ASSESSMENT OF HETEROGENITY IN SOIL PROPERTIES OF NIMBIA FOREST RESERVE IN SOUTHERN GUINEA SAVANNAH OF NIGERIA FOR SITE SPECIFIC MANAGEMENT

By

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DECLARATION

I declare that the work in the thesis entitled "*Assessment of heterogeneity in soil properties of Nimbia Forest Reserve in Southern Guinea Savannah of Nigeria for site specific management*" has been performed by me in the Department of Soil Science under the supervision of Professor J.O. Ogunwole, Dr. A.C. Odunze and Professor J.O. Agbenin.

The information derived from the literature has been duly acknowledged in the text and a list of references provided. No part of this thesis was previously presented for another degree or diploma at any university.

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| --- | --- | --- |
| Name of student | Signature | Date |

CERTIFICATION

This thesis entitled "ASSESSMENT OF HETEROGENITY IN SOIL PROPERTIES OF NIMBIA FOREST RESERVE IN SOUTHERN GUINEA SAVANNAH OF NIGERIA FOR SITE SPECIFIC MANAGEMENT" by Obidike, Evelyn Omelebere meets the regulations governing the award of the degree of Masters of Ahmadu Bello University, Zaria, and is approved for its contribution to knowledge and literary presentation.

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ABSTRACT

Spatial analysis of soil heterogeneity is a vital prerequisite for site specific forest management. This study was aimed at describing the field-scale horizontal spatial variability and developing models for predicting soil aggregate stability from other soil properties in Nimbia Forest Reserve of the Southern Guinea Savanna zone of Nigeria. Geo-referenced topsoil samples (0-0.15 m) and field infiltration were obtained systematically from block NF80 along 300 m transect at 3 m interval (n=100). These samples were analyzed for both physical and chemical properties. Soil data were analyzed using classical and spatial statistical tools. Results revealed large differences between minimum and maximum values of the investigated soil properties. The results showed high degree of variability in the majority of the soil properties with coefficients of variability (CV) ranging from 0.74% to 90.83%. Using the students' t-test statistics at 5 % level of probability, autocorrelation (ACF) and crosscorrelation functions (CCF) were calculated. Calculated ACF revealed strong spatial dependence between adjacent observations (19 lags) of large macroaggregate-associated organic carbon (OCa) and no autocorrelation in total iron. Based on the result of the CCF of wet sieved mean weight diameter (MWDw) versus other soil properties; correlated soil properties such as clay, total phosphorus (TP), dithionite iron (Fed), pyrophosphate-extractable iron (Fep), moisture content and aggregate fraction associated organic carbon (OCa, OCb, OCc, OCd, OCe) were selected and used in various combinations for multiple linear regression (MLR) and state-space analyses. The results showed that state-space models described the variation in MWDw better than the equivalent MLR models. The best model performance explained 99.85 % of the MWDw variation when clay, Total P, Fed, OCa, OCc, OCd and OCe were used in prediction. The relationship of clay, Fed and OCa to all the selected best performed models of each scenarios suggested that these soil properties have effective contribution to the spatial variation of MWDw. Semivariograms were used to quantify the spatial structure of soil properties. All properties, except total iron, exhibited a definable spatial structure, which were described by spherical, exponential, gaussian or linear models. Majority of the soil properties showed strong spatial dependence. Alternative analytical tools such as the state-space and semivariogram under forest conditions; considered the underlying processes of soil properties along transect, identify the local relations between MWDw and selected properties and; quantify these relationships taking measurement and model errors into account. Analysis of variation in soil properties is complex. Nevertheless, spatial statistical tools provided concise information about spatial variation and relationships between soil properties than the classical statistics tools and; this information is crucial for precision in site-specific soil management planning in such forest ecosystems.

TABLE OF CONTENTS

CONTENT		PAGE
TITLE PAGE	- - - - - - - - -	i
DECLARATION	- - - - - - - - -	ii
CERTIFICATION	- - - - - - - - -	iii
ACKNOWLEDGEMENT	- - - - - - - - -	iv
ABSTRACT	- - - - - - - - - -	vi
TABLE OF CONTENTS	- - - - - - - - -	vii
LIST OF TABLES	- - - - - - - - -	xi
LIST OF FIGURES	- - - - - - - - -	xii
LIST OF PLATES	- - - - - - - - -	xiv
LIST OF APPENDICES	- - - - - - - - -	xv
CHAPTER ONE		
INTRODUCTION	- - - - - - - - -	1
CHAPTER TWO		
LITERATURE REVIEW-	- - - - - - - - -	6
2.1	History of Regionalized Variable Theory - - - -	6
2.2	Concept of Regionalized Variable Theory - - - -	7
2.3	Analytical tools employed in Geostatistics - - - -	9
2.3.1	Autocorrelation - - - - - - - - -	10
2.3.2	Cross-correlations - - - - - - - -	13
2.3.3	Semivariogram- - - - - - - - - -	15
2.3.3.1	Characteristics of the semivariogram - - - - -	16

2.3.3.2 Modeling semivariogram- - - - - - - 17

2.3.4 State-space analysis - - - - - - 24

2.3.4.1 Shumway's State-Space Approach - - - - - 26

2.3.4.2 West and Harrison State-Space Approach - - - - 27

2.4 Merits and opportunities in geostatistical relative to classical Fisher's statistics - - - - - - - - - - 28

2.5 Applications of geostatistics in soil science - - - - 30

2.6 Spatial studies involving soil properties: relevance and implications for landscapes. - - - - - - - - - 32

2.7 Characteristics of forest soils relative to agricultural soils - - 33

2.8 Implications of forest exploitation on soil properties - - - 35

2.8.1 Forest fire - - - - - - - - - - 36

2.8.2 Grazing - - - - - - - - - - 38

2.8.3 Forest management - - - - - - - 39

2.8.4 Deforestation - - - - - - - - 42

2.9 Aggregation and aggregate stability in soil - - - - 44

2.9.1 Processes and importance of aggregation in soil - - - - 44

2.9.2 Report of works involving methods of measuring soil aggregation and aggregate stability in managed ecosystems - - - - 47

2.10 Influence of soil properties and management practices on soil aggregation and aggregate stability - - - - - - - - 51

2.10.1 Organic matter content and composition - - - - - 51

2.10.2 Microbial action - - - - - - - 53

2.10.3 Soil physical properties - - - - - - - 55

2.10.4 Inorganic binding agents - - - - - - - 56

2.10.5 Management practices - - - - - - - 58

CHAPTER THREE

MATERIALS AND METHODS - - - - - - - 60

3.1 Physical setting of the study area- - - - - - 60

3.1.1 Location and extent - - - - - - - 60

3.1.2 History and plantation - - - - - - - 60

3.1.3 Teak (Tectonia Grandis Linn. F) - - - - - - 64

3.1.4 Geomorphology and climate - - - - - - 64

3.1.5 Soils - - - - - - - - - 66

3.1.6 Vegetation - - - - - - - - 68

3.2 Sampling - - - - - - - - 68

3.3 Field measurement - - - - - - - 70

3.3.1 Field infiltration measurement - - - - - - 70

3.3.2 Bulk density - - - - - - - - 72

3.4 Sampling preparation - - - - - - - 72

3.5 Laboratory analysis - - - - - - - 72

3.5.1 Physical properties - - - - - - - 73

3.5.1.1 Particle size distribution - - - - - - 73

3.5.1.2 Aggregate size distribution - - - - - - 74

3.5.2 Chemical properties - - - - - - - 75

3.5.2.1 Organic Carbon - - - - - - - - 75

3.5.2.2 Soil organic carbon fractionation- - - - - - 76

3.5.2.3 Biochemically Protected Soil Organic Matter - - - - 76

3.5.2.4 Forms of iron - - - - - - - - - 77

3.5.2.5 Soil pH - - - - - - - - - 78

3.5.2.6 Electrical Conductivity - - - - - - - 78

3.5.2.7 Soil Nitrogen - - - - - - - - 78

3.5.2.8 Cation exchange capacity - - - - - - - 79

3.5.2.9 Exchangeable bases - - - - - - - - 79

3.6 Data analysis - - - - - - - - 80

CHAPTER FOUR

RESULTS AND DISCUSSION - - - - - - - 81

4.1 Descriptive statistics analysis - - - - - - 81

4.2 Point-to-point data distribution through space - - - - 85

4.3 Autocorrelation function - - - - - - - 90

4.4 Cross-correlation function - - - - - - 92

4.5 Classical multiple regressions and state-space analysis - - - 100

4.6 Spatial structure and attributes - - - - - - 111

4.6.1 Semivariogram model - - - - - - - 111

4.6.2 Nugget effect - - - - - - - - 117

4.6.3 Total variance (sill) - - - - - - - 119

4.6.4 Effective range - - - - - - - - 120

4.6.5 Spatial dependence degree - - - - - - 122

CHAPTER FIVE

SUMMARY AND CONCLUSION - - - - - - - 123

REFERENCES - - - - - - - - - 126

APPENDIX - - - - - - - - - - 161

LISTS OF TABLES

TABLES		PAGES
3.1	Summary of means of climatic data of Nimbia Forest Reserve - -	67
4.1	Descriptive statistics for the studied soil variables- - - - - -	82
4.2	Simple linear regression analysis of the ten selected sets of observations versus MWDw and their values of R^2 coefficient - - - - -	101
4.3a	Multiple linear regression equations of wet mean weight diameter for the ten selected soil properties - - - - - - -	103
4.3b	State-space equations of wet mean weight diameter for the ten selected soil properties - - - - - - - - -	103
4.4a	Multiple linear regression equations of wet mean weight diameter for the nine selected soil properties- - - - - - - -	104
4.4b	State-space equations of wet mean weight diameter for the nine selected soil properties - - - - - - - - -	105
4.5	Best performance model for each set of soil properties - - -	109
4.6	Best fitted models and the corresponding parameters describing soil attributes of the study area - - - - - - - -	118

LISTS OF FIGURES

FIGURES **PAGES**

2.1 The parameters of a bounded semivariogram model with a nugget effect - 18

2.2a Linear semivariogram model without sill - - - - - 20

2.2b Linear semivariogram model with sill - - - - - 20

2.3 Spherical semivariogram model - - - - - - 21

2.4 Exponential semivariogram model - - - - - - 21

2.5 Gaussian semivariogram model - - - - - - 23

2.6 Power semivariogram model - - - - - - - 23

2.7 Soil aggregation models of Tisdall and Oades (1982), Oades (1984) and Six *et al*. (2000) - - - - - - - - 46

3.1 State boundary map of Nigeria showing Kaduna State - - - 61

3.2 Kaduna map with Nimbia Forest Reserve - - - - - 62

3.3 Nimbia Forest Reserve map showing the study site (1980 plantation) - 69

4.1 Data distribution 3m by 3m along the 300m transect - - - - 86

4.2 Data distribution 3m by 3m along the 300m transect - - - - 87

4.3 Data distribution 3m by 3m along the 300m transect - - - - 88

4.4 Data distribution 3m by 3m along the 300m transect - - - - 89

4.5 Calculated autocorrelation function (ACF) for the studied soil physical properties - - - - - - - - - 91

4.6 Calculated autocorrelation function (ACF) for total elements - - 93

4.7 Calculated autocorrelation function (ACF) for organic carbon fractions - 94

4.8 Calculated crosscorrelogram function (CCF) between wet mean weight diameter and selected soil properties - - - - - - - 96

4.9 Calculated crosscorrelogram function (CCF) between wet mean weight diameter and selected soil properties - - - - - - - 97

4.10 Calculated crosscorrelogram function (CCF) between wet mean weight diameter and selected soil properties - - - - - - - 98

4.11 Calculated crosscorrelogram function (CCF) between wet mean weight diameter and selected soil properties - - - - - - - 99

4.12 Experimental and best-fitted mathematical semivariogram models based on the least Residual Sum of Squares (RSS) and the maximum coefficient of determination (R^2) value - - - - - - - - - - 113

4.13 Experimental and best-fitted mathematical semivariogram models based on the least Residual Sum of Squares (RSS) and the maximum coefficient of determination (R^2) value - - - - - - - - - - 114

4.14 Experimental and best-fitted mathematical semivariogram models based on the least Residual Sum of Squares (RSS) and the maximum coefficient of determination (R^2) value - - - - - - - - - - 115

4.15 Experimental and best-fitted mathematical semivariogram models based on the least Residual Sum of Squares (RSS) and the maximum coefficient of determination (R^2) value - - - - - - - - - - 116

LISTS OF PLATES

PLATES		PAGES
I	Rock outcrops within the forest plantatio - - - - -	63
II	Even aged plantation - - - - - - - - -	65
III	Field Infiltration sampling using double ring infiltrometer - - -	71

LIST OF APPENDICES

APPENDICES **PAGES**

A Point-to-point coordinates and infiltration rate data of the study area - 161

B Multiple linear regression equations of wet mean weight diameter for the eight selected soil properties - - - - - - - 164

C State-space equations of wet mean weight diameter for the eight selected soil properties - - - - - - - - - 166

D Multiple linear regression equations of wet mean weight diameter for the seven selected soil properties - - - - - - - - 169

E State-space equations of wet mean weight diameter for the seven selected soil properties - - - - - - - - - 171

F Multiple linear regression equations of wet mean weight diameter for the six selected soil properties - - - - - - - - 175

G State-space equations of wet mean weight diameter for the six selected soil properties - - - - - - - - - 179

CHAPTER ONE

INTRODUCTION

Increasing understanding of the role which forest plays in natural ecological systems, had led to increased interest in forest ecosystem. Forest is involved in stabilizing soil, conserving and cycling nutrients, and moderating water supplies, especially in a world currently threatened with climate change and global warming (World Bank, 1992). Jagger and Pender (2000) reported the importance of forest to include: provision of biomass, watershed management, soil nutrient and water retention, fodder for livestock, construction materials, and source of income, cultural and recreational value. In Nigeria, forests cover approximately 10% of the country's land surface and also provide these critical ecosystem goods and services (World Bank, 1992). Over the years however, Nigeria has had a record of one of the world's worst cases of deforestation of primary forest. The country lost 55.7% of its primary forests between 2000 and 2005 (Butler, 2005) to deforestation. Poor forest management program, increase in population, industrial logging, conversion of forest to agricultural land, fuel wood collection and indiscriminate forest fire often set by inexperienced casual hunters have accelerated deforestation of Nigeria's primary forest (World Bank, 1991).

One fundamental biophysical consequence of deforestation is soil degradation; which is of particular concern since dry-land forest soils are very susceptible to wind and water erosion (Lal, 1997; Liu *et al.,* 2002). Soil degradation has been identified as one of the most critical environmental problems in Nigeria for a long time and, this challenge has raised an urgent need to develop effective soil resource management systems that can tackle this problem

and sustain soil productivity to enhance environmental quality, food security and poverty alleviation (Junge *et al*., 2008).

Effective soil resource management systems must be premised on our knowledge of the current soil properties. For instance, ability of a soil to withstand effect of degradation forces will depend largely on the stability of the soil. Soil structural stability affects its susceptibility to detachment by rain drop impact, abrasive force of the wind and micro-aggregates (domain size) influence soils' susceptibility to transport by runoff. Increased runoff enhances surface sealing and loss of organic materials, reduces the infiltration rate and increases the potential for soil erosion (Sarah, 2005). Consequently, there is need to monitor soil state so that forests management practices can be modified, should negative and irreversible changes begin to occur (Moffat and Kennedy, 2002).

Soil structural stability and other soil variables vary widely in time and space i.e., they are heterogeneous. Heterogeneity in soil can be attributed to a complex interrelationship of physical, chemical and biological reactions (Elkateb *et al*., 2003). In the light of these facts, importance of spatial and temporal variability of soil chemical and physical properties should not be underestimated in planning soil management strategy (Coelho *et al.,* 1998). As a result, the evaluation of soil properties and their impact on environmental quality requires adequate analytical tools and experimental designs (van Kessel and Wendroth, 2001).

The conventional Fisher's statistical approach adopted by agronomists and natural resource scientists to analyze effect(s) of agronomic practices on soil properties, has contributed immensely to advance our understanding of soil and crop productivity (Webster, 1985;

Duffera *et al*., 2007). The use of Fisher's statistics in analyzing soil properties at any given location has also contributed to detecting presence of landscape scale variation in soil properties (Stevenson *et al.* 2001). Nevertheless, Fisher's statistics considers all data equal and independent (Kuzyakova *et al.*, 2001) assuming that mean variability is random and contain no reference to the geographical distribution of differences within the sampling units (Trangmar *et al*., 1985). Hence, for site-specific management and precision agriculture, sustainable forest management in addition to a synoptic and spatially explicit analysis of variance, state space statistics has demonstrated superiority for credible analysis of spatial and temporal information (Robert *et al.,* 1996; Coelho *et al.,* 1998; Shukla *et al.,* 2004a); conventional statistical results often have high uncertainty and low confidence levels (Nielsen *et al.,* 1995; Nielsen *et al.,* 1997; Timm *et al.,* 2003a). In contrast to conventional statistics, application of spatial statistics in soil science studies takes advantage of spatial dependency of soil variable(s) by making use of the characteristics of each observation location.

Shaw and Carter (2002) studied effects of forest harvesting on soil properties and concluded that site-specific forestry requires detailed characterization of spatial distribution of forest soil properties in order to prescribe appropriate management schemes. Forest plantations are mainly established on poor soil conditions or rugged topography and anthropogenic effects resulting from planting and felling processes make forest soils to be subjected to high variability in morphological and mechanical stresses than agricultural soils. Greacen and Sands (1980) suggested that the degree and extent of heterogeneity are therefore more in forest soils relative to arable soils. Therefore, the variables of these soils cannot be easily measured using conventional sampling designs and their dynamics may

not be completely portrayed by statistics that ignore spatial correlation. Warrick and Nielsen (1980) and Warrick *et al.* (1986) examined the variability of soil properties within a given field using the coefficient of variation (CV); while the CV gives a relative estimate of property variability, it provides no information on how the variability is distributed in space and time. Any good practice in statistical inference consists not only in obtaining estimates but also in assessing the reliability of those estimates (Bard, 1974).

