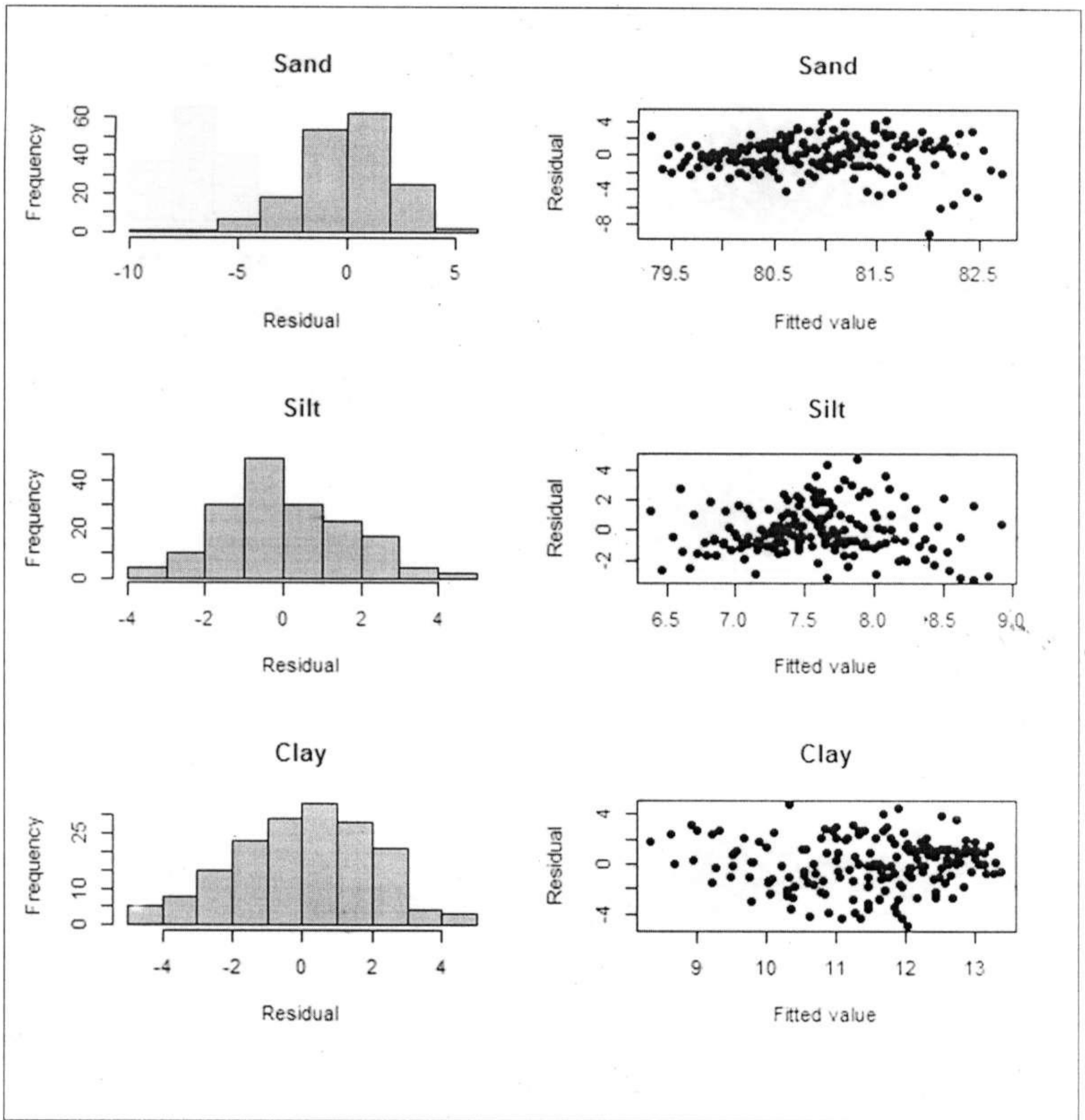



Figure 16: Histograms and Residuals versus fitted value plots for sand, silt and clay fractions