JUSTIFICATION AND OBJECTIVES

Forest system is a natural resource most accurately described by several state variables. To this end, spatial characterization of soil properties within and between different soil units becomes necessary. The spatial variability of forest soil properties is too complex to be studied deterministically; a stochastic approach that gives premium to the behavior of soil variable in space and time can however, be a more appropriate approach to analyze soil heterogeneity (Matheron, 1971). Geostatistics is a set of statistical estimation tools involving quantities which vary in space and time. Geostatistics can be applied to identify spatial landscape scale processes and generate reliable prediction, and is a more effective research tool in comparison to conventional statistics to understand and explain landscape-scale variation in forest and agricultural systems (Morkoc *et al.,* 1985; Wendroth *et al.,* 1992; Nielsen *et al.,* 1999; Dourado-Neto *et al.,* 1999; Timm *et al.,* 2000, 2001). Under such conditions, according to Wendroth *et al.* (1998), local trends are best verified with nearest neighbor analysis. Several statistical tools have been used to evaluate the variability of soil properties, which can contribute to improve management and the understanding of plant-soil-water and atmosphere interactions (Vieira *et al*., 1981; Cassel, 1983; Wendroth *et al*., 2001; 2003; Dourado-Neto *et al*., 1999; Timm *et al*., 2003a; 2004;

Tominaga *et al*., 2002; Martínez and Zinck, 2004). Relatively, few studies (Shaw and Carter, 2002; Ogunwole *et al.,* 2005; Samndi, 2006; Timm *et al*., 2006) have evaluated the spatial variability of soil properties in forest ecosystems. This work is an attempt to characterize and describes heterogeneity in soil physical and chemical properties of a forest ecosystem.

The general objective of this study was to assess the heterogeneity of soil properties of Nimbia Forest Reserve in Southern Guinea Savannah of Nigeria for site-specific management. The specific objectives were to:

I. Describe the field-scale horizontal spatial variability in soil properties of a block in the Forest Reserve.

II. Describe the degree of linear associations within and between the selected soil properties of a block in the Reserve.

III. Develop models for predicting the soil aggregate stability from other soil properties.

CHAPTER TWO

LITERATURE REVIEW

2.1 HISTORY OF THE REGIONALIZED VARIABLE THEORY

The term regionalized variables was coined by Matheron (1965) to describe those sets of measurements, distributed across time and space, presenting a mutual dependence inherited from the proximity of their sampling location. The problems of estimating and mapping these variables arose in meteorology (Gandin, 1965) and in mining (Matheron, 1965) where the concentrations of minerals and the thickness of ore bodies vary in space. Gandin (1965) describes the application of optimum interpolation, developed by Kolmogorov (1941), for estimating the values of atmospheric pressure and rainfall at sites between the recording stations.

The need for solutions was more pressing in mining because of the enormous costs incurred, and it was in mining that the advance in spatial analysis was made. Matheron (1965, 1971) brought together a number of isolated results in spatial statistics (Kolmogorov, 1941; Krige, 1951; Matem, 1960; Yaglom, 1962) into a coherent body of theory, the theory of regionalized variables. This theory describes comprehensively and quantitatively the kind of variation that is characteristic of geological deposits and many other properties of the earth's surface.

Regionalized variable theory was developed largely by Matheron at the Paris School of Mines, and it is now applied widely in mining (Guarascio *et al.,* 1976; David, 1977; Journel and Huijbregts, 1978; Verly *et al.,* 1984) for estimating the concentrations of minerals in ore bodies and recoverable reserves, and in planning operations. The theory of regionalized

variables is intended for solving specific mathematical problems, namely, the structural description of the spatial variation in natural materials and the development of an optimal tool for data interpolation and interpretation of the results (Kuzyakova *et al*., 2001). The set of techniques used to analyze regionalized variables is known as geostatistics. Geostatistical methods are applicable throughout the discipline of earth sciences, especially where information is fragmentary and there is a need to maximize its use.

Although the phenomenon of spatial variation of soil properties had been recognized earlier (Wilding *et al*., 1965; Beckett and Webster, 1971), it was not until the late 1970s and early 1980s that soil scientists began to pay attention to methods of interpolating values of soil properties directly from point observations. The study of how geostatistical methods can assist soil variability has been a subject at international soil science meetings since 1983 (Giltrap, 1984; Nielsen and Bouma, 1985) and remains a theme of current interest.

2.2 CONCEPT OF REGIONALIZED VARIABLE THEORY

The concept of the regionalized variable theory is that interpolation from points in space should not be based on a smooth continuous object. It should be, however, based on a stochastic model that takes into consideration the various trends in the original set of points. The theory considers that within any dataset, three types of relationships can be detected:

- Structural component (spatial trend or just the mean)
- Correlated variation (Random, spatially autocorrelated regionalized variable or local spatial autocorrelation)
- Uncorrelated variation or random noise (stochastic variation, not dependent on location)

The general statistical approach to prediction embodied in the theory combines a deterministic component, such as that of trend surface analysis, with a stochastic one, so that the spatial variation in a property is expressed by:

$$( ) = \sum \quad ( ) + \varepsilon( ) \qquad [2.1]$$

where, denotes the spatial coordinates in one, two or three dimensions, the f_k, k= 0, 1, . . ., are functions of the spatial position, the , are unknown coefficients, and $\varepsilon( )$, is a random component that is itself spatially dependent (Webster, 1985; Oliver *et al*., 1989).

Thus, the first term on the right hand side of equation [2.1] represents the deterministic element of the variation, and the stochastic element is embodied in the second. Earth scientists have discovered empirically that the stochastic component is by far the larger in most instances. To make use of this notion and generalize equation [2.1] certain stationarity assumptions are made.

a) The first order stationarity which assumes that the expected values of z at any location x or the random function z(x) is the mean μ or the same at all locations throughout the study region.

$$[( )] = \qquad [2.2]$$

where is the arithmetic mean in the classical statistics.

But where there is a drift or trend, a suitable function describing this structural component that replaces is given by the expression;

$$[( ) - (+ h)] = 0 \qquad [2.3]$$

where h is the vector of separation between sample locations.

b) The second order stationarity does not apply if a finite variance and covariance cannot be defined as in the case of trend phenomena that is for any h the difference $( ) - (+ h)$ must have a finite variance which is independent of position or location within the region (David, 1977).

$$[( ) - (+ h)] = [( ) - (+ h)] = 2 (h) \quad [2.4]$$

These assumptions that the mean and the variance of the differences are both stationary constitute Matheron's Intrinsic Hypothesis (Matheron, 1971). The quantity γ(h) is known as the semi-variance: it is half the expected squared difference between two values. As above, it depends on h, and the function that relates γ to h is the semi-variogram or increasingly just the variogram. Where the intrinsic hypothesis holds, the variogram contains all the information about the spatial variation of the property of interest. Furthermore it enables the semi-variances to be estimated from a sample of a single realization of the underlying process.

2.3 ANALYTICAL TOOLS EMPLOYED IN GEOSTATISTICS

Geostatistics is a method for characterizing the regular component of the variation in natural objects including soils. The application of geostatistics in soil science ensures that a quantitative description of the spatial variation of soil improves accuracy in the estimation of soil properties for data interpolation and map compilation and forms the basis for a rational design of soil sampling (Webster, 1985). It can be regarded as a collection of numerical techniques that deal with the characterization of spatial properties (Olea, 1999), offering 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 is based on the concepts of regionalized variables, random functions and stationarity (Trangmar *et al*., 1985) and include two fundamental components (Isaaks and Srivastava, 1989) namely: i) spatial continuity analysis and ii) interpolation. Geostatistical tools like autocorrelograms, crosscorrelograms, semivariograms, kriging, state-space models, etc, are now used to study the spatial variability of soil properties, and can potentially lead to management practices that allow a better understanding of the interactive processes within the soil-plant-atmosphere system (Vieira *et al*., 1981; Vauclin *et al*., 1982; Morkoc *et al.*, 1985; Shumway, 1988; Katul *et al*., 1993; Wendroth *et al*., 1997; Dourado-Neto *et al*., 1999; Nielsen *et al*., 1999; Wendroth *et al*., 2001; Timm *et al*., 2001; Webster *et al*., 2005; Timm *et al*., 2006; Li *et al*., 2007; Balasundram *et al*., 2008).

2.3.1 Autocorrelation

The autocorrelation function is a tool that reflects the local variation between samples for different separation distances, being used to identify the range of the spatial correlation of the observations of a property (Journel and Huijbregts, 1991). This was done with the objective of evaluating the spatial correlation of the observations using a t-test at 5% probability. For a property Y, its mean and variance are calculated to reflect the sampled population, assuming that the set is representative and obtained randomly. In many cases the observations are not independent of each other, and it is possible to calculate an autocorrelation coefficient, when plotted as a function of the distance between observations will indicate their level of auto-dependence. For stationary processes (those in which the

static properties are independent of space or time), the covariance between observations is a function of the number of lags h between their sampling points. Time series are collected along time at intervals of minutes, hours, months, etc, and space series along transects (or grids) at spacing of cm, m, km, etc. Autocorrelation coefficients for pairs separated by a specified distance, *h* given by Salas *et al*. (1988) is;

$$(h) = \frac{[\ (\ ),\ (\ \ )]}{[\ (\ )]\ \ [\ (\ \ \ )]} \qquad [2.5]$$

where cov and var are covariance and variance respectively.

The variance is calculated according to equation [2.6],

$$= \frac{1}{-1} \quad (\ \ - \ \ \square) \qquad [2.6]$$

and the autocovariance by Salas *et al*. (1988);

$$[\ (\ ),\ (\ \ + h)]$$

$$= {}^{1} \qquad [\ (\ ) - \ \ \square][\ (\ \ + h) - \ \ \square] \qquad [2.7]$$

The autocorrelation function for a specified distance $h = 0$, for pairs ( ), ( ) is 1 ie r(0) = 1. For pairs ( ), (+ 1) at distance $h = 1$ and ( ), (+ 2) at distance $h = 2$, values of r(1) and r(2) can be obtained respectively. The maximum value of r(h) is 1 at zero distance (h = 0) and values decrease with increasing h. A plot of the autocorrelation function values r(h) verses the distance (lag) h is called autocorrelogram.

Autocorrelograms have been used to express spatial changes in field-measured soil properties and the degree of dependency among neighbouring observations (Webster and

Cuanalo, 1975; Vieira *et al*., 1981; Sisson and Wierenga, 1981). Such information aids identification of the maximum sampling distance for which observations remain spatially correlated and can be used in designing soil sampling schemes (Vieira *et al*., 1981) or defining minimum cell size for interpolation by moving average techniques (Webster, 1978). Spatial analysis of soil properties using autocorrelograms has been restricted to data sampled at regular spacing along transects (Webster and Cuanalo, 1975; Gajem *et al*., 1981) or grids (Vieira *et al*., 1981) and time intervals.

Autocorrelation confidence interval (CI) can be measured to determine whether an autocorrelation coefficient, (h) is significantly different from zero or not, in different ways;

- using the accumulative probability function, (e.g., ± 1.96 for a 95% probability level) for a standardized normally distribution function (Davis, 1986), and the number of observations (n). Therefore,

$$. \quad . = \frac{\pm}{\sqrt{}} \qquad [2.8]$$

- the accumulative probability function under the assumption that (h) is normally distributed, C.I. (h) for each respective lag distance can be calculated by Barlett (1946);

$$. \ (h) = \pm \frac{}{\sqrt{}} \quad 1 + 2 \qquad [2.9]$$

Morkoc *et al*. (1985) applied equation [2.9] to determine sorghum yield before and after detrending operations.

- using autocorrelation length, λ (the distance over significant correlation exists) commonly defined for a transect by the relation (Nielsen and Wendroth, 2003);

$$(h) = \qquad (-h/\lambda) \qquad [2.10]$$

Where the value of =1 and that of (h) is diminished to e^{-1} at a lag distance of h=λ. With =1, the magnitude of λ is calculated from;

$$(h) - \exp(^{h} \quad) \qquad [2.11]$$

where n is the number of observations along the transect.

2.3.2 Cross-correlations

Cross-correlation analysis considers the spatial and temporal relationship between two different kinds of measurements. While each kind of measurement manifests its own spatial and temporal autocorrelation, an analysis of the cross-correlation reveals over what distances or intervals in space or time, the two measurements are related to each other (Nielsen and Wendroth, 2003). Having two sets of variables Y and W observed at the same locations x_i or times t_i, their spatial cross-correlation structure can be analyzed by calculating coefficients of crosscorrelation. The cross-correlation coefficient, r_c describes the degree of linear association between pairs of the two different kinds of values or variables separated by a given distance (Davis, 1986; Shumway, 1988; Wendroth *et al.,* 1997) and are calculated with;

$$(h) = \frac{[\quad (\quad),\quad (\qquad)]}{\overline{\quad 2} \quad \overline{\quad 2}} \qquad [2.12]$$

where:

$$[\ (\ ),\ \ (\ \ +h)] = {}^{1} \qquad [\ (\ ) - \ ][\ \ (\ \ +h) - \ ] \qquad [2.13]$$

while and are the variances defined below;

$$= \frac{1}{-1} \quad [\ (\ ) - \ \square] \qquad [2.14]$$

$$= \frac{1}{-1} \quad [\ \ (\ ) - \ \ \square] \qquad [2.15]$$

A plot of r_c as a function of h represents the crosscorrelogram. For h = 0 (observations taken at the same position xi), the value $r_c(0)$, is the linear regression coefficient obtained through classical statistics. For the first neighbor pairs [Y(xi), W(xi+1)] collected at a distance h in one direction (h = 1), the coefficient r_c (1), and for the other direction (h = -1), the coefficient $r_c(-1)$. This is because in the case of two variables, each of them has different neighbors for each direction, i.e., two pairs – (Yi, Wi+1) and (Yi, Wi-1). The same procedure is used for more distant neighbors, obtaining values of $r_c(h)$ and $r_c(-h)$. A crosscorrelogram indicates how far two different observations are spatially related (Wendroth *et al.,* 1997).

According to Nielsen and Wendroth (2003), it is more difficult to estimate the significance of $r_c(h)$ as compared to r(h). Significance tests such as *t* test are usually based on the assumption that values of Y(xi) and W(xi) are normally distributed and that values of Y(xi) are independent of each other and those of W(xi) are also independent of each other. Taking this into consideration, the significance level of r_c is often assessed by;

$$= \frac{\overline{\quad}}{\overline{\quad}} \qquad [2.16]$$

where n is the number of pairs used for the calculation of r_c. The level of significance of the test is obtained by comparing the value of t in equation [2.16] with critical values of t for (n-2) degrees of freedom.

In general, crosscorrelation function is not symmetric, i.e., $r_c(h) \neq r_c(-h)$. However, where there is a known physical relation between two spatial series (Y and W), the crosscorrelogram tend to be symmetry (Nielsen and Wendroth, 2003).

2.3.3 Semivariogram

The core tool in geostatistical analysis is the semivariogram; a principle component analysis of all the measured data to determine parameters that best explain variability (Hui *et al.,* 1998), i.e. a measure of dissimilarity between two points in space separated by a distance *h.* A semivariogram represent dependence of semivariances on distance, *h* that is it characterizes the difference between pairs of observations separated by a distance h, rather than on their individual magnitude or their product of deviations from the mean (Kuzyakova *et al*., 2001; Nielsen and Wendroth, 2003). Theory of regionalized variables considers the difference between pairs of values of a property at places or locations separated by any distance and express these as variances.

Assuming the value of a regionalized variable z(x) and z(x+h) at location x with x and x+h as spatial coordinates and h as vector with both distance and direction separating them. The per observation variance (semivariance) between pairs or average variance associated with differences in value of z over a distance h, is assessed by;

$$(h) = -[\ (\ ) - \ (\ \ + h)] \qquad [2.17]$$

While for n pairs of observations by the same distance, semivariance can be estimated by the following formula (Burgess and Webster, 1980a)

$$(h) = 1_{\ 2} \qquad [\ (\ ) - \ (\ \ + h)]^2 \qquad [2.18]$$

Where:

h = the separation distance between location x_i or x_{i+h}

$Z(x_i)$ or $Z(x_{i+h})$ = the measured values for the regionalized variables at location x_i or x_{i+h}

N = the number of pairs at any separation distance h

Plotting semivariances against distance *h* is known as semivariogram and it basically measures the reduction in variance between sampled points as separation distance decreases. Semivariogram is the main characteristic of the spatial structure of natural object variation. In practice, the semivariogram is modeled using several authorized models (Oliver, 1987; Isaaks and Srivastava, 1989). These models are then fitted to the semivariogram data.

2.3.3.1 Characteristics of the Semivariogram

Key features of semivariogram models are described by three parameters, namely nugget, sill and range.

Nugget: Nugget is a measure of the amount of variance imposed by errors in sampling, measurement and other unexplained source(s) of variation or random variance. Ideally, the experimental semivariogram should pass through the origin when the distance of sample separation is zero. However, many soil properties have non-zero semivariance called nugget variance or effect (Journel and Huijbergts,

1978) as h tends to zero. The nugget effect, c_0, represents unresolved variation while the structured component, c_1, represents the spatially correlated variation.

- **Sill:** Sill refers to the total vertical scale of the semivariogram whereby the semivariance becomes constant as distance between sample location increases. The sum of nugget variance, c_o and spatial correlation variation, c_1 approximately equals the sill or sample variance for stationary data. The sill, c_0+c_1, is a 'priori' variance.
- **Range:** Range is the separation distance that reflects a cutoff between spatial dependence and spatial independence. This implies that at separation distance greater than the range, sampled points crease to be spatially correlated (i.e. random). Samples separated by distance closer than the range are spatially related while those separated by distance greater than the range are not spatially related because the semivariance equals variance, implying random variation (Trangmar *et al.*, 1985). The range also defines the maximum radius from which neighboring samples are drawn for interpolation by kriging. Range depends on the scale of observation and the spatial interaction of soil processes affecting each property at the sampling scale used (Gajem *et al*., 1981; Yost *et al*., 1982a). The range, a, represents the scale (or frequency) of spatial variation.

2.3.3.2 Modeling Semivariogram

A mathematical model may be fitted to the experimental semivariogram and the coefficient

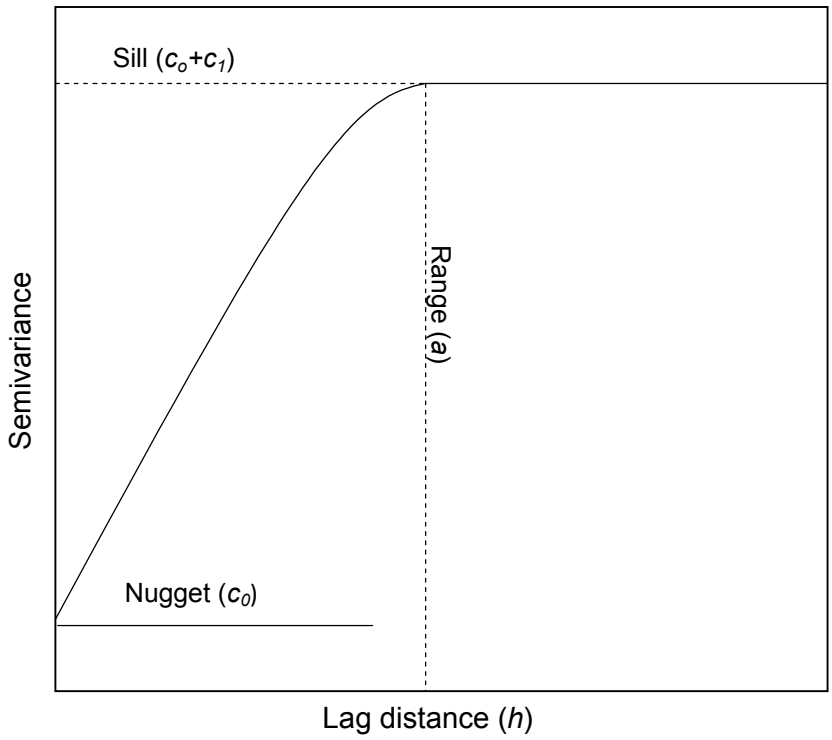


Figure 2.1: The parameters of a bounded semivariogram model with a nugget effect.

of this model can be used for a range of geostatistical operations such as spatial prediction (kriging) and stochastic or conditional simulation. A model is usually selected from one of a set of authorized models. Models are of two principal classes depending on whether or not experimental semivariogram exhibits a sill. Transitive (bounded) models have a sill (finite variance), and indicate a second order stationary process. Unbounded models do not reach an upper bound; they are intrinsic only (McBratney and Webster, 1986). McBratney and Webster (1986) and Chiles and Delfiner (1999) provide a review of some of the most widely used authorized models. The main types of semivariograms, formulas for their description, and processes determining the type of variation are presented below;

- **Linear model (see Figure 2.2a and b):**

Linear model is the simplest form of semivariogram model that can be fitted in one dimension. It can be transitive (without sill) or intransitive (with sill).

1. Linear without sill: It has a slope and may have an intercept or nugget variance. If the slope is zero then the semivariogram is said to show pure nugget effect implying no spatial dependence at the scale of investigation since all of the variances occur within the smallest sampling interval.

$$(h) = \quad + \quad - \qquad [2.19]$$

2. Linear with sill: The limiting case of transitive model, caused mainly by sharp inflection.

$$(h) = \begin{matrix} + & - & h < \\ + & & h \geq \end{matrix} \qquad [2.20]$$

❖ **Spherical model (see Figure 2.3):**

The spherical model actually reaches the specified sill value, at the specified range, *a*. The variation is determined by the moving average of randomized process and defined by;

$$(h) = \begin{matrix} + & 1.5 - 0.5 & - & 0 < h \leq \\ & + & h > \end{matrix} \qquad [2.21]$$

❖ **Exponential model (see Figure 2.4):**

The variance is influenced by the poisson processes and approaches the sill asymptotically with no strict finite range. The formula of the exponential model is;

$$(h) = \quad + \quad 1 - \qquad - - \qquad [2.22]$$

where r is a distance parameter controlling the spatial extent of the function. The semivariance creases to increase beyond some point, so for practical purposes a common used rule of thumb is to take this as the effective range, a';

$$' = 3 \quad ; \quad (\ ') = \quad + 0.95 \qquad [2.23]$$

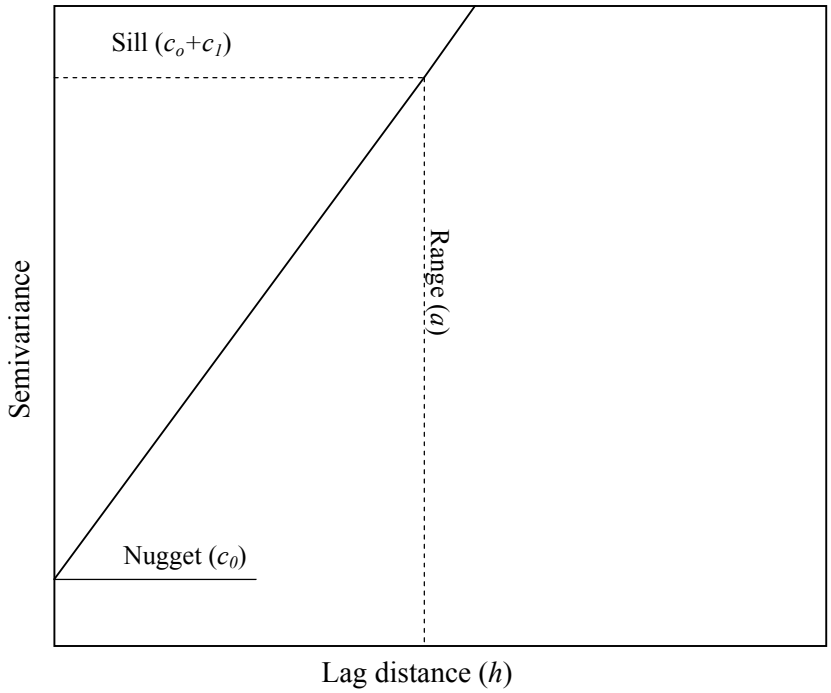


Figure 2.2a: Linear semivariogram model without sill

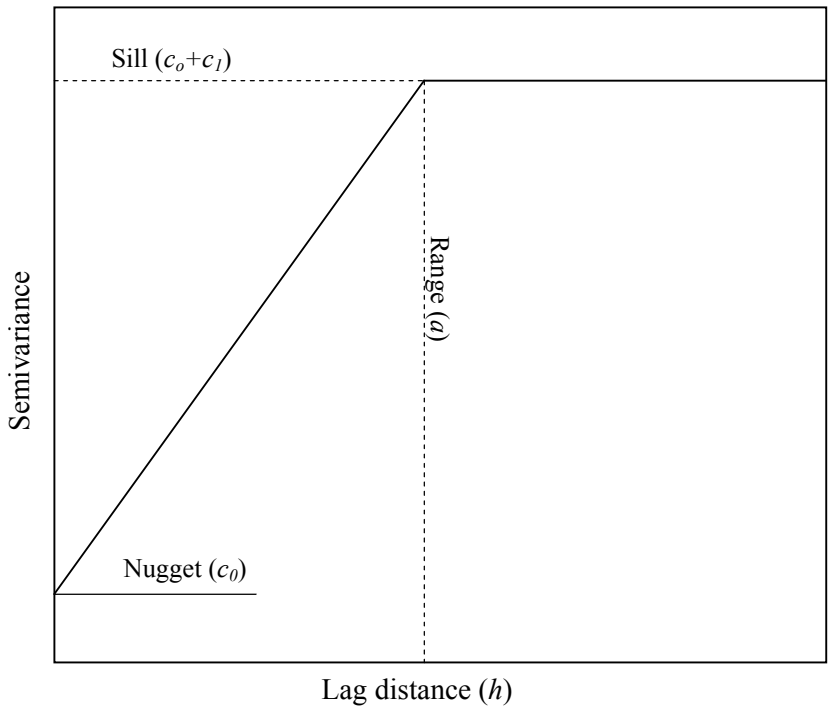


Figure 2.2b: Linear semivariogram model with sill.

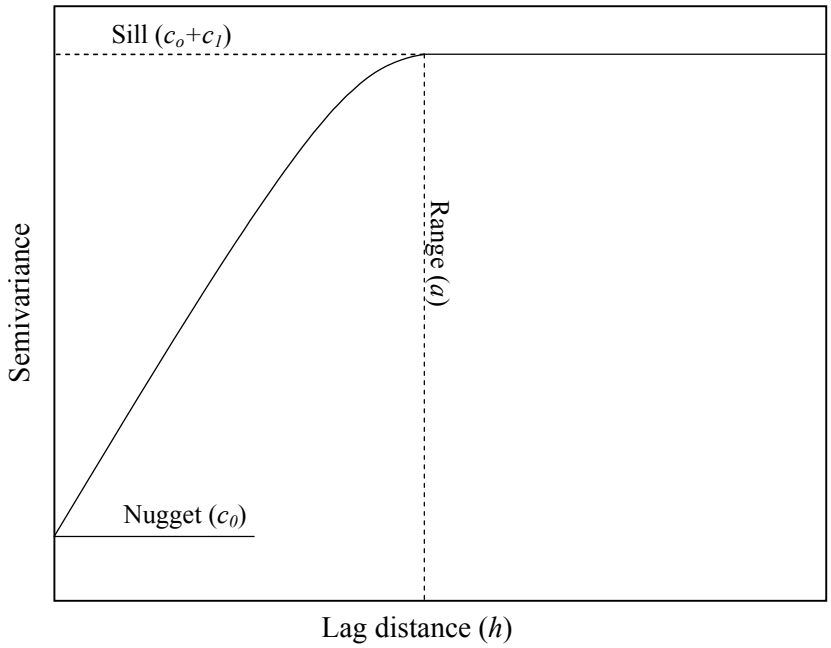


Figure 2.3: Spherical semivariogram model

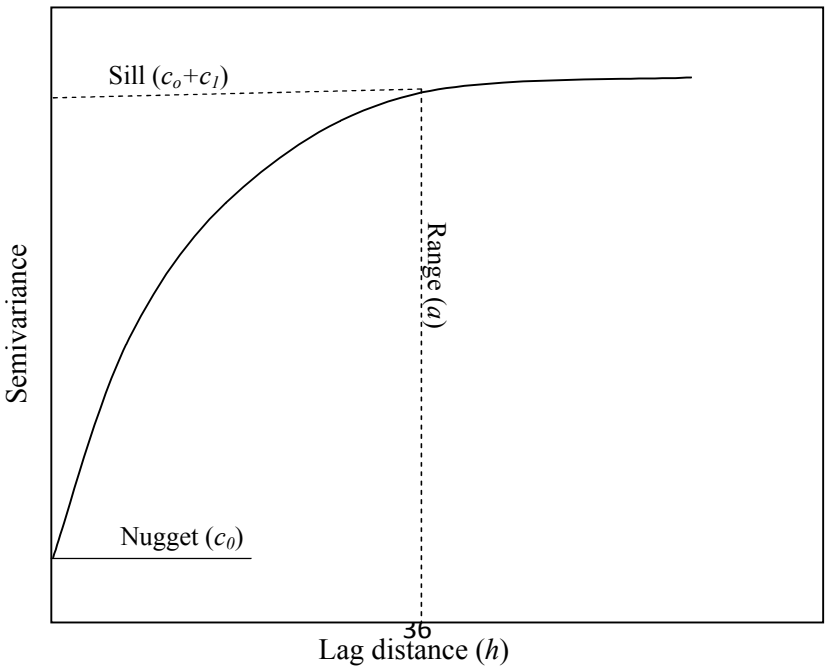


Figure 2.4: Exponential semivariogram model.

- **Gaussian model (see Figure 2.5):**

  The Gaussian model, with its parabolic behavior 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. It is a gradual approximation to nugget and the model is estimated by;

$$(h) = \quad + \quad 1 - \quad - \qquad [2.24]$$

  Where; *r* is a distance parameter as in the exponential case.

- **Power model (see Figure 2.6):**

  The power model does not reach a finite sill and does not have a corresponding covariance function. Power-law semivariogram models are appropriate for properties exhibiting fractal behavior.

$$(h) = \quad + \quad (h \ ) \quad 0 < \quad < 2 \qquad [2.25]$$

In general, the spherical and exponential models exhibit linear behavior at the origin, appropriate for representing properties with a higher level of short-range variability. The exponential and Gaussian models approach the sill asymptotically, with *a'* representing the practical range, the distance at which the semivariance reaches 95% of the sill value. Gaussian, exponential and spherical models with a finite sill are referred to as transition models and have corresponding covariance functions given by

$$(h) = [\quad + \quad] - \quad (h) \qquad [2.26]$$

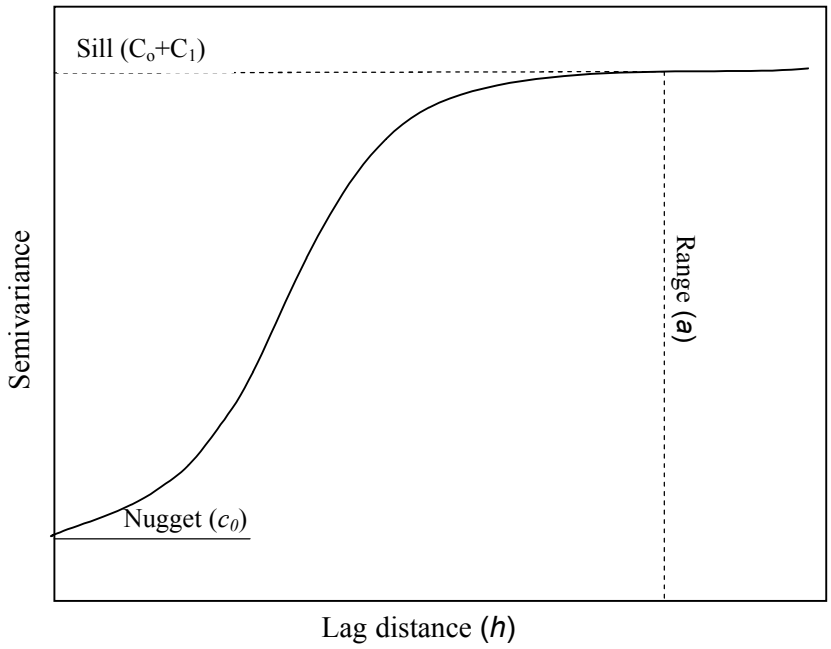


Figure 2.5: Gaussian semivariogram model

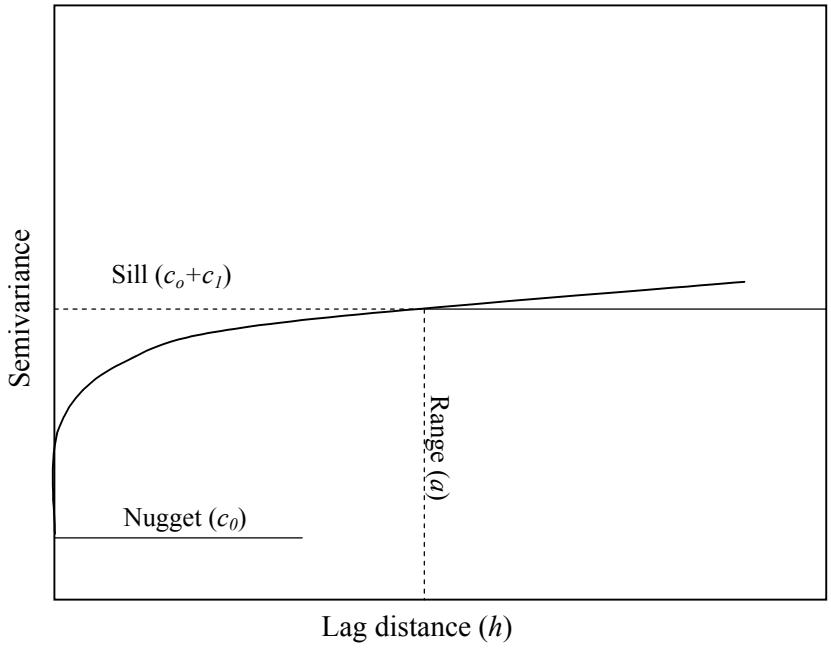


Figure 2.6: Power semivariogram model.

2.3.4 State-space analysis

The state-space model of a stochastic process is based on the property of Markovian systems that establish the independence of the future of the process in relation to its past, once given the present state. In these systems, the state of the process condenses all information of the past needed to forecast the future. The model can be constructed on the basis of physical laws and relationships, rate laws of chemical reactions, or system identification (Ljung and Soderstrom, 1983; Ljung, 1999). A state-space model is a set of first-order differential or difference equations (state equation) and an observation of equation to describe the relationship between the input and output of a dynamic system (Timm *et al*., 2003). The observation equation is expressed as;

$$(\quad) = \quad (\quad) \quad (\quad) + \quad (\quad) \qquad [2.27]$$

where observation vector, ( ), of the process is generated as a function of the state vector, ( ). The state equation is given as;

$$(\quad) = \emptyset \quad (\quad) + \quad (\quad) \qquad [2.28]$$

The observation vector ( ) is related to the state vector ( ) through the observation matrix ( ) and by the observation error, ( ). On the other hand, the state vector ( )at position *i* is related to the same vector at position *i-1* through the state coefficient matrix $\boldsymbol{\emptyset}$ (transition matrix) and an error associated to the state ( ) with the structure of a first order autoregressive model. It is assumed that ( ) and ( ) is normally

distributed and independent as well as being non-correlated among themselves for both lags.

The above equations contain distinct perturbations or noises, one associated with observations, ( )) and the other with state, ( ). According to Gelb (1974), the development of methods to process noise-contaminated observations can be credited to the work carried out by Gauss and Legendre (around 1800) that developed the method of the minimum squares for the linear models. Plackett (1950) developed a recursive solution for the minimum square method in linear models. Kalman (1960) using a state-space formulation, developed a very good recursive filter for estimations in stochastic, dynamic linear systems, being well known today as the Kalman Filter KF.

Kalman-Filter can be used to predict the states and estimate the parameters (Ljung and Soderstrom, 1983) of the state-space models in spatial and temporal statistics of soils and their vegetation (Nielsen *et al.,* 1994; Wendroth *et al.,* 1999; Stevenson et *al.,* 2001; Wendroth *et al.,* 2001; Timm *et al.,* 2003b; Wendroth *et al.,* 2003). Russell (1977) used two-dimension state-space models to describe and predict the transformation of available and unavailable soil nutrients. Mansell *et al.* (1977) used four- dimension state-space models to describe the mechanisms of phosphorus transfer among solution, adsorbed, immobilized (chemisorbed), and precipitated phases within a soil. According to Timm *et al.* (2003b), depending on the objectives of a study involving the state-space methodology, three different types of estimates can be made: a) when the time (or space) at which an estimate is wished coincides with the last observed value, the problem is said to be one of filtering; b) when the time (or space) of interest is inside the set of observations, i.e., the complete set of data is used to estimate the point of interest, the problem is said to be one of

smoothing; and c) when the time (or space) of interest is after the last observation, the problem is said to be one of forecasting. Therefore, any linear or non-linear model (Katul *et al*., 1993) can be represented in the state-space formulation, i.e., by a system of two equations: one for the observations vector and another for the evolution of the state vector.