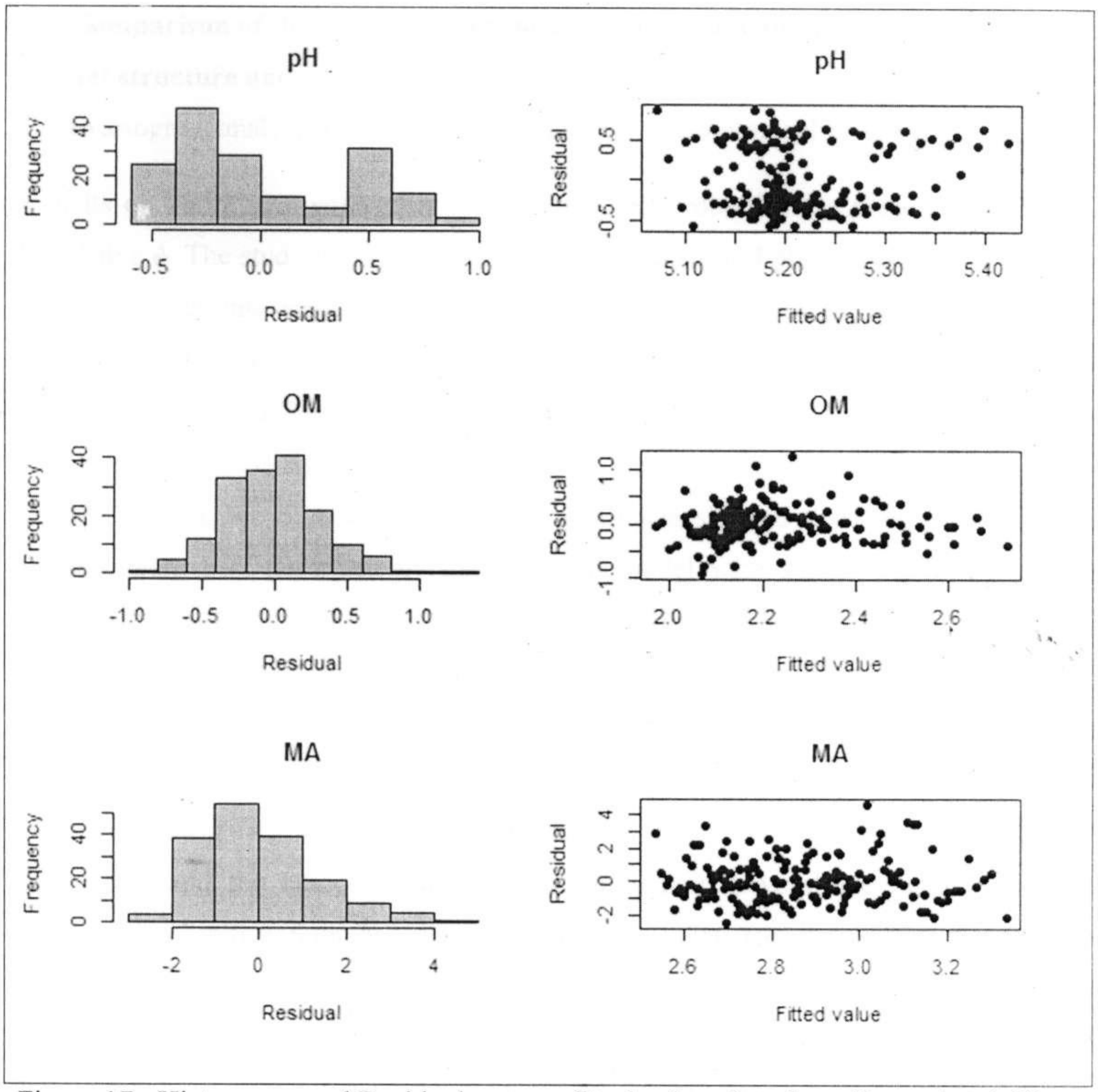



Figure 17: Histograms and Residuals versus fitted value plots for soil reaction (pH), organic matter and microbial activity

## 4.5 Comparison of the spherical, exponential and Gaussian models for best-fit spatial structure and variability

Semivariogram analysis of soil physical, chemical and biological properties

Results on variogram parameters of measured soil properties are presented in Table 3 and Table 4. The study was made in order to interpolate soil properties such as sand, silt and clay fractions, organic matter, soil reaction and microbial activity spatially at varying distances with the *Faidherbia albida*. Semi-variogram parameters (nugget, sill, and range) for each measured soil property were analyzed with the Spherical, Exponential and Gaussian Models to provide the structure of variability as shown in Table 5 and Table 6 Analysis of the semivariance showed that sand and microbial activity were best described by the spherical model with spatial dependence of the distance being 12.39m and 10.32 respectively. Whilst soil reaction and organic matter were best described by both the spherical and exponential models with ranges of 5.44 ; 7.86 and 1.97-9.95 respectively. The best fitted models were identified based on the model with the least sums of square error. The variograms using ordinary kriging are as presented in Figure 18 to Figure 19.Where the graphs flatten is an indication of no correlation and the autocorrelation is essentially zero beyond the range, leading to increased variability. Sample locations separated by distances closer than the range are spatially autocorrelated, whereas locations farther apart than the range are not autocorrelated. This means that there is increased variability in the soil properties as the distance increases. The details of ordinary kriging interpolation techniques as well as the sums of square error associated with the ordinary kriging maps are given in and Table 7 and Table 8. The degree of spatial variation of these measured soil parameters was determined by finding the ratio of nugget to sill value of semivariograms (Amirinejad, 2011). Less than 25% was considered to be an indicator of strong spatial dependence and between 26 and 75% was an indication of moderate spatial dependence. Spatial dependence is the spatial relationship of variable values for those defined over space such as location. The results for sand, clay, organic matter and microbial activity showed moderate spatial dependence using the spherical model, whilst the results for silt and soil reaction for all models showed strong spatial dependence and sand, clay, microbial activity and organic matter (using exponential and gaussian model) indicated strong spatial dependence in Table 9 and Table 10.

Table 11: Variogram parameters for sand, silt and clay fractions

| | SAND | | | SILT | | | CLAY | | |
|---|---|---|---|---|---|---|---|---|---|
| Variogram type | Sph | Exp | Gau | Sph | Exp | Gau | Sph | Exp | Gau |
| Nugget(Co) | 1.97 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.31 | 0.00 | 0.00 |
| Sill(Co+C) | 4.94 | 4.49 | 3.93 | 2.44 | 2.67 | 2.46 | 4.72 | 4.95 | 4.27 |
| Range(a) | 12.39 | 2.44 | 1.95 | 4.49 | 2.26 | 2.10 | 8.00 | 2.83 | 2.20 |
| SSErr | 9.87 | 17.10 | 36.70 | 6.78 | 7.46 | 5.40 | 8.81 | 6.45 | 22.70 |
| Co/ (Co+C) (%) | 39.9 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 27.8 | 0.0 | 0.0 |
| Spatial dependence | Moderate | Strong | Strong | Strong | Strong | Strong | Moderate | Strong | Strong |
| Best fitted model | Spherical | | | Gaussian | | | Exponential | | |

Where Sph is the spherical model, Exp is the exponential model, Gau is the Gaussian model, SSErr is the sum of square error and Co/ (Co+C) (%) is the nugget to sill ratio

Table 12: Variogram parameters for Organic matter, soil pH and microbial activity

| | OM | | | pH | | | MA | | |
|---|---|---|---|---|---|---|---|---|---|
| Variogram type | Sph | Exp | Gau | Sph | Exp | Gau | Sph | Exp | Gau |
| Nugget(Co) | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.31 | 0.00 | 0.00 |
| Sill(Co+C) | 0.15 | 0.14 | 0.01 | 0.15 | 0.19 | 0.14 | 1.97 | 1.86 | 1.79 |
| Range(a) | 9.95 | 1.97 | 2.25 | 7.86 | 5.44 | 3.01 | 10.32 | 1.30 | 1.54 |
| SSErr | 0.01 | 0.01 | 0.05 | 0.03 | 0.03 | 0.04 | 0.31 | 0.78 | 1.70 |
| Co/ (Co+C) (%) | 46.7 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 66.5 | 0.00 | 0.00 |
| Spatial dependence | Moderate | Strong | Strong | Strong | Strong | Strong | Moderate | Strong | Strong |
| Best fitted model | Spherical, Exponential | | | Spherical , Exponential | | | Spherical | | |

Where pH is soil reaction, OM is organic matter content and MA is the microbial activity, Sph is the spherical model, Exp is the exponential model, Gau is the Gaussian model, SSErr is the sum of square error and Co/ (Co+C) (%) is the nugget to sill ratio