The state-space approach can also be used like the kriging and co-kriging (Alemi *et al*., 1988; Deutsch and Journel, 1992) to interpolate data spatially (or temporally). However, the philosophy behind these tools is different. For kriging and co-kriging the condition of stationarity of the data is required, which is not the case in state-space (Shumway, 1985). Based on the linear system of dynamic equations (2.27 and 2.28), two forms of the state-space analysis or approach exist. The first is Shumway's state-space approach used by several researchers in agronomy (laid most emphasis on the state equation) and the second approach was introduced by West and Harrison (1989, 1997), with most emphasis on the observation equation, although not frequently used in agronomy.

2.3.4.1 Shumway's State-Space Approach

The first approach presented by Shumway (1988) and later by Shumway and Stoffer (2000), gives more attention to the equation of the evolution of the state of the system, where the matrix of the transition coefficients, $\emptyset$, in equation (2.28), is a matrix of dimension *jxj* that indicates the spatial measure of the linear association among the variables of interest. These coefficients are optimized through a recursive procedure, using an algorithm of the KF type (Shumway and Stoffer, 1982) in which the method of maximum likelihood is used together with the mean maximization algorithm of Dempster *et al*. (1977). Equations (2.27 and 2.28) are solved assuming initial values for the mean and

the variance of each variable in the covariance matrix R of the noise of the observations, for the covariance matrix Q of the noise associated with the state vector, for the matrix Ø of the transition coefficients, and for the observation matrix M. Because Shumway (1988) considers the matrix M as being a unit matrix (identity), equation (2.27), becomes;

$$(\quad) = \quad (\quad) + \quad (\quad) \qquad [2.29]$$

The unit matrix M is fixed during all steps of variable estimation, showing greater emphasis of this approach on the equation of state evolution, and not to the observation equation.

2.3.4.2 West and Harrison (1989, 1997) State-Space Approach

The bayesian formulation presented by West and Harrison (1989, 1997) was originally published by Harrison and Stevens (1976). In this case a general parametric formulation is used by which the observations are linearly related to parameters (equation 2.27), that have a dynamic evolution according to a random walk (equations 2.28), with the possibility of the incorporation of uncertainties associated to the model itself and to the parameters of the model. The probabilities of the model and its parameters are continuously updated in time/space using the Bayes theorem (Cantarelis, 1980). The acceptance and use of this approach was not as quick as expected, particularly by those without a deep knowledge in statistics, due to the difficulties in establishing values or their law of variation for the parameters " ( )" and " ( )". To make this approach more accessible, Ameen and Harrison (1984) used discount factors to calculate the covariance matrix of the noise parameters, ( ). Discount factors relate to the relevance of the observations during the evolution of time/space – with the most recent information usually being more relevant in the modeling process. The smaller the discount factor, the less importance is given to

previous information. Hence, the use of these factors assures that the stochastic influence on the evolution of the parameters is not directly made explicit through the noise; ( ). The stochastic influence is derived by the combination of a relation that establishes only the deterministic evolution of ( ) and the random process guaranteed by the discount matrix.

2.4 MERITS AND OPPORTUNITIES IN GEOSTATISTICS RELATIVE TO CLASSICAL FISHER'S STATISTICS

Variability of soil properties within mapping units or sampling units (field, experimental plots or pedons) are traditionally acknowledged and described by classical statistical methods (Webster, 1971; Wilding and Drees, 1983). The analysis of results with classical statistical methods assumes that the sampling unit mean is the expected value everywhere in the unit, with an estimation error expressed by the within-unit variance. This approach is based on the absence of spatial correlation between the values of parameters analyzed in the sampling units. All data are considered equivalent and independent (Kuzyakova *et al.*, 2001) assuming that mean variability is random and contain no reference to the geographical distribution of differences within the sampling units. (Trangmar *et al*., 1985). Although, several studies (Campbell, 1978; Burgess and Webster, 1980a; Gajem *et al.*, 1981; Vieira *et al*., 1981; Yost *et al*., 1982a; McBratney *et al*., 1982) have shown that this random aspect of soil variability contains a component that is spatially dependent. This implies that within a given distance or range of spatial dependence, differences in soil properties can be described as a function of their spatial separation. In order to decrease the initial variation of soil properties during long-term experiments, classical Fisher's statistics used a number of methods: an increase of the size of statistical sample, taking mixed

samples, analysis of average samples and the establishment of replicate experiments with the randomized block design (Kuzyakova *et al*., 2001; Jùnior *et al*., 2005). However unaccounted variations in soil management practices, soil forming factors and processes and other environmental conditions sometimes cause discrepant results in field experiment even within a given soil type.

The spatial variability of soil properties is too complex to be studied deterministically; a stochastic approach (Matheron, 1971) is a more appropriate method. In contrast to classical statistics, geostatistics based on the theory of regionalized variable enables the interpretation of results based on the structure of their natural variability, taking into consideration spatial dependence within the sample size (Goovaerts, 1997). Geostatistics are statistical approaches based on the study of regular variation component, rather than on the removal of the interfering variation that is variation on a point-by-point basis (Beckett and Webster, 1971; David, 1977; Burrough, 1983; Cressie, 1991). In this approach, a regular component characterized by certain spatial structure and a random component are distinguished in the soil spatial variation. The random component includes variation caused by both experimental errors and affecting factors that cannot be studied under specific experimental conditions (Kozlovskii, 1970; 1997). This method also allows one to characterize the regular component of variation and to interpolate data.

Geostatistics is widely applied for interpolation of soil properties and provide statistical optimal and unbiased predictions as well as certain estimate on the error of interpolation (McBratney and Webster, 1983a; Tao, 1995; Wang *et al*., 2003). Furthermore, Oliver *et al*. (1989) reported that geostatistics is an exact interpolator because estimation variance themselves can be estimated. Laslett *et al*. (1987); Myers (1994); Voltz and Goulard (1994)

compared geostatistical tool with other techniques of interpolation (distance-weighted average, trend surface, spline etc) and concluded that geostatistical tools was the only one that performed reliably in all circumstances. Geostatistical tools can also be applied to accurately and precisely predict landscape-scale variation (Stevenson *et al*., 2001) because it considered localized variation across field. Other reports (Morkoc *et al*., 1985; Wendroth *et al*., 1992; Li *et al*., 2001; Timm *et al.,* 2003b) have observed that geostatistical tools can be an effective research tool for understanding the physical, chemical and biological processes that controls the soil-plant-atmosphere system and therefore to adopt a better management practices with less environmental impact.

2.5 APPLICATIONS OF GEOSTATISTICS IN SOIL SCIENCE.

Geostatistical analysis of soil can greatly contribute to better understanding of the randomness and quantify the scale and the intensity of soil spatial variation. This technique has been applied to solving wide range of problems in soil science. Goovaerts (1998); Jiang (2002); Liang *et al*. (2005); Balasundram *et al.* (2008) had successfully applied the technique in their study of spatial distribution of soil physical, chemical and biological properties, showing that geostatistics is a powerful tool for the description and modeling the spatial variability of the soil abiotic and biotic properties. Geostatistics has been used to estimate nutrients and other soil constituents at unvisited sites and over larger areas (Burgess and Webster, 1980b; McBratney *et al.,* 1982; Webster and McBratney, 1987), to improve the efficiency of sampling (Burgess *et al.,* 1981; Webster and Burgess, 1984; Oliver and Webster, 1986a), and to rationalize spatial classification (Wackemagel *et al.,* 1988; Oliver and Webster, 1989). Moffat *et al.* (1986) used geostatistics to explore the processes responsible for variation in structure of the Chalk and Tertiary surfaces in the

Chiltern Hills, while Yost *et al.* (1982a); Oliver and Webster (1986b) used it to identify the causes of spatial variation in soil properties. Soil scientists predict spatial variability of soil properties with different kriging method over large spatial scale (Trangmar *et al*., 1987; Miller *et al*., 1988; Voltz and Webster, 1990; Chien *et al.*, 1997; Tsegaye and Hill, 1998; Lark, 2002; Li *et al.,* 2007). Increasing concern about how to estimate temporal changes of spatially varying soil properties led Papritz and Webster (1995) and Heuvelink *et al*., (1997) to estimate temporal changes of spatially autocorrelated soil properties using co-kriging method with pseudo-crossvariogram.

Sun *et al.* (2003) focused on evaluation of spatial and temporal changes of soil quality in the hill region of sub-tropical China. They aimed at assessing the suitability of geostatistical analysis for monitoring changes of soil quality in the area and concluded that geostatistics is an effective tool in monitoring soil quality changes. Several authors (Halvorson *et al*., 1995; Ogunwole *et al*., 2005; Timm *et al*., 2006) examined the application of geostatistics to investigating the spatial variability in soil physical properties and also opined that geostatistics is a useful tool in monitoring and evaluating soil quality changes.

Due to the multi-dimensional spatial processes involving soil variables (water, temperature, soil salinity, infiltration etc) and crop yield, soil scientists (Warrick *et al.,* 1986; Shunway *et al*., 1988; Ahuja and Nielsen, 1990) used state-space model, a geostatistical tool in soil analysis. Li and Lascano (1999) used state-space model to describe the spatial correlation between cotton lint yield, soil water, and phosphorus and site elevation. It has also been used to describe adequately the spatial association of wheat grain yield, soil based saturation and water storage capacity on a newly land shaped field in North Carolina (Cassel *et al.,* 2000). Nielsen *et al*. (1999); Wendroth *et al*. (1999) tested state-space

modeling to quantify localized variations and their findings indicated that this model provided an insight into the spatial pattern of soil and crop variables. Similarly, Timm and his colleagues used state-space model to evaluate sugar-cane production (Timm *et al*., 2003a) and the relation between soil physical and chemical properties (Timm *et al*., 2004). With this model, they tend to identify and eliminate factors involved in field processes for better understanding of the relation between measured soil variables and crop yield for optimal management of sugar-cane production in Brazil. They concluded that state-space model is a powerful tool for precision agriculture allowing management optimization of soil resources since it opens the possibility to examine physical and chemical properties that affects the crop yield within heterogeneous fields. This was also observed by Jùnior *et al*. (2005); Duffera *et al*. (2007); while examining spatial variability of soil physical properties for site specific management.

2.6 SPATIAL STUDIES INVOLVING SOIL PROPERTIES: RELEVANCE AND IMPLICATIONS FOR LANDSCAPES

Large areas of land have been managed as homogeneous, although presenting a considerable spatial variability inherent to soil, causing the appearance of zones of distinct soil physical properties and distinct soil fertility (Wendroth *et al.,* 2003). Moreover, soil scientists are restricted to limited observation of the earth surface, necessitating the extrapolation of soil properties from known to unknown locations. The precision of such extrapolation or the successful transfer of land use experience from known to unknown site is greatly influenced by the variability of soil both within samplings and between locations, and other environmental parameters. The desire to record, store and retrieve data from soil observations, including their exact locations and elevation on the ground paved the way for

the studies of the spatial variations of soil properties within the subjectively delineated landscape unit, ranging from global scale to micro scale (FAO, 1974).

Soil spatial variability occurs at different scales and is related to variation of parent material, climate, relief, organisms and time, that is related to the interaction of several processes of soil formation (Trangmar *et al.*, 1985) and/or effects of adopted management practices for each agricultural use (McGraw, 1994). As a result, the nature of variability identified by spatial studies of soil properties depends largely on the scale of observation, the property in question and the methodology used in conducting the investigation, (Wilding and Drees, 1983). Soil variability have largely been studied in different context: soil cartography (Beckett and Webster, 1971), evaluation of soil fertility (Melsted and Peck, 1973), planning and interpretation of field research (Wilding and Drees, 1983), and the study of physical and chemical properties of soil under different management regime (Trangmar *et al.,* 1987).

2.7 CHARACTERISTICS OF FOREST SOILS RELATIVE TO AGRICULTURAL SOILS

Forest land is usually land that is too poor, too rough, or too inaccessible to be farmed profitably and make up large ecosystems. Historically, the better soils have been cultivated while the poorer remained in native vegetation or if cleared, has been abandoned and left to return to forest cover. Soils in forest could result as a natural or only slightly disturbed material that took centuries to develop under permanent forest cover. A succession of genetic soil layers could be present, ranging from the very important surface organic layers down to the mineral parent material. Steinaker and Wilson (2005) observed that continual depositing of tree litter upon the ground for many decades developed the characteristic

surface layers of organic matter found in forest areas. Relatively little organic matter is lost by the infrequent and incomplete harvesting done on forest land (Jobbágy and Jackson 2000). Organic matter on the surface and in lower layers is maintained by relatively slow oxidation resulting from cool, shaded microclimatic conditions and from lack of disturbing effects of cultivation used on agricultural land. On most agricultural land, the surface organic layers and surface soil horizons have been mixed and altered beyond identity by decades of cultivation. Large amounts of organic matter and nutrients are annually lost when crops are harvested. Furthermore, the incorporated organic matter decomposes more rapidly because cultivation and high temperatures help speed up oxidation. When forest vegetations are removed and the land is used for agriculture, the soil structure generally deteriorates. This deterioration, evidenced by reduced pore space, increased bulk density, increased compaction, reduced content of water-stable aggregates, and reduced rates of infiltration, has marked effects on surface water runoff, stream flow, and sedimentation (Gifford, 2000).

The structure of forest soils is developed and maintained by many factors of the forest environment. The soil surface is protected from impact of raindrops because forest canopy and surface organic layers absorb the energy of falling raindrops. Agricultural soils are exposed to a variety of stresses (direct beating action of raindrops) that may destabilise the inherent aggregate structure (Young and Ritz, 2000; Christensen, 2001). Soil colloids are suspended and are washed into and deposited in the larger pores that are necessary for rapid infiltration and percolation of water. Organic matter on and in soils help improve and maintain soil structure. Organic colloids and materials synthesized by soil fungi and bacteria are important in the formation of soil aggregates. Soils used for agriculture

however, do not usually have enough organic matter in the surface layers to maintain the large populations of microorganisms found in forest soils. Reduced action of microorganisms as well as reduced organic colloid content is thus partially related to poor structure of many agricultural soils.

In addition to microorganisms, soils in forests have relatively high population of macroorganisms that favors soil structure and produces many large burrows and channels. The large number of root channels, as well as the excellent structure of "forest soils", undoubtedly accounts for the rapid infiltration rates and reduced runoff of surface water so often reported from forest land. Cultivating agricultural land that is too wet frequently produces cloddy or puddled conditions that cause a decrease in aggregation and porosity (Majdi *et al.,* 2005). Generally, the use of heavy machinery and excessive grazing of both agricultural and forest soils usually compact surface soil layers and cause increased water runoff, decreased soil porosity and water infiltration rates

2.8 IMPLICATIONS OF FOREST EXPLOITATION ON SOIL PROPERTIES

Bada and Verinumbe (2005) noted that forest exploitation is as old as human habitation. Forest resources especially in developing countries are undergoing severe exploitation pressures due to demographic growth and socio-economic development. Unsustainable exploitation of forest resources by growing population and its dependence on forest for fulfillment of requirement like fuel, fodder and timber has caused rapid loss of vegetation leading to severe land degradation, reduction in soil fertility and increased soil erosion (New Era, 1997; Maskey and Joshy, 1998). The indiscriminate felling of trees and clearing of forest areas for agriculture, overgrazing, forest fire and improper land use pattern among others have given rise to scarcity of such essential needs of rural people such as fuel wood,

fodder, and small timber resulting in serious environmental/soil degradation (Karkee, 2004).

2.8.1 Forest fire

Wildfires are one of the most wide-spread factors responsible for ecosystem degradation around the world, by destroying the vegetative cover and increasing nutrient and soil losses by leaching and erosion (Chandler *et al.,* 1983; Naveh, 1990). Fire greatly alter the physical characteristics of soil; during burning plant cover and litter layers are consumed and mineral soil is heated up resulting in changes of soil bulk density, porosity, texture, colour, moisture content and permeability (Wells *et al.,* 1979; Ekinci and Kavdir, 2005). Recovering of soil health is very low after soil fire. Choromanska and DeLuca (2001) reported that carbon and nitrogen mineralization decreases after fire and did not recover after nine months of their study period. The changes and composition of soil microbial biomass and enzymes activities are also indicators of fire stress in managed ecosystems (Dick and Tabatabai, 1992; Dick, 1994; Bergstorn *et al.,* 1998). Soil aggregate stability and soil organic matter constituents also decrease due to combustion of cementing organic substances (Giovannini *et al.,* 1988; Fernandez *et al.,* 1997). According to Giovannini and Lucchesi (1997) and Guerrero *et al.* (2001), soil physiochemical changes are related to temperature reached during fire. Heating of soil up to 600°C resulted in decreased organic matter content, but increased macro-aggregation. This heat induced aggregation has been attributed to dehydration of soil gels and thermal transformation of the cementing iron and aluminum oxide with temperature >220°C (Giovannini *et al.,* 1990). Loss of soil organic carbon was shown to differ among soil aggregate fractions; fire mainly reduced soil organic carbon pools associated with macro-aggregate whereas micro-aggregate- associated carbon

was not affected (Garcia-Oliva *et al*., 1999). They suggested that the macro-aggregate-C loss by combustion will weaken biological aggregate mechanism in the long term.

In the short term, fire causes an increase of available nutrient in the soil, mainly in the form of water-soluble component of ash (Pyne, 2001). There are two schools of thought on forest fire, one strongly believes that fire is alien to this ecosystem and should completely be eradicated from forest whereas the others believes that fire is an integral part of this ecosystem and they are necessary for the maintenance of the ecological functions. Prescribed and regular or low frequency forest fire can eliminate undesirable vegetation from the land, modify level of N, P, pH, SOM and clay mineral to generate enhanced CEC and re-establish desired vegetation (Hernandez *et al*., 1997; Johnson and Curtis, 2001; Krishnaswamy and Richter, 2002; Certini, 2005; Silva and Batalha*,* 2008). On the other hand, wild or high frequency forest fire alter soil features; negatively influencing soil biological properties, disturb surface cover, increase surface runoff and erosion and degrade soil ecosystems (Leigh and Vermei, 2002; Bond and Keeley, 2005; Silva and Batalha, 2008).

2.8.2 Grazing

Grazing associated with animal activity is known to alter hydraulic and mechanical properties of soil. Trampling animals cause soil deformation by exerting high ground-contact pressures under their hooves (Yong-Zhong *et al.,* 2005; Zhao *et al.,* 2007). Besides soil compression, shear stresses further destroy soil structure due to kneading and

homogenization, which cause a change in macroporosity and the connectivity of the pore system. Such changes depend not only on the magnitude of applied stresses, but also on aggregate stability at the time of trampling, which depends on soil moisture (Zhao *et al.,* 2007). Generally, grazing has been found to affect the physical condition of soil near the surface, because of hoof action, nutrient storage and cycling potential through grazing intensity, urine and dung deposition (Liebig *et al.,* 2006).