### 4.6 Spatial distribution map

The results on of analyzed parameters of the spherical, exponential and Gaussian models were used for ordinary kriging in order to produce the spatial distribution maps of the soil properties as presented in Figure 20 to Figure 21. Spatial maps of sand fraction (Figure 22) indicate a high sand content in the spherical model in both the North west and North east direction, and an increase in sand is seen in the North east direction in the exponential model and no proper distribution pattern is seen in Gaussian model. Spatial maps of silt fraction (Figure 23) in the Gaussian model indicated that the silt content increased in the center of the study area predominantly than the spherical and exponential models. There were stratifications in the silt proportion across the tree, this maybe associated to termite activity around the trees. The clay fraction has shown in the spatial maps increased in the South west and South east direction as shown by the exponential model and the Gaussian model portrayed a stronger pattern of stratification layers across the study area in the clay fraction. According to the spherical and Gaussian models organic matter increases in the North east direction. The distribution patterns differ because the equations are different. The spatial distribution maps indicated that the ordinary kriging predictions for soil reaction (pH) with the spherical and exponential model that soil reaction increased in the far edges of the field and slightly in the center of the study area whilst the Gaussian model showed little increases in soil reaction in the center of the study area. All the three models for soil reaction have stratification layers across the field indicating no proper distribution patterns. An increase of microbial activity around the tree line or center of the study area was seen in the North east direction in the spherical model as well as the exponential model showing a strong correlation as microbial activity was higher along the tree line and a distorted spatial pattern in the Gaussian model (Figure 24). The distribution maps of the soil properties across the study area have implications for management practices such as variable application rate of fertilizers, water and many more. For example, the spatial distribution of organic matter content, soil reaction and microbial activity had closely related patterns.