Overgrazing causes a decline in soil physical, chemical and biological properties, resulting in dramatic changes in vegetation. Moreover, modifications in nutrient cycling led to permanent degradation of land productivity and destruction of the ecosystem (Pei *et al.,* 2008). Higher bulk densities and lower elemental concentrations in heavily grazed areas may also be caused by erosion. Increased bulk densities and decreased organic carbon concentrations in grazed areas are due to the combined effect of loss of organic matter following animal trampling, and lower above- and below-ground organic matter input as a consequence of grazing (Smit and Kooijman, 2001; Steffens *et al.,* 2008). Overgrazing has led to significant changes in plant cover and in some places to the complete absence of vegetation cover. The degradation of vegetation exposes soil surface directly to wind and water erosion, leading to loss of the fertile top soil and its content of nutrients and seeds (Kumbasli *et al.,* 2010). The soil becomes compacted by animals trampling, thereby affecting the water infiltration and impairing plant germination, regeneration and growth (Xie and Wittig, 2004). These processes may cause low water storage capacity and loss of soil fertility (Zhao *et al.,* 2007). Grazing is more complicated in forest areas, because the grazed vegetation is overgrown by trees, altering the effect of grazing in different ways

(Smit and Kooijman, 2001). However, grazing animals on forest soils may be important on long term determination of ecosystem sustainability (Binkley *et al.,* 2003).

2.8.3 Forest management

Sustainable forest management is the management of long-term dynamics of forest ecosystems, while coping with short-term disturbance, in order to sustain the function to which forest is devoted. Therefore, management strategies must be focused on ecosystem persistence and a sufficient degree of ecosystem stability (Führer, 2000). The four major criteria for the sustainability of a forest ecosystem are: maintenance of biological diversity, viability of ecological processes, productivity of soil, water and air and the ability to provide for sustained human use (Georgia Forestry Commission, 2000). Many aspects of these outlines are currently not being met and will continue to have detrimental effects if not quickly addressed.

One of the most widespread management methods is the introduction of forest species (Maestre and Cortina, 2004). But reforestation practices cause complex perturbations in the soil and impede, at least temporarily, the continuation of soil functions (Ballard, 2000). The intensity and duration of such perturbations depend on characteristics of the soil, because soils are vulnerable to forest practices to different extents (Francaviglia *et al.,* 2004). Further, type of forest species also affects the soil in various ways. Therefore, selection of tree species is often an integrated part of management options. Tree species strongly influence aspect of soil carbon in terms of carbon stock, cycling and chemistry (Binkely, 1995; Vesterdal and Raulund-Rasmussen, 1998). Deployment of genetically improved, fast growing and disease resistant families is a key factor for enhancing forest

plantation productivity (McKeand *et al.,* 2003). Fast-growing tree species accumulate "live" carbon more rapidly than slow-growing species, thereby giving a period of more rapid carbon sequestration into biomass (Cannell, 1996). For example, acidic soil conditions beneath spruce (*Picea* spp.) canopies have been reported to lower microbial biomass and produce lower rates of microbial CO_2 than the soils beneath beech (*Fagus* spp.) or oak (*Quercus* spp.) forests (Anderson and Domsch 1993). Soils beneath scrub oak have been shown to contain 100% more soil organic carbon and 12% lower litter carbon compared to soils under Coulter pine at age 40 (Quideau *et al.,* 2000).

Another management strategy challenging forest managers is the aspects of fire and silvicultural practices like thinning. Literatures describe the effects of prescribed forest burning, forest thinning and other silvicultural treatments on ecosystem components and processes, particularly in forest soils (Stephens, 1998; Carey and Schumann, 2003; Stephens and Moghaddas, 2005a). Johnston and Crossley (2002) advocate that soil biological components and soil physical properties play greater role in forest ecosystem management. Researchers have reported drastic effects of forest thinning and prescribed burning effects on soil respiration (Ma *et al.,* 2004; Kobziar and Stephens, 2006), lethal soil temperatures (Busse *et al.,* 2005), leaf litter fauna (Apigian *et al.,* 2006), surface organic matter (Jurgensen *et al.,* 1996), soil compact and aggregate stability (Incerti *et al.,* 1987; Moghaddas and Stephens, 2007), hydraulic conductivities (Gent *et al.,* 1984) and coarse woody debris (Stephens and Moghaddas, 2005b). Although, fire treatment often includes widespread mechanical removals or on-site mastication of large amounts of non-merchantable material, changes to soil physical properties as a result of forest management are of paramount importance to site productivity (Grigal, 2000).

Harvesting system is another form of forests disturbances. Traditionally, forest management practices focuse on clear-cut and replanting system (Elliot *et al.,* 2009; Vesterdal and Leifeld, 2010). Clear-cut form of harvesting reduces forest ground cover, discourages continuous canopy cover, remove soil nutrients especially in nutrient-deficient environment (Miller *et al.,* 1989). During period of long-lasting openings in forest canopy associated with regeneration phase, there is reduction in the amount of forest ground cover by litter and organic materials. Ground cover amounts are the most important component of forest environment for protecting the mineral soil from the erosion (Elliot *et al.,* 2009). Forests therefore have great influence on soil carbon stock, nutrient cycling, moisture retention, structural stability (Deploey, 1985; Hopmans *et al.,* 2005). When soil structure breaks down, particle detachment and runoff are increased to enhance surface sealing, reducing infiltration rate and increase potential for soil erosion (Sarah, 2005). With increasing understanding of forest ecosystem, partial-cut or nature-based forestry harvesting system which implies use of proven practices for sustainable forest management is a useful tool (Pommerening and Murphy, 2004). This management form is inspired by natural forests where disturbance occurs down to the single tree level, i.e. there is almost continuous crown cover over time (Vesterdal and Leifeld, 2010). An important characteristic in nature-based forestry is the input of organic materials to soils that is more continuous compared to traditional clear cutting and replanting systems. As forest ecology is better maintained, it has less structural breakdown due to raindrop impact and less carbon is probably also lost from soils by decomposition compared to the clear cutting system, where soil structure and carbon stock decrease in the period following clear cutting and replanting (Yanai, 2000).

2.8.4 Deforestation

Forest biodiversity and the natural functioning of forest ecosystems contribute immensely to sustainable and healthy environment. Indeed, the drastic alteration of forest systems through large-scale deforestation can open up opportunities for environmental deteriorations (Riesco, 2005). The complex integration of primary natural resources- soil, water and vegetation- is vital for maintaining terrestrial ecosystem functions and productivity (Islam and Weil, 2000). Deforestation is the process of indiscriminate clearing of forests without simultaneous replanting and the land used for subsequent agricultural and other project development. Deforestation alters every element of local ecosystems such as the ecology of local flora and fauna and aquatic conditions, and most significantly microclimate and soil (Patz *et al.,* 2000), constituting a major health, environmental, ecological and socio-economic challenge.

In Nigeria, the annual rate of deforestation is 5.0%, compared to a global rate of 0.6% (NFNBR, 2001). The World Development Indicator estimated an average annual deforestation rate of 3,984 sq.km for Nigeria from 1990-2000. The total area under forest cover is put at 135 sq. km, while the rate of forestland conversion is 2.6 percent (World Bank, 2001). Nigeria has therefore lost more than half of its forest in five years and is globally considered as the world's highest deforested country. Between 2000 and 2005, Nigeria lost 55.7% of its primary forests - defined as forests with no visible signs of past or present human activities (Butler, 2005). Increase in population, continuous decline in the amount of agricultural land, logging and the collection of fuel wood are cited as leading causes of indiscriminate exploitation of natural forests (World Bank, 1991; Mojiri *et al.,* 2011). On a global scale, according to World Bank (1991) about 60% of the deforestation

in the developing world may be attributable to the advance of agricultural practices, about 20% to logging operations (including mining) and 20% to household use of fuel wood.

Conversion of forest and grasslands into agricultural land is one main concern worldwide in the context of environmental degradation and global climate change (Khormali *et al.*, 2009). This change has many interlink effects that can appear through the reduction of chemical and physical qualities of soil resources (Cavelier *et al.,* 1999; Liu *et al.,* 2002; Johnson and Lewis, 2007; Seeger and Ries, 2008). According to FAO (1993), soil degradation is the sum of geological, climatic, biological and human factors which lead to degradation of physical, chemical and biological potential of soil, and which endanger biodiversity, land use and survival of human communities. Lal (1997) stressed that soil degradation leads to a decline in soil quality with a continuing reduction of productivity.

Larson and Pierce (1991) defined soil quality as the capacity of a soil to function within the ecosystem boundaries and to interact positively with surrounding ecosystems (Khormali and Shamsi, 2009). Cultivation of forestland affects the distribution and supply of soil nutrients by directly altering soil properties and by influencing biological transformations in the rooting zone. It diminishes the soil carbon within a few years of initial conversion and substantially lowers mineralizable nitrogen (Majaliwa *et al.*, 2010). Yousefifard *et al.* (2007) investigated decline in soil quality as a result of forest cultivation in Cheshmeh Ali region. Results showed that organic matter, available phosphorous, cation exchange capacity, microbial respiration and mean weight diameter (MWD) decreased. The study of effect of rangeland change to agricultural land on some soil physical and chemical properties in South of Isfahan showed significant changes in bulk density, pH, EC and mean weight diameter (Hajabbasi *et al*., 2007). Lemenih (2004) investigated the effects of

land use changes on soil quality and native flora degradation and restoration in the highlands of Ethiopia. Results showed that deforestation and then long-term cultivation caused decrease in organic matter, total nitrogen, and also indicated changes in soil surface (0-10 cm) phosphorous, potassium, available potassium, Ca+Mg, saturation point and cation exchange capacity. Deforestation is believed to diminish soil quality and lead to a permanent degradation of land productivity (Mojiri *et al.,* 2011).

2.9 AGGREGATION AND AGGREGATE STABILITY IN SOILS

2.9.1 Processes and importance of aggregation in soils

Soil aggregation is the process whereby primary soil particles (sand, silt, clay) are bound together into secondary units usually by natural forces and substances derived from root exudates and microbial activity (SSSA, 1997). This dynamic process is complex because of the interaction of many abiotic and biotic factors and processes involved (Kooistra and Tovey, 1994; Topp *et al.,* 1997; Bronick and Lal, 2005), including soil properties, microbial activities, and environment and soil management factors.

Several theories and conceptual models (Figure *2.7*) have been proposed to figure out the soil aggregation process (Amezketa, 1999). Most of these models proclaim that soils consist of ever-changing aggregates of different sizes bound together by organic and inorganic compounds (Tisdall and Oades, 1982; Dexter, 1988). Blanco-Canqui and Lal (2004) reported different models underlying soil aggregation including both directions from microaggregate to macroaggregate or the opposite. Among these models, Tisdall and Oades (1982) model, still a pioneering conceptual model, described aggregate hierarchy. In this

model, soil organic matter (SOM) is considered the principal binding agent of aggregate formation and starts with the microaggregates before macroaggregates.

This model was revised by Oades (1984) who indicated that roots and hyphae holding macroaggregates (> 250 μm) together form the nucleus of microaggregate (20 to 250 μm) formation in the centre of the macroaggregates. Six *et al*. (1999) identified four dynamic stages of macroaggregate turnover, microaggregate formation, and soil organic carbon stabilization in microaggregates. Their model indicated that macroaggregation is stabilized by fresh plant debris and roots and by fine inter-aggregate particulate organic matter (POM). The fine organic particles are sequestered in the microaggregates formed inside the macroaggregates. Stable microaggregates are released and then build into new macroaggregates. Generally, the aggregates produced from these processes occur in variety of sizes often grouped into macroaggregates (>250 μm) and microaggregates (<250 μm) (Tisdall and Oades, 1982). Aggregate size orders are varied in their response to these environmental stresses with macroaggregates being more susceptible to the disruptive forces than microaggregates. Horn and Smucker (2005) reported that aggregate formation and aggregate strength depend on swelling and shrinking processes and biological activities

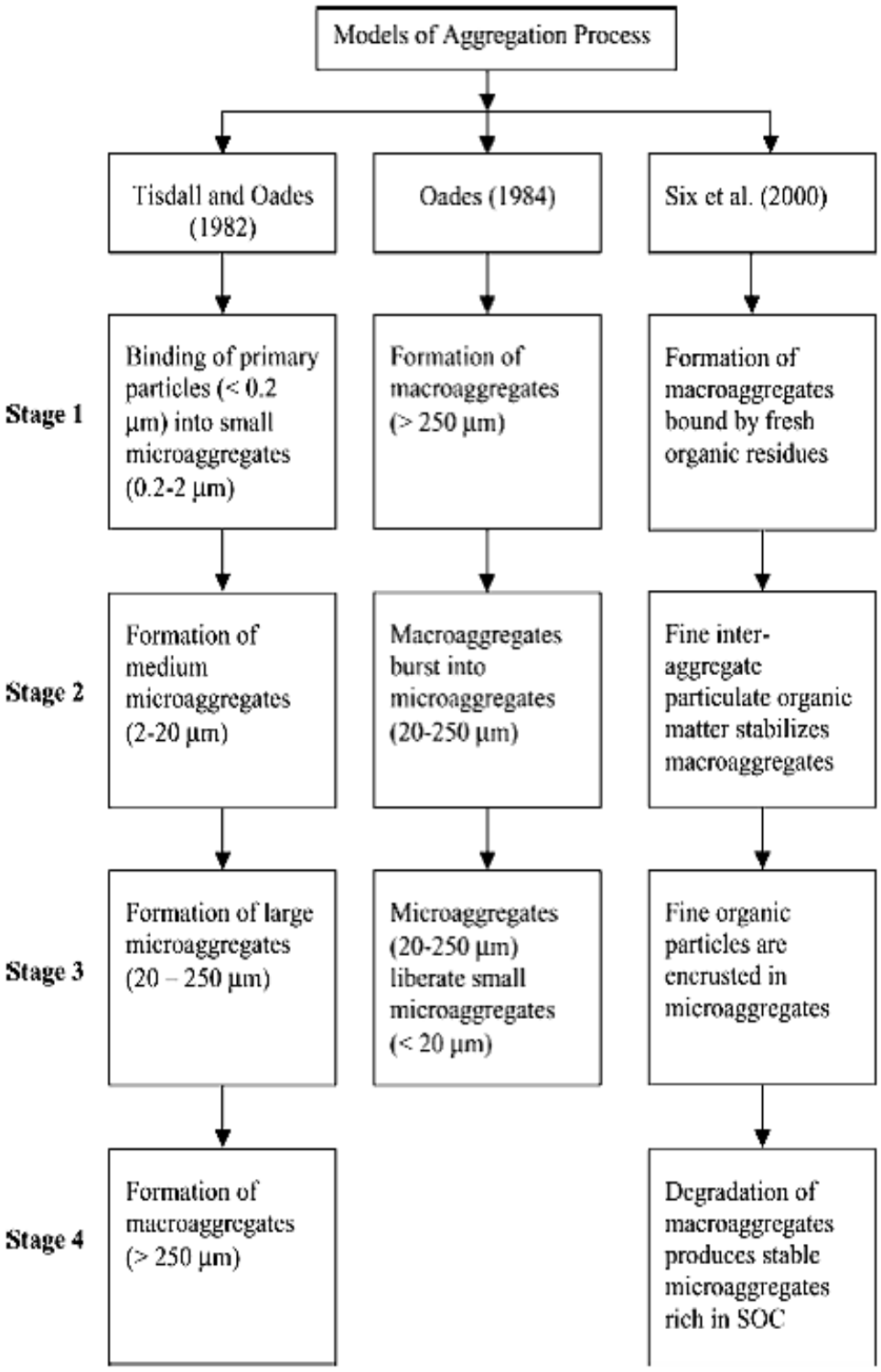


Figure 2.7: Soil aggregation models of Tisdall and Oades (1982), Oades (1984) and Six *et al*. (2000) (from Blanco-Canqui and Lal, 2004).

and kinds of organic exudates as well as on the intensity, number and time of swelling and drying events.

Aggregate stability is often used as a measurement of soil structure. Soil aggregate distribution and stability measurements have been proposed as soil quality indicators (Coote *et al.,* 1988; Chan and Mead, 1988; Six *et al.,* 2000). Soil structures are important soil property to be evaluated because it mediates many biological and physical processes in soils (Six *et al*., 2000; 2002). For example, soil structure determines porosity and infiltration, hence water availability to plants and soil erosion susceptibility (Six *et al.,* 2000). Well aggregated soils provide stable contraction for farm implements, adequate physical conditions for penetration, growth and anchorage of plant roots, and free drainage with moderate retention of rainfall. Furthermore, well aggregated soils are more resistant to erosion than primary particles of sand, silt, clay and organic matter. Johnson, (1992); Ellert and Gregorich, (1996) suggested that is very important to maintain soil structure (a state variable) to improve land management practices and reduce the environmental impact of agricultural practices.

2.9.2 Reports of works involving methods of measuring soil aggregation and aggregate stability in managed ecosystems

Methods of evaluating aggregate stability of soil have been proposed since the pioneering work of Yoder (1936). These methods arose due to the diverse factors and mechanisms of disaggregation which act on different organizational structures of soil structure that should be reflected by the measurement. The principal mechanisms of disaggregation are slaking of aggregates by compression of entrapped air, differential swelling of clays which provoke a micro-fissuration of the aggregate, impact of rain drops and physiochemical dispersion.

Soil aggregate stability depends on their mineral and organic constituents, exchangeable sodium percentage, the oxides and hydroxide of iron and aluminum (Le Bissonnais and Singer, 1993) and soil organic matter (Chenu, 1989; Haynes and Swift, 1990).

Several pre-treatments have been proposed and used by numerous authors to accommodate the different mechanism of soil disaggregation. A pre-treatment describe by Yoder (1936) with modifications by Mikha and Rice (2004) states that 50 g of dried soil sample be placed on top of a sieve and slaked by rapidly adding 1 Litre of water until the soil is covered by water. The submerged soil is left in water for 10 minutes followed by 10 minutes wet sieving. Different aggregate size classes can be obtained, dried and subsample, used to determine the sand content of each fraction. Subsample of intact aggregate (2-5 g) with a five-fold volume (10-25 ml) of 5 g l^{-1} Sodium hexa-meta-phosphate was left over night and shaken for 4 hrs. The dispersed organic matter and soil collected on 53 μm mesh sieve is washed with deionized water and dried at 105°C for 24 hrs to estimate sand-free aggregate.