SAND

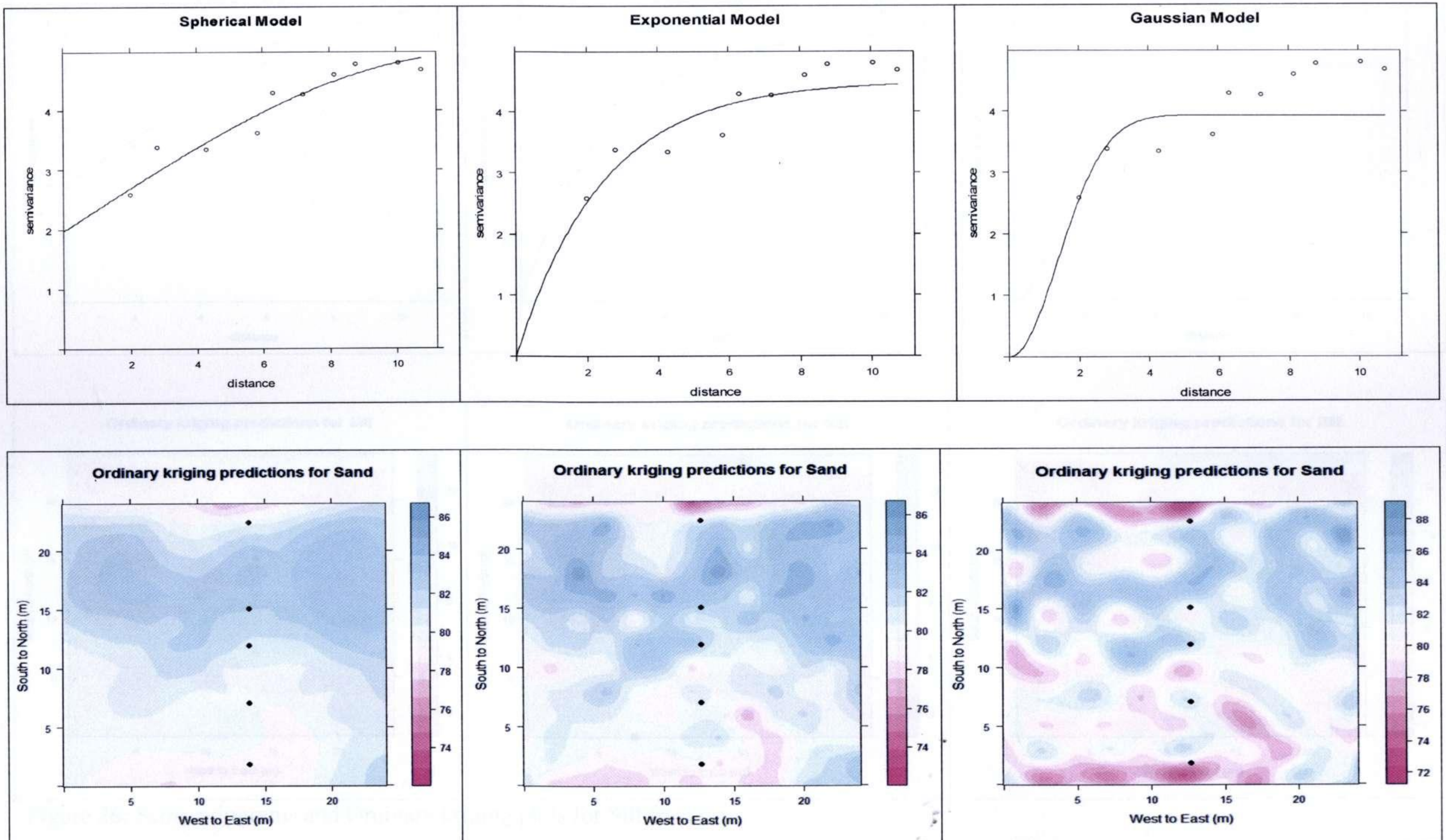



Figure 25: Semivariograms and Ordinary kriging plots for Sand fraction

SILT

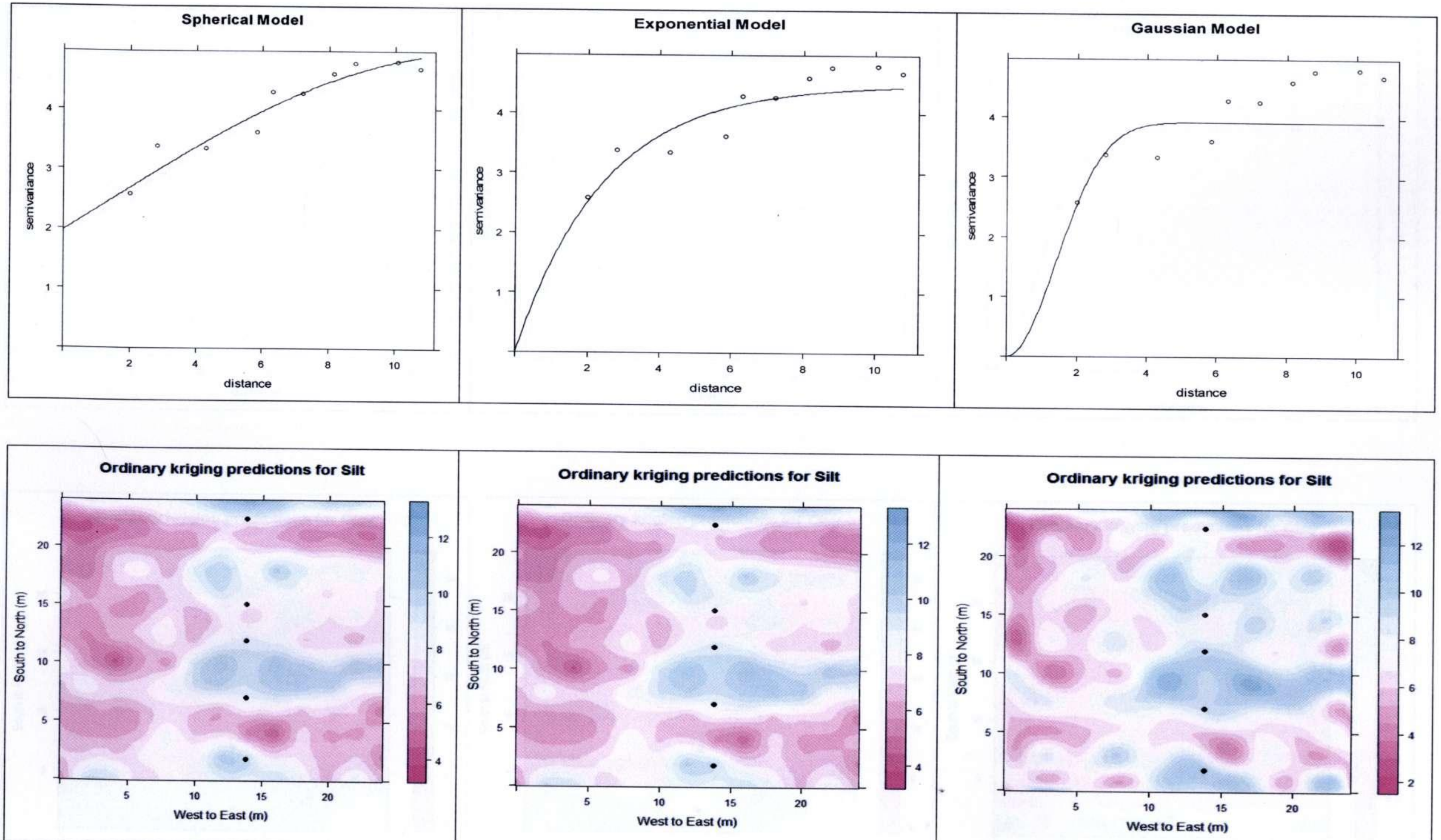



Figure 26: Semivariograms and Ordinary kriging plots for Silt fraction

CLAY

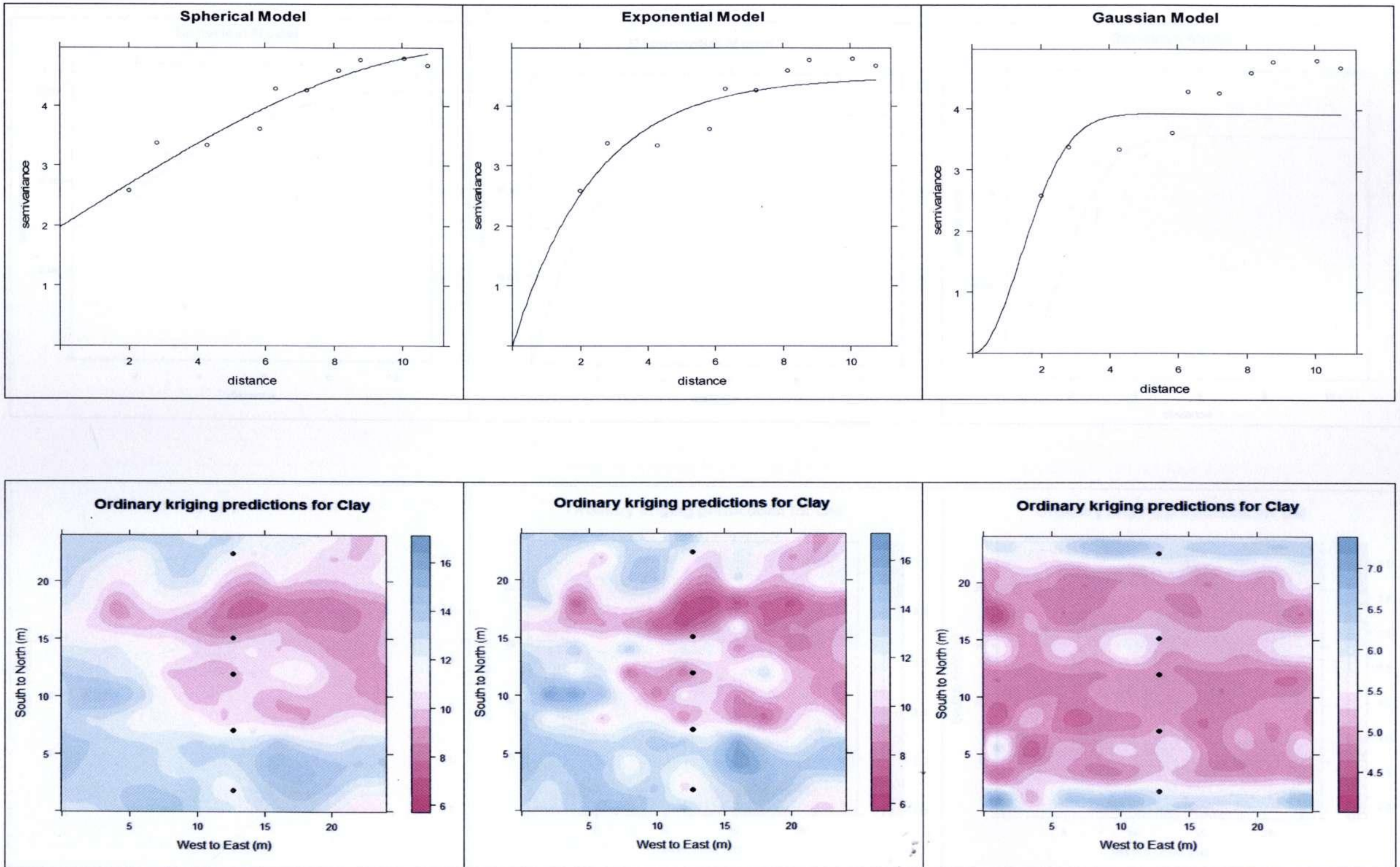



Figure 27: Semivariograms and Ordinary kriging plots for Clay fraction

OM

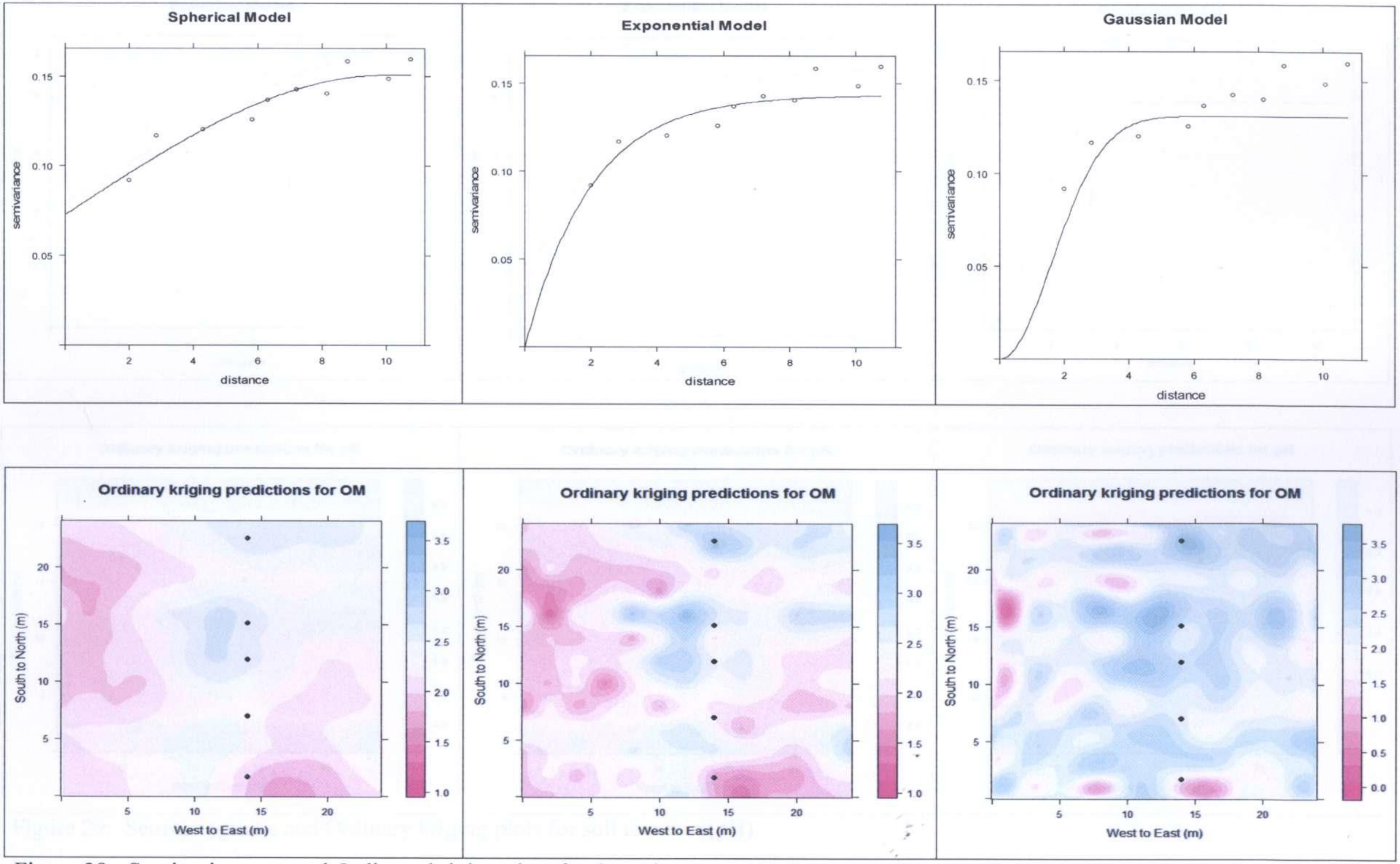



Figure 28: Semivariograms and Ordinary kriging plots for Organic matter (OM) content