Elliott (1986) adopted a wet sieving method in aggregate size separation. In his work, soil samples obtained at field capacity were passed through a series of three sieve at room temperature (21°C) to obtain four aggregate size classes namely: >2000 μm (large macro-aggregate); 250-2000 μm (small macro-aggregate); 53-250 μm (micro-aggregate) and <53 μm (silt and clay fractions). Prior to the wet sieving, moist soil sample is passed through 8 mm sieve and air dried. The soil sample is then submerged on top of a 2 mm sieve for about 5 mins before sieving. The sieving is an automated process of moving the sieve up and down at a height of about 3 cm for about 50 consecutive times within an interval of 2 mins. After the removal of organic material that floats on top of the water, the sample will be poured to the next sieve size and the same sieving procedure repeated. The aggregate

fractions that were retained in each sieve are then oven dried at 50°C for 24 hrs, weighed and stored.

This method by Elliott (1986) was modified by Elliott and Cambardella (1991); Cambardella and Elliott (1994) where fractionation of soil aggregate were achieved by capillary wetting of soil to field capacity to prevent slaking following immersion. Wetted soils are immersed in water on a nest of sieve (2000 μm, 250 μm and 53 μm) and shaking vertically 3 cm for 50 times in 2 mins. Soil aggregate retained on the sieve are oven dried at 50°C for 24 hrs and weighed. Materials less than 53 μm are not collected but content are determined by calculation of the difference between whole soil and some of the aggregate fractions on the three nest of sieves.

Another technique of estimating aggregate stability is described by Kemper and Rosenau (1986). Soil samples placed on nest of sieves of diameters 2 mm, 1 mm, 0.5 mm and 0.25 mm are pre-soaked in distilled water for 10mins before oscillating vertically in water along amplitude. The resistant aggregate are oven dried at 105°C for 24 hrs, weighed and corrected for sand fraction to obtain the proportion of true aggregate.

The pre-treatment describe by Beare *et al.* (1994) involves wetting field-moisten soils under constant head (3.0 cm of H_2O) and separated into five aggregate size classes (2000 μm, 250 μm, 106 μm, 53 μm and <53 μm) by wet-sieving using a 2 cm stroke for 300 secs at 0.52 cycles s^{-1}. Aggregates are then dried on the sieves in a dehumidifying chamber (10^oC, 24 hrs), transferred to breakers, and dried at 35^oC (48 hrs) before recording the final dry masses. Subsamples of each fraction (0.25-2.0 g) are dried at $105^{\circ}C$ to allow correction to a final dry weight.

Treatment method of measuring aggregate stability proposed by Le Bissonnais (1996) integrated key aspect of the older method while been adapted to a wide range of different soil types. It consists of three breakdown mechanisms: slaking (provoked by immersion in water), micro-cracking (provoked by slow capillary wetting) and mechanical breakdown (provoked by shaking in water after slow capillary wetting). Briefly, this method involves three pre-treatments with different subsamples before sieving in alcohol:

i) Slow wetting, where the aggregates are capillary rewetted with water on a tension table at a potential of -0.3KPa for >60 mins.

ii) Rapid wetting, where 5 g of aggregate are immersed in deionized water for 10 mins.

iii) Stirring after pre wetting, where the aggregates are saturated in ethanol for 30 mins then agitated in deionized water in an Erlenmeyer end over end for 20 mins.

The dry aggregate size distribution is performed by mechanically or manually shaking nest of sieves to obtain different size fraction. Van Bavel (1950) method was modified by Kemper and Rosenau (1986) and is used to estimate the mean weight diameter (MWD) for both wet and dry stable soil aggregates. The MWD is calculated as the sum of the mass fraction remaining on each sieve after sieving, multiply by the mean aperture of the adjacent sieve. Thus,

$$\text{MWD} = \quad \text{x}\,\omega \qquad [2.30]$$

where: = mean diameter of each size fraction (mm)
= proportion of the total sample weight in the corresponding size fraction.

The use of MWD, however, is questionable if the aggregate distribution is skewed, that is,

relatively non- symmetrical (Stirk, 1958). In addition, there are often complications when different sites and/or management practices are compared for soil structural differences by means of the MWD. Three confounding factors have been identified: pretreatment of soil samples (Beare and Bruce, 1993; Gollany *et al.*, 1991), antecedent water content (Angers *et al.*, 1993a; Perfect *et al*., 1990), and sand content (Angers *et al.,* 1993b; Caron *et al.,* 1992; Elliott, 1986; Gollany *et al.*, 1991; Perfect *et al.*, 1990).

2.10 INFLUENCE OF SOIL PROPERTIES AND MANAGEMENT PRACTICES ON SOIL AGGREGATION AND AGGREGATE STABILITY

Stability of soil aggregate is related to complex factors: organic matter content and composition, microbial action, inorganic binding agent, clay minerals and clay content, physical properties (surface area, soil moisture content etc) and management practices (Oades, 1986; Goldberg *et al.,* 1988; Torrent, 1994, 1995), as a result mechanism for stabilization of soil aggregates vary with soil types.

2.10.1 Organic matter content and composition

Soil organic matter is important in maintaining soil structural stability, aiding the infiltration of air and water, promoting water retention and reducing erosion (Gregorich *et al.*, 1994); hence the loss of soil carbon is usually linked to the deterioration of soil physical properties. Soil organic matter is closely related to aggregate stability (Tisdall and Oades, 1982; Elliot, 1986) and soil erodibility (Kay, 2000). Soil bulk density and porosity are functions of soil organic matter, aggregate stability, size distribution and soil particle density (Mapa, 1995; Baldock and Nelson, 2000). A decrease in organic matter leads to a decrease in the aggregate stability, an increase in bulk density and decrease in the porosity,

thereby reducing soil infiltration, water and air storage capacities (Franzluebbers, 2002; Wall and Heiskanen, 2003; Celik, 2005).

Haynes and Swift (1990) observed a reduced aggregate stability in arable soil samples but increased aggregate stability in pastures soil samples. Soils in pasture fields have high soil organic matter content resulting in a reduced wettability because of the hydrophobic characteristics of soil organic matter (Caron *et al.,* 1996) and the formation of many additional intermolecular associations. In contrast, arable soils with a lower soil organic matter rewet much faster and results in a reduced aggregate stability.

Considerable controversy exists from various studies on the actual role of organic matter in soil aggregate stability. Some workers (Hamblin and Greenland, 1977; Dormor, 1983) reported that it is the fractions of organic matter rather than the amount that are important in modifying the structural stability of aggregate whereas others (Chaney and Swift, 1984; Christensen, 1986) found a direct correlation between total soil organic matter content and aggregate stability. There are also different opinions regarding the actual fraction of organic matter (humic, lignin, polysaccharides, carbohydrates or lipids) that are responsible for improving soil aggregation.

Polysaccharides (produced by micro-organisms when metabolizing particulate organic matter) have a transient effect functioning as bridges to bind soil particles or sometime acting as glue for maintaining particles together (Jastrow, 1996). Piccolo and Mbagwu (1999) attributed the short-term effect of polysaccharides on soil aggregate stability to their transient nature. Though, Haynes and Swift (1990) and Angers *et al.* (1993) showed that amendment of aggregate with glucose produced stable aggregates. Insam (1996) insisted

that since carbohydrates are easily degraded by micro-organism, they cannot participate in long-term stabilization of soil aggregates.

The role played by carbohydrates is variable depending on its source and nature especially when they act in conjunction with the more humified or resistant soil organic matter pools (Caron *et al.*, 1992; Piccolo and Mbagwu, 1999) compared with those produced by micro-organisms (Bronick and Lai, 2005). Humic substances are recalcitrant as a result of their chemical resistance and their interactions with clays and organic soils components conferring physical protection against microbial degradation (Chorover *et al.*, 2004). Aggregate stability has been associated with humified organic matter in sandy soils (Dutarle *et al.,* 1993) and with humic acid than either the total organic content or the carbohydrate content (Piccolo and Mbagwu, 1990; Mbagwu and Piccolo, 1998). The difference in results may be related to the sources, nature and the residence time of the organic materials producing these fractions in the soil. The implication is that other binding agents are involved in aggregate stabilization.

2.10.2 Microbial action

Micro-organisms increase the stability of aggregate in several ways. They increase the repellency of soil aggregates, presumably by exuding hydrophobic substances (Capriel *et al.,* 1990; Hallett and Young, 1999) resulting in stabilization of the aggregates by decreasing their rate of wetting. Among soil micro-organisms, fungi are the most important agent involved in soil aggregation through fungal mycelia network, although roots and bacteria have a significant role as well (Degens, 1997; Tisdall *et al.*, 1997).

Fungi act mainly by mechanical enmeshment of soil particles (Degens, 1997). Fungi and bacteria exude extracellular polysaccharides which bond the particles and increase inter-particle cohesion (Chenu and Guerif, 1991; Oades and Water, 1991). The role of fungi in soil aggregation can be direct by cementing capacity of extracellular compounds released or indirect due to a physical network of hyphae maintaining soil particles together (Eviner and Chapin, 2002; Pietrowski *et al.*, 2004). In accordance with the aggregate hierarchy theory and pore exclusion principle, enmeshment of particles by fungi is a major factor in the formation of macro-aggregates (Tisdall *et al.,* 1997; Bossuyt *et al,* 2001), while production of mucilage enhances the formation of micro-aggregates (Chenu, 1989; Oades, 1993). Bacteria stabilize the soil by binding together small particles into larger particles, achieved by several mechanisms (Bar-Or and Danin, 1989) including physical binding of soil particles by entangled filaments adhesion to mucilaginous sheaths or shine layers and attachment of particles to sites along the bacterial cell walls. This binding increases the organic matter content of soil (Danin *et al.*, 1989), increasing the soil's resistance to both wind and water erosion.

In coarse textured sandy soils, aggregation is weakly related to microbial biomass and products (Degens *et al.*, 1994; Degens and Sparling, 1996) because only the hyphal network is able to cross-link the abundant sand particles to form stable aggregates. However, in clay soils, both bacteria and fungi and their products play a role in aggregation (Denef and Six, 2003; Degens and Sparling, 1996).

2.10.3 Soil physical properties

Aggregate stability often exhibit large inter-annual and seasonal variability. Such variations occur regardless of residue treatments due to direct influence of climate on soil moisture

(Perfect *et al.,* 1990; Angers *et al.,* 1999). Soil moisture effects on aggregate stability are particularly evidence in soils with low organic matter content (Haynes, 2000).

Soil water content at the time of sampling impacts aggregate stability when it is measured on field moisture samples (Perfect *et al.,* 1990). Furthermore, even though aggregate stability is measured on air-dried sample, the antecedent water content has been shown to affect aggregate stability (Caron *et al.,* 1992). The effect of moisture on aggregate characteristics cannot be generalized and alone, have no consistent effect on soil aggregate size and stability (Yang and Wander, 1998). Instead, soil moisture interacts with other events to influence aggregation. Soil moisture can affect aggregation directly through physical or chemical process (Utomo and Dexter, 1982) and/or indirectly through their action on microbial activity (Denef *et al.,* 2001). Effects of soil moisture on soil structure are still unclear, since both increases and decreases in water stable aggregate have been observed following wetting and drying (Denef *et al*, 2001). The contradictory result found in the literature can be explained by differential initial moisture conditions of the aggregates, organic matter contents, intensities and durations of drying and rewetting phases and aggregate stability methods. As suggested by Suwardji and Eberbach (1998); inter annual and seasonal variability in aggregate stability results from seasonal wetting and drying interacting with the accumulation of plant and microbial debris associated with the growing plant.

Another soil physical property that greatly influences soil aggregation is the soil textural properties. The importance of soil textural (clay and silt) properties on soil organic carbon (SOC) content cannot be over emphasized as clays are an important component in the direct stabilization of organic molecules and micro-organisms (Amato and Ladd, 1992; Feller *et*

al., 1992) which in turn influences soil aggregate stability. Feller *et al*. (1992) reported that independent of climatic variation (precipitation, temperature and duration of the dry season), SOC increases with clay and silt content. Therefore, small variation in topsoil texture could have large direct effect on SOC and indirectly on aggregation (Bationo and Buerkert, 2001). Carbon content and status in the soil is closely related to clay and silt content and clay types which influences the stabilization of organic carbon (Manu *et al.*, 1991). As clay interact with SOC and both are intimately related with aggregate, all soil properties affecting one also affects the other and soil aggregation as a whole (Bone *et al.*, 2008). Thus, pH, CEC, ions and the mineralogical nature influence soil aggregation. In general, aggregation is high in high-activity clays (double layered crystal structure, 2:1 clay) dominated soils and in non-crystalline 1:1 clay (allophone and imogolite) with high variable charge (Tisdall and Oades, 1982; Oades and Waters, 1991). Consequently, the mineralogical characteristics can influence the potential soil stability and the relationship between soil organic matter content and soil stability.

2.10.4 Inorganic binding agents

Polyvalent cations (aluminum and iron) habitually improves soil aggregation through bridge formation between inorganic minerals or clay and SOC. Aggregate containing clays, aluminum and iron oxides or hydroxides promotes soil organic carbon incorporation conferring aggregate stability (Bone *et al.*, 2008). Matus *et al*. (2006) demonstrated that soil organic matter accumulation in Chilean volcanic soils is produced by Al stabilization rather than climatic conditions and clay content of the soil. Some scientists reported positive effect of Fe on aggregation (Colombo and Torrent, 1991; Ferreira Fontes, 1992; Igwe *et al.*, 1995), whereas others observed no effect (Greenland *et al.,* 1968; Borggaard, 1983). The

reason for these variable effects of Fe on aggregation may not be unconnected with i) differences between Fe not determined in their studies or ii) other soil characteristics that influence the aggregating capacity of Fe.

Bivalent cations such as calcium (Ca) and magnesium (Mg) also improve soil aggregation; however in some soils Mg may have a deleterious effect on aggregation due to a higher swollen effect on clays present in such soil (Zhang and Norton, 2002). Calcium is a critical element for the stabilization of soil organic matter and soil aggregatse through its role in the formation of clay-polyvalent cation-organic matter complexes (Muneer and Oades, 1989b; Clough and Skjemstad, 2000). Its stabilization effect is mostly observed at the micro-aggregation level (Grant *et al.*, 1992; Baldock *et al.*, 1994) because Ca exacts its effect at the organo-mineral complexation scale, it can also indirectly increase macro-aggregation by stimulating microbial activity in acidic soil (Chan and Heenan, 1999). Consequently, the use of soil amendment in form of lime, gypsum or dolomite increases (10%) the aggregation level (Muneer and Oades, 1989a; Chan and Heenan, 1998). An initial temporal decrease of 1-3% in aggregate stability has however; been observed upon application of lime to variable charged soils (Roth and Pavan, 1991) and microbial activity (Chan and Heenan, 1998; 1999). Nevertheless, this decrease in aggregation seems to be reversed in the long term (Roth and Pavan, 1991; Chan and Heenan, 1998) and is more pronounced if the Ca is added together with an organic matter source (Baldock *et al.,* 1994).

2.10.5 Management practices

The negative effects of unsustainable land use and management practices on soil physical properties and the resulting soil degradation have been widely recognized. Management

practices influence soil aggregation by affecting the dynamics of carbon (quantity and quality of soil organic matter) and the function of the microbial populations to varying degree depending on the soil type and climate (Fabrizzi *et al.,* 2009). In this regard, management practices including tillage methods, residue management, amendment application, organic matter management and crop rotation among others can have enormous influence on soil aggregation and its stability (Wu and Tiessen, 2002; Bone *et al.,* 2008).

Tillage is a major factor dictating loss of soil organic matter (SOM), hence aggregate disruption (Rasmussen *et al.*, 1989) in addition to crop residue removal by grazing or harvesting (Rasmussen and Collins, 1991). Repeated inverting and pulverizing soil expose soil organic matter to mineralization, compact the subsoil and disturb plant and animal communities (Cannell and Hawes, 1994; Bone *et al.,* 2008). The process leads to decrease in SOM, CEC and reduction in potential biological and biochemical activities (Doran *et al.,* 1998; Riffaldi *et al.*, 2002), the main problem is aggregate destruction (Golchin *et al.,* 1998; Bossuyt *et al.*, 2002; Plante and McGill, 2002; Achmed *et al.*, 2003). Furthermore, root and fungal network are disrupted, decreasing the stability of soil aggregate and favouring leaching, losses of nutrients and erosion (Castillo *et al.*, 2006; Borie *et al.*, 2006).

Aggregate dynamics vary among different crops, crop rotations and cover crops (Bronick and Lai, 2005). The influence of different crops is according to their chemical composition and root tending to be short-lived under tillage (Chan and Heenan, 1996). Cover crops increase C inputs, CEC, soil aggregate stability and may enhance microbial biomass. The influence of crops and crop rotation is important on soil aggregation due to plant roots and their rhizospheric effects. Roots enmesh, realign soil particles and release exudates, which result in physical, chemical and biological alterations that influence soil aggregation

(Bronick and Lai, 2005). Aggregation tends to increase with increasing root length density, microbial association and glomalin, among other effects (Rillig et al., 2002). Aggregate stability is greater in rhizosphere soil than non-rizosphere soil (Caravac *et al.,* 2002) due to an increased rhizo deposition, root density, root turnover, hyphal growth, and microbial biomass, all of which directly or indirectly are influencial in maintaining particles together.

CHAPTER THREE

MATERIALS AND METHODS

3.1 PHYSICAL SETTING OF STUDY AREA

3.1.1 Location and extent

Nimbia Forest Reserve is located in Kaduna State, Southern Guinea Savanna zone of Nigeria (Figure 3.1). It lies between longitudes 8°30′ and 8°35′ E and latitudes 9°29′ and 9°31′ N with an elevation of about 600 m above mean sea level. The forest reserve is located in Jema□a Local Government Area of Kaduna State (Figure 3.2), 70 km south east of Jos, along Jos – Kafanchan road. Nimbia Forest Reserve covers an area of about 2,282.4 hectares. However, only 2,202 hectares (8.5 square miles) has been established. This established area comprises 220 blocks (compartments) of about 8 hectares in size each, with about 6 meters in-between the compartments. The total area is visibly divided into 4 parts by an access road called compartment ride for managerial purposes. It is long and narrow in shape, bounded on the south by Gimi River and on the north by the Lioc stream. The reserve is marked by a series of short steep steps separated by long stretches of level undulating ground with marked outcrops of basaltic boulders (Plate I).