pH

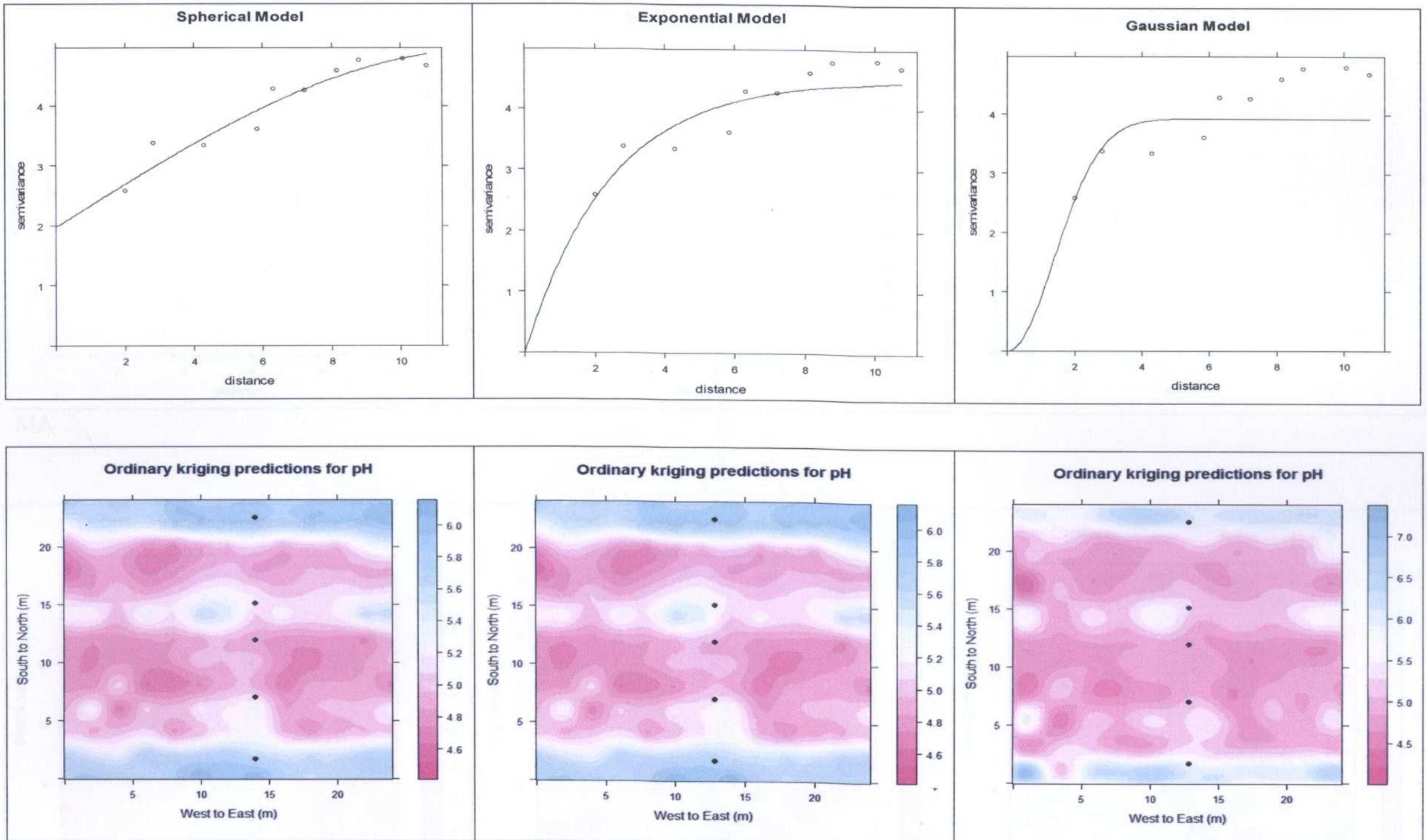
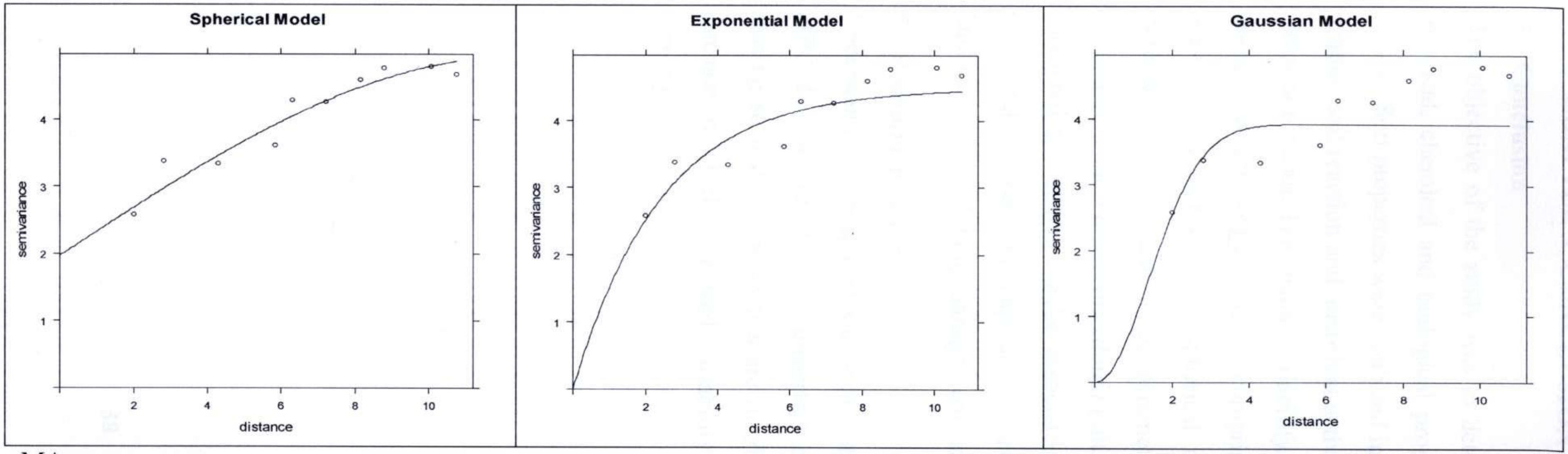



Figure 29: Semvariograms and Ordinary kriging plots for soil reaction (pH)




MA

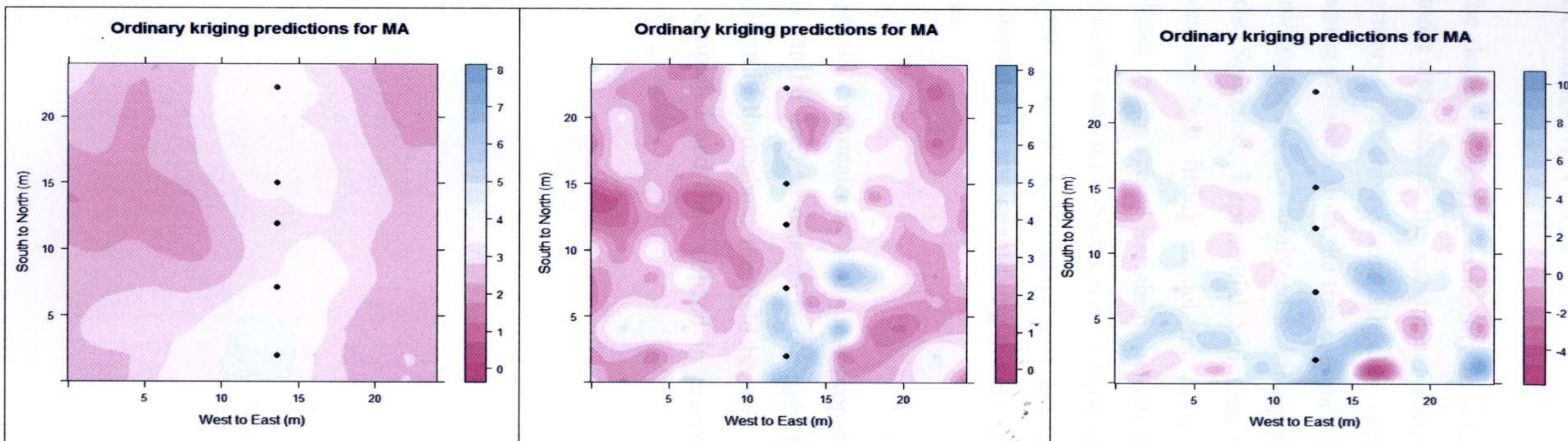



Figure 30: Semivariograms and Ordinary kriging plots for microbial activity (MA)

# CHAPTER 5: CONCLUSION AND RECOMMENDATION

## 5.1 Conclusion

The objective of the study was to determine the degree of spatial variability of selected physical, chemical and biological properties under and outside the canopies *Faidherbia albida*. Soil properties were analyzed in the laboratory to determine sand, silt, clay, organic matter, soil reaction and microbial activity at varying distances from the tree canopies in 0-20cm soil depth. The spatial variability of the soil properties was analyzed and mapped by using ordinary kriging which comprised of the Spherical, Exponential and Gaussian. Results indicated that the spherical model was the best fitting model for most soil parameters. The measured soil parameters exhibited strong spatial variability which were attributed to the *Faidherbia albida* (silt, organic matter and microbial activity) while other measured parameters maybe associated with parent material and management practices. Thus spatial variability maps are important in understanding and quantifying the effects of land use and developing management interventions.

## 5.2 Recommendation

Understanding the spatial variability of soil physical, chemical and biological properties under *Faidherbia albida* is important because it can be used to determine the right tree spacing so that the properties are distributed uniformly throughout the field because the distance to which increased variability can be estimated and thus utilized in precision farming.

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# CHAPTER 7: APPENDICES

Appendix 1: ANOVA for Sand fraction

| Anova Table (Type III tests) | Sum Sq | Df | F value | Pr(>F) |
|---|---|---|---|---|
| (Intercept) | 52146 | 1 | 11621.9 | < 2e-16 *** |
| Block1 | 5 | 1 | 1.0371 | 0.30999 |
| Block2 | 14 | 1 | 3.0805 | 0.08109 |
| Block1:Block2 | 0 | 1 | 0.0322 | 0.8577 |
| Residuals | 740 | 165 | | |

Signif. codes: 0

summary(model) 0'***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

| | Df | Sum Sq | Mean Sq | Mean Sq | F value | Pr(>F) |
|---|---|---|---|---|---|---|
| Block1 | 1 | 28 | 27.96 | 6.231 | 0.0135 | * |
| Block2 Block1:Block2 | 1 | 73.9 | 73.93 | 16.477 | 7.59E-05 | *** |
| Residuals | 1 | 0.1 | 0.14 | 0.032 | 0.8577 | |
| | 165 | 740.3 | 4.49 | | | |

Signif. codes: 0

summary. (Model) '***' 0.0 01 '**' 0.01 '*' 0.05 '.' 0 .1 ' ' 1

Coefficients:

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 79.04629 | 0.73323 | 107.805 | <2e-16 *** |
| Block1 | 0.09408 | 0.09238 | 1.018 | 0.31 |
| Block2 | 0.16214 | 0.09238 | 1.755 | 0.0811 |
| Block1:Block2 | 0.00209 | 0.01164 | 0.18 | 0.8577 |

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.118 on 165 degrees of freedom

Multiple R-squared: 0.1211, Adjusted R-squared: 0.1051

F-statistic: 7.58 on 3 and 165 DF, p-value: 8.83e-05

Appendix 2: ANOVA for Silt fraction

Anova Table (Type III tests)

| | Sum Sq | Df | F value | Pr(>F) |
|---|---|---|---|---|
| (Intercept) | 452.97 | 1 | 175.4599 | < 2e-16 *** |
| Block1 | 0.18 | 1 | 0.0691 | 0.79294 |
| Block2 | 4.41 | 1 | 1.7064 | 0.19327 |

| | | | | |
|---|---|---|---|---|
| Block1:Block2 | 7.30 | 1 | 2.8277 | 0.09454 |
| Residuals | 425.97 | 165 | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

| | Df | Sum Sq | Mean Sq | F value | Pr (>F) |
|---|---|---|---|---|---|
| Block1 | 1 | 35.4 | 35.41 | 13.717 | 0.000289 *** |
| Block2 | 1 | 0.4 | 0.36 | 0.141 | 0.708218 |
| Block1:Block2 | 1 | 7.3 | 7.30 | 2.828 | 0.094543 |
| Residuals | 165 | 426.0 | 2.58 | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.607 on 165 degrees of freedom

Multiple R-squared: 0.09184, Adjusted R-squared: 0.07533

F-statistic: 5.562 on 3 and 165 DF, p-value: 0.001165

Coefficients:

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 7.367249 | 0.556181 | 13.246 | <2e-16 *** |
| Block1 | 0.018423 | 0.070072 | 0.263 | 0.7929 |
| Block2 | -0.091534 | 0.070072 | -1.306 | 0.1933 |
| Block1:data.df$Block2 | 0.014845 | 0.008828 | 1.682 | 0.0945 . |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.607 on 165 degrees of freedom

Multiple R-squared: 0.09184, Adjusted R-squared: 0.07533

F-statistic: 5.562 on 3 and 165 DF, p-value: 0.001165

Appendix 3: ANOVA for Clay fraction

Anova Table (Type III tests)

| | Sum Sq | Df | F value | Pr(>F) | |
|---|---|---|---|---|---|
| (Intercept) | 1541.37 | 1 | 391.0919 | <2e-16 | *** |
| Block1 | 6.71 | 1 | 1.7032 | 0.1937 | |
| Block2 | 2.66 | 1 | 0.6738 | 0.4129 | |
| Block1:Block2 | 9.44 | 1 | 2.3962 | 0.1235 | |
| Residuals | 650.30 | 165 | | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

| | Df | Sum Sq | Mean Sq | F value | Pr(>F) | |
|---|---|---|---|---|---|---|
| Block1 | 1 | 126.5 | 126.46 | 32.086 | 6.42e-08 | *** |
| Block2 | 1 | 84.8 | 84.75 | 21.504 | 7.15e-06 | *** |
| Block1:Block2 | 1 | 9.4 | 9.44 | 2.396 | 0.124 | |
| Residuals | 165 | 650.3 | 3.94 | | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Coefficients:

| | Estimate | Std. Error | t value | Pr(>\|t\|) | |
|---|---|---|---|---|---|
| (Intercept) | 13.59012 | 0.68720 | 19.776 | <2e-16 | *** |
| Block1 | -0.11299 | 0.08658 | -1.305 | 0.194 | |
| Block2 | -0.07107 | 0.08658 | -0.821 | 0.413 | |