3.1.2 History of the plantation

The natural vegetation was cleared in 1957, by the then Jema□a Native Authority and planted up with mainly teak (*Tectonia grandis*) and a few *Gmelina arborea* stands. According to Howard (1976), the first trial plantation of teak started in 1957, and between 1958 and 1966, 98.42 hectares were planted. The planting continued through the seventies

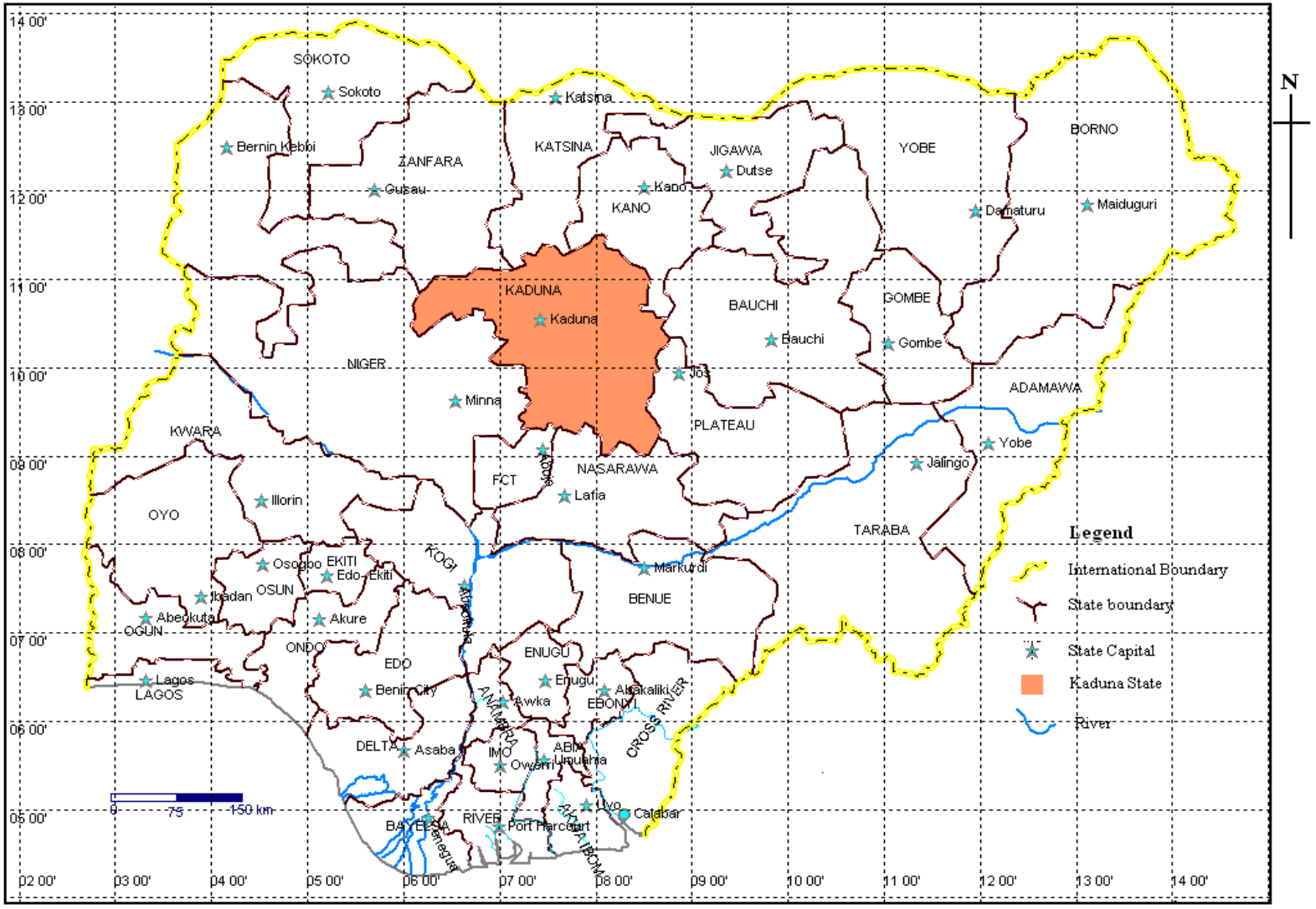


Figure 3.1: State boundary map of Nigeria showing Kaduna State.

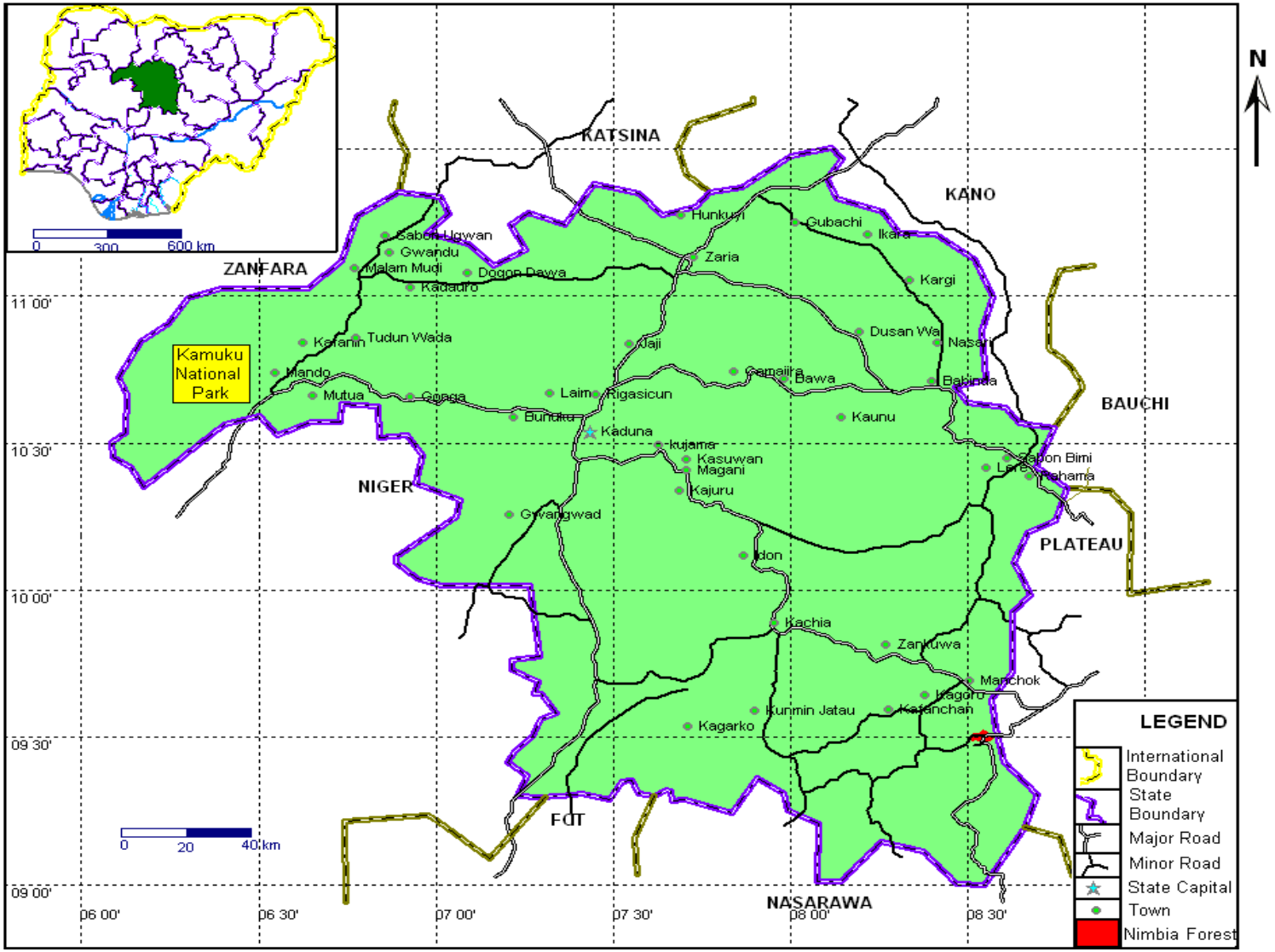


Figure 3.2: Kaduna map with Nimbia Forest Reserve



Plate I: Rock outcrops within the forest plantation

with the last planting carried out in 1991. The trial plots of the 1957 and 1958 were first cleared, leaving only the plots planted between 1964 and 1991. In 2005, the remaining plots were cleared, leaving the reserve as an even aged plantation (Plate II).

3.1.3 Teak (*Tectonia grandis* Linn. F)

Teak is a native of tropical and subtropical India and Southeast Asia. It tolerates a relatively wide range of climatic conditions in areas of rainfall ranging below 762 mm to over 3,810 mm per annum with minimum and maximum temperatures of 13 and 37˚C respectively. Keay (1989) describes teak as a large deciduous tree with a height of about 30 m and a girth of 3 m. The bole is usually fluted and sometimes with slight stresses. The bark is gray to brownish, fibrous with shallow longitudinal fissures, slash pale to brown to yellowish. Leaves are 25 – 60 cm long by 22 – 32 cm broad. It is broadly ovate to broadly elliptic, blunt or shortly acuminate at the apex. Flowers are white in much branched pyramidal panicles up to 45 cm long and wide at the ends of the branches. Fruits are more or less globosely about 18 mm in diameter, with a hard shell covered with stellate hair.

3.1.4 Geomorphology and Climate

The eastern end of Nimbia Forest Reserve is the last part of Assop escarpment. It descends in a series of steps with long level stretches interrupted by steep boulder-strewn descents. It descends more gently west ward to Jama□a-Jagindi plains. The forest reserve drains southwest into the Gimi River and west towards the stream that forms the western boundary as described by Howard (1963). The northern and southern parts of the reserve are bounded by Lioc stream and Gimi River respectively. Odumodu (1983) stated that the climate of Nimbia is determined by altitude and its location in relation to the seasonal migration of the



Plate II: Even aged plantation

Inter-Tropical Convergence Zone. The position of Nimbia with respect to its altitude (600m above sea level) induces orographic or topographic rain. Rainfall records for the period (1969-1991) indicate that the mean annual rainfall is about 1260.11mm. The maximum rainy months are from May through September, with July being the heaviest rainy period. The length of rainy season in this area is about 220 days. The mean annual temperature for periods of 1973 to 1987 is 21.78˚C. The minimum temperature occurs from December through January. This is the period when the cold dry harmattan or the tropical continental air mass from across the Sahara dominates the climatic scene. During these months, the minimum temperatures are as low as 12.9 and 11˚C while the mean maximum temperature for the hottest month (March) is 25˚C.

The relative humidity ranges from 16% in February to 80% in July and August for the periods of 1960 to 1981. The highest relative humidity was obtained in July and August when the rainfall is heaviest. The monthly means values for the year 1974 to 1984 indicate that the highest evaporation rate (110.0 mm) occurs in March. This rate is expected, as it tends to be the hottest (25.30˚C) month. The lowest rates of evaporation, 49.1 mm and 48.9 mm were recorded in July and August respectively. This low rate of evaporation is attributed to low temperature as a result of the high amounts of rainfall (280.94 and 269.84 mm respectively) experienced in these months.

3.1.5 Soils

The soils in the southern half of the reserve were derived from colluvial materials over saprolite. This was developed from a recent volcanic flow or Newer basalt as evidenced by the distribution of basaltic boulders. According to Howard (1963), soils in the northern half

Table 3.1: Summary of means of climatic data of Nimbia Forest Reserve.

Month	Rainfall (mm) 1969-1991	Pan Mean Monthly Evaporation (mm) 1974 – 1984	Mean Daily Relative Humidity (%) 1960-1981	Mean Daily Temperature (˚C) 1973-1987		
				Maximum	Minimum	Mean
January	0.17	88.9	17	27.2	11.0	19.10
February	3.1	97.5	16	29.4	15.4	22.40
March	19.68	110.0	25	30.7	19.9	25.30
April	82.87	90.6	50	30.6	18.6	24.60
May	166.00	71.5	67	28.2	18.2	23.20
June	189.54	58.4	72	26.6	17.3	22.00
July	280.97	49.1	80	23.3	16.5	20.00
August	269.84	48.9	80	24.4	16.2	20.00
September	208.52	57.0	73	26.0	16.7	21.40
October	37.90	69.7	53	27.8	16.2	22.50
November	0.86	87.8	23	27.3	14.2	20.80
December	0.61	86.6	18	27.1	12.9	20.00
Mean	1260.11					

Source: Samndi (2006)

were developed from rocks of the basement complex, as indicated by the presence of schist and granite. The eastern part of the reserve developed from basaltic parent material. The soils of the study area as indicated on the soil map of Nigeria (FDALR, 1990) belong to the unit 15F and are classified as Typic Dystrustepts (USDA)/ Dystric Cambisols (FAO). The soils also belong to the Nimbia series which developed from weathered olivine basalt and classified as Eutrophic Brown soil by D□Hoore (1964). Barrera (1968), classified the soil as Eutric Cambisols, while Ezenwa (1988) classified them as Ultic Paleustalfs, Plinthustalfs and Plinthustults.

3.1.6 Vegetation

The natural vegetation of Nimbia ranges from the Southern Guinea Savanna woodland to a dry type of rain forest. Keay (1959) and Clayton (1957) described the vegetation as a transitional zone between forest zone and the tree savanna. Ezenwa (1988) stated that the forest reserve comprised of forest and savanna tree species. The forest species consists of *Khaya senegalensis, Khaya grandifolia, Chlorophora excelsa, Sterculia tragacatha, Napoleana vogalii, Millettia thonningii, Malacanthus alnifolia* and *Cola gigaantea.* The savanna woodland species included *Daniellia oliveri, Erythropheum guinense, Vitex doniana, Isoberlina spp* and *Parkia clappertonia.* Howard (1963) earlier identified the tree species when he carried out the vegetation and site survey of Nimbia Forest Reserve.

3.2 SAMPLING

For the purpose of this study, geo-referenced soil samples were taken from block NF80 along 300 meters transect at 3 meters interval. Soils were sampled at 0-0.15 m depth with

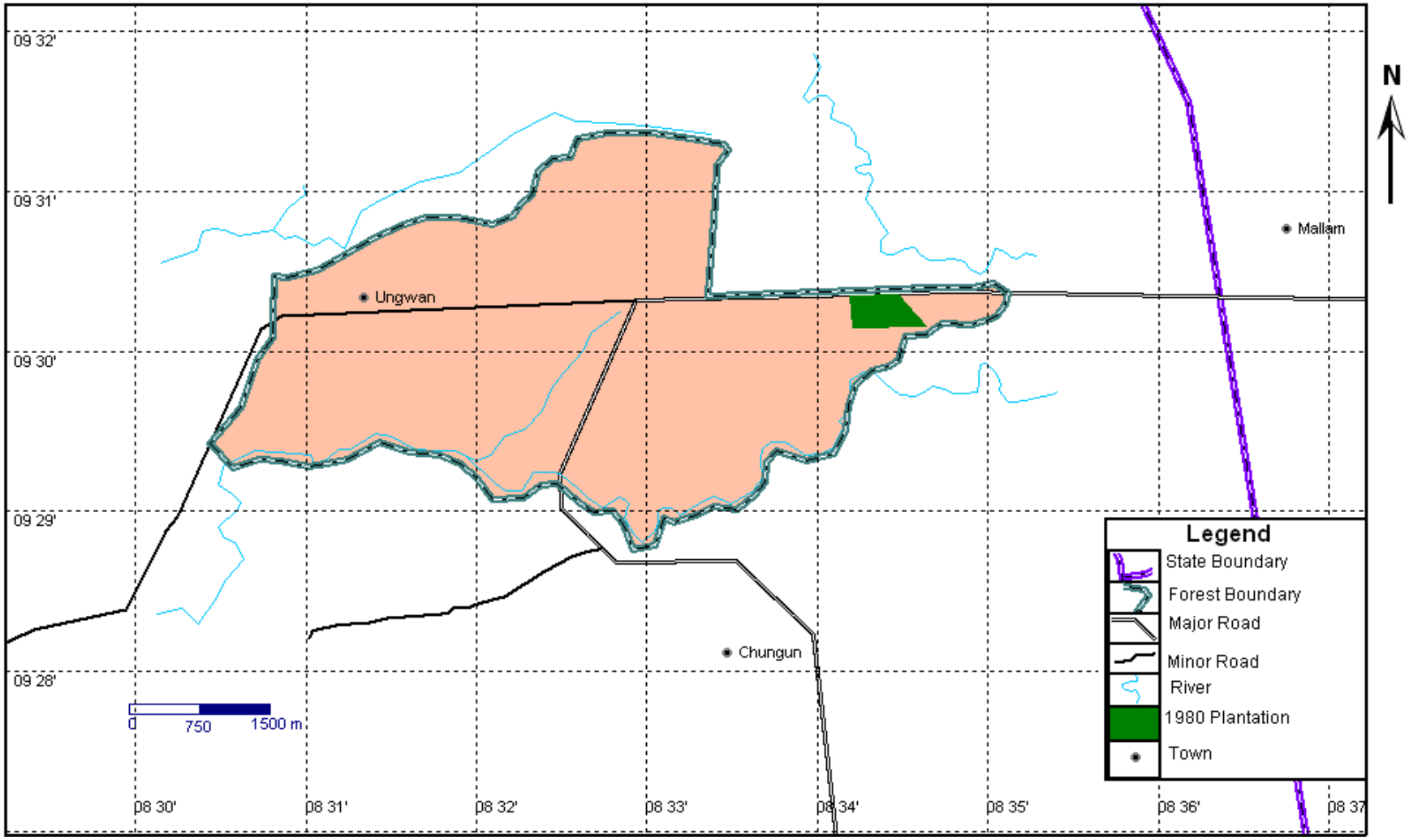


Figure 3.3: Nimbia Forest Reserve map showing the study site (1980 plantation)

the aid of a soil auger. After sampling, field infiltration rate were determined using double ring infiltrometer. A total of 100 disturbed soil samples and undisturbed core samples were taken from the field for laboratory analysis.

3.3 FIELD MEASUREMENT

3.3.1 Field infiltration measurements

A total of 100 infiltration runs were carried out along a 300 m transect at 3 m interval, between 6thJune and 21st June, 2009. The measurements were made with the aid of a double ring infiltrometer. The double ring infiltrometer is a set consisting of a large outer ring and a small inner ring. Two sets of different diameters but the same length were used. The first set has an outer ring of 54 cm and an inner ring of 29 cm diameter. The second set has an outer ring and an inner ring of 56 cm and 30 cm diameter respectively, (Eijeikamp Agrisearch Equipment No. 09.04).