Block1:Block2 -0.01689 0.01091 -1.548 0.124

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.985 on 165 degrees of freedom

Multiple R-squared: 0.2533, Adjusted R-squared: 0.2398

F-statistic: 18.66 on 3 and 165 DF, p-value: 1.796e-10 anova(ajuste)

Analysis of Variance Table

Clay

| | Df | Sum Sq | Mean Sq | F value | Pr(>F) |
|---|---|---|---|---|---|
| Block1 | 1 | 126.46 | 126.457 | 32.0859 | 6.420e-08 *** |
| Block2 | 1 | 84.75 | 84.753 | 21.5042 | 7.147e-06 *** |
| Block1:data.df$Block2 | 1 | 9.44 | 9.444 | 2.3962 | 0.1235 |
| Residuals | 165 | 650.30 | 3.941 | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Appendix 4: ANOVA for Organic matter content

Anova Table (Type III tests)

| | Sum Sq. | Df | F value | Pr(>F) |
|---|---|---|---|---|
| (Intercept) | 39.830 | 1 | 329.4991 | < 2.2e-16 *** |
| Block1 | 0.134 | 1 | 1.1125 | 0.293071 |
| Block2 | 0.242 | 1 | 2.0051 | 0.158653 |

Block1:Block2 1.227 1 10.1503 0.001726 **

Residuals 19.945 165

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

summary(model)

```
             Df Sum Sq Mean Sq F value  Pr(>F)
Block1        1  1.675  1.6754  13.860 0.00027 ***
Block2        1  1.057  1.0566   8.741 0.00357 **
Block1:Block2 1  1.227  1.2270  10.150 0.00173 **
Residuals   165 19.945  0.1209
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residuals:

```
     Min       1Q   Median       3Q      Max
-0.94894 -0.22407 -0.01738  0.18965  1.25714
```

Coefficients:

```
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    2.184615   0.120350  18.152  < 2e-16 ***
Block1        -0.015993   0.015163  -1.055  0.29307
Block2        -0.021471   0.015163  -1.416  0.15865
Block1:Block2  0.006086   0.001910   3.186  0.00173 **
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3477 on 165 degrees of freedom

Multiple R-squared: 0.1656, Adjusted R-squared: 0.1504

F-statistic. 10.92 on 3 and 165 DF, p-value: 1.404e-06

Coefficients:

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 2.184615 | 0.120350 | 18.152 | < 2e-16 *** |
| Block1 | -0.015993 | 0.015163 | -1.055 | 0.29307 |
| Block2 | -0.021471 | 0.015163 | -1.416 | 0.15865 |
| Block1:Block2 | 0.006086 | 0.001910 | 3.186 | 0.00173 ** |

Residual standard error: 0.3477 on 165 degrees of freedom

Multiple R-squared: 0.1656, Adjusted R-squared: 0.1504

F-statistic: 10.92 on 3 and 165 DF, p-value: 1.404e-06

Appendix 5: ANOVA for soil pH

Anova(model,type="III")

| | Sum Sq | Df | F value | Pr(>F) |
|---|---|---|---|---|
| (Intercept) | 229.381 | 1 | 1354.1315 | <2e-16 *** |
| Block1 | 0.055 | 1 | 0.3254 | 0.5692 |
| Block2 | 0.126 | 1 | 0.7425 | 0.3901 |

| | | | | |
|---|---|---|---|---|
| Block1:Block2 | 0.305 | 1 | 1.8004 | 0.1815 |
| Residuals | 27.950 | 165 | | |

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1

Summary (model)

| | Df | Sum Sq | Mean Sq | F value | Pr(>F) |
|---|---|---|---|---|---|
| Block1 | 1 | 0.286 | 0.28637 | 1.691 | 0.195 |
| Block2 | 1 | 0.079 | 0.07887 | 0.466 | 0.496 |
| Block1:Block2 | 1 | 0.305 | 0.30498 | 1.800 | 0.182 |
| Residuals | 165 | 27.950 | 0.16939 | | |

Residuals:

| Min | 1Q | Median | 3Q | Max |
|---|---|---|---|---|
| -0.5880 | -0.3346 | -0.1705 | 0.4280 | 0.8805 |

Coefficients:

| | Estimate | Std. Error | t value | Pr (>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 5.242618 | 0.142468 | 36.799 | <2e-16 *** |
| Block1 | -0.010239 | 0.017949 | -0.570 | 0.569 |
| Block2 | -0.015467 | 0.017949 | -0.862 | 0.390 |
| Block1:Block2 | 0.003034 | 0.002261 | 1.342 | 0.182 |

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4116 on 165 degrees of freedom

Multiple R-squared: 0.02342, Adjusted R-squared: 0.005662

F-statistic: 1.319 on 3 and 165 DF, p-value: 0.27

Appendix 6: ANOVA for Microbial activity

Anova Table (Type III tests)

| | Sum Sq | Df | F value | Pr(>F) | |
|---|---|---|---|---|---|
| (Intercept) | 71.421 | 1 | 38.6298 | 4.037e-09 | *** |
| Block1 | 0.659 | 1 | 0.3564 | 0.5513 | |
| Block2 | 0.515 | 1 | 0.2788 | 0.5982 | |
| Block1:Block2 | 0.085 | 1 | 0.0459 | 0.8306 | |
| Residuals | 305.060 | 165 | | | |

Signif. Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residuals:

| Min | 1Q | Median | 3Q | Max |
|---|---|---|---|---|
| -2.5475 | -0.9583 | -0.2012 | 0.6873 | 4.5946 |

Coefficients:

| | Estimate | Std. Error | t value | Pr(>\|t\|) | |
|---|---|---|---|---|---|
| (Intercept) | 2.925370 | 0.470673 | 6.215 | 4.04e-09 | *** |
| Block1 | 0.035404 | 0.059299 | 0.597 | 0.551 | |
| Block2 | -0.031308 | 0.059299 | -0.528 | 0.598 | |
| Block1:Block2 | -0.001600 | 0.007471 | -0.214 | 0.831 | |

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.36 on 165 degrees of freedom

Multiple R-squared: 0.01849, Adjusted R-squared: 0.0006427

F-statistic: 1.036 on 3 and 165 DF, p-value: 0.3782