At each site, the cutting edges of both the inner and the outer rings were well seated on the soil surface (Plate III). The process was done with care to avoid soil disturbance in the inner ring. Infiltration was commenced by first applying water into the outer ring at a shallow depth. The water therein was allowed to infiltrate into the soil for sometimes. This was done with the view of providing a buffer to discourage lateral flow and encourage one-dimensional vertical flow (Clemmens, 1981). Immediately, water was added to the inner ring to simulate field heads usually encountered during irrigation. Infiltration was read at 5 mins, 15 mins, 30 mins, 60 mins, and 120 mins i.e. at 5 mins, 10 mins, 15 mins, 30 mins, and 60 mins interval. Samples were also taken to determine the initial soil moisture content



Plate III: Field Infiltration sampling using double ring infiltrometer

(SMC) for each sample point before the infiltration run. The infiltration rates (IR) were calculated using the expression below;

$$(\quad / \ h) = \frac{(\quad)}{(\quad)} \qquad [3.1]$$

3.3.2 Bulk density

Bulk density was determined using core method of Blake and Hartge (1986). Core soil samples were dried in oven at 105˚C until the samples were at constant weight. Soil bulk density was calculated based on the sample weight and core section volume.

$$\text{Soil bulk density } (\rho b) = \frac{\quad}{)\quad(} \qquad [3.2]$$

3.4 SAMPLE PREPARATION

The collected bulk soil samples were air-dry in the laboratory for several days. Part of the samples were gently crushed with porcelain pestle and mortar and passed through a 2 mm sieve to remove coarse fragments. The less than 2 mm portion were stored in polythene bags for laboratory analysis. While the other uncrushed part were passed through 5 mm sieve and used for aggregate size analysis.

3.5 LABORATORY ANALYSIS

Laboratory determinations for both soil physical and chemical properties were carried out. These comprise particles size distribution, dry and wet aggregate size distribution (physical properties) and total organic carbon, organic carbon fractionation, iron oxides, soil pH, electrical conductivity, soil nitrogen, cation exchange capacity (CEC), exchangeable bases and total elements (Total phosphorus, potassium, calcium, magnesium, sodium and iron).

3.5.1 Physical properties

3.5.1.1 Particle size distribution

Particle size distribution was determined by hydrometer method as described by Gee and Bauder (1986). Clay, silt and sand were determined by dispersing the soil sample in calgon (hexametaphosphate) solution. The dispersed sample were shaken on a reciprocating shaker after which particle size distribution were determined with aid of Boyoucous hydrometer at 40 seconds (clay + silt) and 2 hours (clay only) interval. The textural classes were determined with the aid of USDA textural triangle.

$$C = R - R_L + (0.36T) \quad [3.3]$$

where: C = corrected hydrometer reading (g/l)

R = hydrometer reading (g/l)

R_L = Blank reading (g/l)

T = temperature of the suspension (˚C)

$$\%\text{Clay} = \text{———————} \text{ x} \text{—} \quad [3.4]$$

$$\%\text{Silt} = \text{———————} - \%\text{Clay} \quad [3.5]$$

$$\%\text{Sand} = 100 - (\%\text{Clay} + \%\text{Silt}) \quad [3.6]$$

3.5.1.2 Aggregate Size Distribution

Dry Sieving: Dry aggregate size distribution was determined by dry sieving. Two hundred grams of soil were passed through a set of sieves with diameter ranging from 5 mm – 0.05 mm mounted on a CSC scientific sieve shaker. The sieve were arranged in descending order of diameter from top to bottom, the < 0.05 mm soil aggregates were collected in the collecting pan placed below all other sieves. The nest of sieves was shaken for 60 seconds and the soil aggregates retained in each sieve were collected and weighed. The aggregate size stability characterized by mean weight diameter (MWD) is defined according to Van Bavel (1950) as;

$$\text{MWD} = \quad \text{x}\,\omega \qquad [3.7]$$

where: x_i = mean diameter of any particular size range of aggregate separated by sieve.

$_i$ = weight of aggregate in the size range as fraction of the total dry weight of sample.

Wet sieving: Wet aggregate size distribution was determined by slaking method (Elliott, 1986). Two hundred grams of air dried soil were wetted by rapid immersion (slaked) in for one minute water using sieve sizes of 2 mm, 1 mm, 0.25 mm and 0.05 mm with an average stroke per minute of 46, 36, 13 and 3 for each of the sieve sizes respectively. The sieving was carried out in the order of decreasing mesh size. After sieving with the proceeding sieve size (2 mm) the filtrate was transferred onto the proceeding sieve (1 mm), 0.25 mm and then 0.05 mm sieve. The <0.05 mm aggregate fraction was allowed to settle down and the water was decanted gently. The fractionated aggregates were dried in the oven at 60-70˚C for 48 hours and weighed. The proportion of aggregate fraction was corrected for

sand and mean weight diameter determined according to Van Bavel (1950) as in the dry sieving.

Since there is no binding of organic carbon with sand particles and sand contents differ between aggregate size fractions, fractions ≥ 0.05mm were corrected for the sand content (Six *et al.,* 1998). The sand contents were estimated by determining the particle size distribution of each aggregate size fractions. Sand free C concentrations were calculated with the following formula:

$$\text{Sand free aggregate} = \frac{}{\%} \qquad [3.8]$$

3.5.2 Chemical Properties

3.5.2.1 Organic Carbon

Soil organic carbon was analyzed by wet oxidation method of Walkey- Black (Nelson and Sommer, 1986). One gram of air dried, less than 2 mm soil were placed in 250 ml flask. 10 ml of 1N Potassium dichromate ($K_2Cr_2O_7$) solution were pipette into the flask and swirled gently for soil dispersion. Then 20ml concentrated H_2SO_4 were rapidly added, the flask were gently swirled immediately until soil and reagent mixed. After swirling the flask it were allowed to stand on a sheet of asbestos for about 30 minutes. One hundred mills of distilled water were added and allowed to cool before adding 3 drops of indicators. A blank were run without soil to standardize the dichromate. Both were titrated against Ferrous Sulphate ($FeSO_4$).

$$\%OC = \frac{(\text{blank} - \text{titre}) \times 0.3 \times \text{m} \times \text{f}}{\text{weight of soil}} \qquad [3.9]$$

where: f = corrected factor (1.33).

m = concentration of $FeSO_4$.

3.5.2.2 Soil organic carbon (SOC) fractionation

Soil organic carbon content was determined in each of the fractionated aggregates by dichromate oxidation method (Nelson and Sommers, 1982). Hence the following fractions were separated.

Sieve size	Measure OC	Conceptual SOC
5 - 2 mm	Large particulate organic carbon	Unprotected
2 - 1 mm	Medium particulate organic carbon	Unprotected
1 - 0.25 mm	Fine particulate organic carbon	Unprotected
0.25 - 0.05mm	Intra aggregate particulate organic carbon	Physically protected
<0.05 mm	Silt and clay associated organic carbon	Chemically protected

3.5.2.3 Biochemically protected soil organic carbon (SOC)

The biochemically protected SOM was determined by acid hydrolysis (Tan *et al.*, 2004). One gram each of the bulk soil sample passed through a 250μm sieve was weighed and placed into 50 ml digestion flask, 25 ml of 6N HCl (Paul *et al*., 2001) were added to this flask and shaken thoroughly by hand. A digestion block was used to heat the soil sample at 100°C until only the soil residue was left. The residue was transferred to a 50 ml centrifuge tube with 40 ml 0f distilled water and centrifuged for 30 mins. The supernatant was discarded. HCl was then removed from the residue by washing twice with 40 ml of distilled water through centrifuging; the supernatant was discarded each time. Finally the residue

was dried at 60^0C over night and weighed to compute the mass loss. Non hydrolysable carbon was determined in the acid hydrolyzed samples by dichromate oxidation method as described by Nelson and Sommers (1982). The quantity of the non hydrolysable SOC gave an idea of the biochemically protected SOC.

3.5.2.3 Forms of Iron (Fe)

Dithionite – Extractable (Fe_d): Total free oxides of Fe were extracted with dithionite-citrate mixture buffered with sodium bicarbonate according to Mehra and Jackson (1960). One gram of soil sample was weighed into a 50ml centrifuge tube and 40 ml of 0.3M Na-citrate with 5 ml 1M $NaHCO_3$ solution were added. The mixtures were placed in a water bath maintained at 80˚C. One gram of dithionite salt were added and stirred constantly for 15 mins. This procedure was repeated until the reddish colour of the mixture disappear indicating total Fe removal. After 15 mins digestion, 5 ml of saturated NaCl and 5 ml acetone were added. The suspensions were centrifuged for 5 mins at 1600 rounds per min and clear supernatant were decanted into 100ml flask. The sample will then be washed twice with 20 ml NaCl and decanted. Fe_d were determined from the extract by Atomic Absorption (AAS).

Oxalate Extractable Iron (Fe_{ox}): The amorphous (inorganic) form of Fe was extracted by method described by Schwertmann (1964). Two grams of soil were saturated with 10 ml 0.2M acidified ammonium oxalate solution. The samples were placed in a box to maintain darkness, shaken on a reciprocating shaker for 4 hours and centrifuged. The Fe_{ox} in the extract were then determined by AAS after 10 times dilution.

Pyrophosphate Extractable Iron (Fe_p): Organically-bound form of Fe was extracted with

0.1M sodium pyrophosphate ($Na_4P_2O_7$) solution as described by Mckeaque (1967). Two grams of soil sample were saturated with the extracting solution. The saturated samples were in the dark overnight on a reciprocating shaker. The suspension were transferred into 50 cm^3 centrifuge tube and centrifuged. Fe_p in the extract were determined by AAS after 10 times dilution.

3.5.2.4 Soil pH

Soil pH was determine in water and in 0.01M CaCl at 1:2.5 soil/solution ratio, using a pH meter with a glass electrode, after equilibrating for 30 minutes (Jurinak, 1978).

3.5.2.5 Electrical conductivity (EC)

The EC (1:2.5) soil/ water ratio extract were determined using a direct EC meter at room temperature. Results were expressed in micromhos cm^{-1} and thereafter converted to decisiemens per meter (dsm^{-1}) were adjusted to that of 25˚C, using the appropriate factors (US Salinity Lab. Staff, 1954).

3.5.2.6 Soil Nitrogen

Total Nitrogen (N) was determined by Kjeldahl method (Bremner, 1982), a wet oxidation method which involves digestion of the soil sample to convert N to ammonium (NH_4) and determination of the NH_4 in the digest by titration. One gram of soil were weighed into a digestion tube, followed by 5 g of Kjeldahl catalyst mixture then by 10mls of concentrated sulphuric acid (H_2SO_4). The solutions were heated on a digestion block at 300˚C (maximum) until digestion is completed. After cooling, the contents were washed into a 100 ml volumetric flask and make up 100 mls with distill water.

Ten mls of the aliquot were transferred into a distillation flask using a pipette. Ten mls of 10N NaOH solution were added and then attached to a distillation apparatus immediately where NH_4-N was trapped into 10 mls of 2% boric acid (H_3BO_3). These distillates were titrated with 0.025M H_2SO_4 to a pink or purple end point. Blank titration will also be determined without soil sample. Percentage Nitrogen content in the soil was calculated thus;

$$\%N = \frac{\cdot \quad \times \quad \times(\quad \times)\times}{\quad \times} \qquad [3.10]$$

where; VD = Volume of Digest
NA = Normality of Acid
T = Actual titre
B = Blank titre

3.5.2.7 Cation exchange capacity (CEC)

Cation exchange capacity is usually expressed in centimole per kilogram of soil (cmol/kg Soil) and is a measure of the quantity of readily exchangeable cations neutralizing negative (-ve) charges in the soil. The CEC values were measured using ammonium acetate (1N NH_4OAC) at pH 7 as described by Rhoades and Thomas (1982).

3.5.2.8 Exchangeable Bases (EB)

Soils were analyzed for Ca, Mg, K and Na, following the extraction with 1N ammonium acetate (1N NH_4OAC) at pH 7, using 1:10 soil/solution ratio. Na^+ and K^+ in filtered extracts were determined with a Gallen Kamp Flame Analyzer while Ca^{2+} and Mg^{2+} were determined by a Palkin-Elmer Model 290B atomic absorption spectrophotometer (Chapman, 1965).

3.6 DATA ANALYSIS

Laboratory data generated were analyzed for measures of central tendency (mean, median, minimum and maximum) and dispersion (skewness, kurtosis, standard deviation, coefficient of variability and regression) using SAS version 9 (2004)

Spatial heterogeneity were determined using spatial statistical tools of autocorrelation, semi-variance, cross-correlation and state-space, to describe spatial associations between variables using Applied Statistical Time Series Analysis (ASTMA) designed by Shumway (1988).

Data were analyzed by the state-space approach, using the equation developed by Shumway (1988), under application of the transformation:

$$= \frac{[\quad -(\quad -2)]}{4} \qquad [3.11]$$

where: m = mean of X_i
s = standard deviation.

This transformation allows the state coefficients Φ_{pp} in the above equation to have magnitudes directly proportional to their contribution to each state variable used in the analysis.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 DESCRIPTIVE STATISTICS ANALYSIS

Exploratory data analysis was performed in order to get elementary knowledge of the data set and presented in Table 4.1. The descriptive statistics for the study area revealed differences (low to high) in the amount of the variability of the soil variable. Large differences were found between minimum and maximum values of the investigated soil properties indicating variation in soil properties. Similar trend of results were also observed by Gokalp *et al.* (2010).

Based on the coefficient of skewness and kurtosis (Table 4.1), many of the investigated soil properties were significantly skewed (0.49) or significantly kurtotic (1.96). This may not be unconnected to the uneven burning of plant biomass prior to rainy season and the micro-topographical variation of the study area. However, for these soil properties, the mean and the median values were similar, with the median neither equals to or less than the mean despite skewness of the distribution. An indication that the outliers did not dominate the measure of central tendency, this is in line with the report by Shukla *et al*. (2004b).

The coefficient of variation (CV) of a soil property, expressed as the ratio of standard deviation to the mean is the magnitude of variability was ranked according to Wilding, (1985); Shukla *et al.,* (2004c), into different classes: low (<15%), medium (15-35%) and high (>35%). The CV (table 4.1) of the measured soil properties ranged from 0.74% to

Table 4.1: Univariate or descriptive statistics for the studied soil variables.

Variable	N	Minimum	Maximum	Mean	Median	Std Dev	CV (%)	Skewness	Kurtosis
Ele (m)	100	620	641	629.27	629	4.64	0.74	0.35^{NS}	0.84^{NS}
ρb(g/cm^3)	100	0.78	1.28	1.03	1.03	0.10	9.33	0.17^{NS}	0.15^{NS}
MC(cm^3/cm^3)	100	8.08	17.19	12.37	12.25	1.71	13.80	0.25^{NS}	0.36^{NS}
IR(mm/2hrs)	100	50.50	1371.5	411.78	371.5	244.01	59.26	1.29^{*}	2.09^{*}
pH_w	100	5.10	7.20	6.06	6.05	0.57	9.46	0.02^{NS}	-1.09^{NS}
pH_{Ca}	100	4.00	6.40	5.11	5.10	0.60	11.72	0.15^{NS}	-0.76^{NS}
EC(dsm^{-1})	100	0.01	0.05	0.01	0.01	0.007	49.03	3.56^{*}	13.47^{*}
Clay (%)	100	15.00	47.00	30.66	31.00	8.28	26.99	0.09^{NS}	-1.06^{NS}
Silt (%)	100	14.00	49.00	25.94	22.00	9.18	35.40	0.83^{*}	-0.61^{NS}
Sand (%)	100	24.00	65.00	43.40	43.00	8.91	20.54	0.31^{NS}	-0.45^{NS}
TN (%)	100	0.12	0.37	0.18	0.18	0.05	28.08	1.57^{*}	3.05^{*}
TP (%)	100	0.12	0.80	0.27	0.23	0.10	39.03	1.89^{*}	6.10^{*}
TK (%)	100	0.04	0.17	0.10	0.09	0.02	21.39	0.63^{*}	1.61^{NS}
TNa (%)	100	0.01	0.06	0.03	0.03	0.01	39.03	0.74^{*}	-0.14^{NS}
TCa (%)	100	0.001	0.008	0.003	0.003	0.001	40.21	1.48^{*}	3.81^{*}
TMg (%)	100	0.05	0.16	0.10	0.10	0.02	22.42	0.18^{NS}	-0.24^{NS}
TFe (%)	100	1.78	2.61	2.34	2.33	0.13	5.53	-0.86^{*}	2.75^{*}
Feox (%)	100	0.13	1.68	0.18	0.17	0.15	84.35	9.90^{*}	98.69^{*}
Fed (%)	100	0.02	0.11	0.05	0.04	0.02	36.34	0.78^{*}	1.16^{NS}
Fep (%)	100	0.004	0.02	0.01	0.01	0.004	34.54	0.44^{NS}	0.17^{NS}
ExK (cmol/Kg)	100	0.04	0.56	0.18	0.14	0.10	58.10	0.81^{*}	0.41^{NS}
ExNa (cmol/Kg)	100	0.01	1.57	0.46	0.36	0.42	90.83	1.25^{*}	0.52^{NS}
ExCa (cmol/Kg)	100	1.40	11.40	4.71	4.40	2.09	44.35	0.68^{*}	0.13^{NS}
ExMg (cmol/Kg)	100	0.70	6.30	3.02	2.90	1.37	45.32	0.26^{NS}	-0.99^{NS}
CEC (cmol/Kg)	100	2.00	20.80	13.39	13.80	3.25	24.29	-0.63^{*}	0.84^{NS}
TOC (%)	100	1.72	3.95	2.66	2.59	0.44	16.48	0.47^{NS}	-0.14^{NS}
BOC (%)	100	1.81	6.23	3.49	3.53	0.80	23.02	0.89^{*}	1.61^{NS}
OCa (%)	100	0.80	5.69	2.70	2.59	1.06	39.44	0.42^{*}	-0.16^{NS}

OCb (%)	100	1.10	5.39	2.63	2.49	0.85	32.15	1.01^{*}	1.50^{NS}
OCc (%)	100	1.60	6.08	3.13	2.94	0.91	29.01	1.06^{*}	1.00^{NS}
OCd (%)	100	1.70	7.08	3.48	3.19	1.16	33.20	1.05^{*}	0.84^{NS}
OCe (%)	100	1.90	7.18	3.49	3.29	0.98	27.98	1.18^{*}	2.20^{*}
MWDw(mm)	100	0.24	0.92	0.47	0.46	0.13	26.74	0.69^{*}	0.89^{NS}
MWDdry(mm)	100	0.96	1.96	1.37	1.36	0.22	16.35	0.33^{NS}	-0.49^{NS}
AS	100	0.14	0.64	0.35	0.35	0.10	29.07	0.34^{NS}	0.04^{NS}

Ele = Elevation, ρb = Soil bulk density, MC = Moisture content, IR = Infiltration rate, pH_w = pH in water, pH_{Ca} = pH in $CaCl_2$, EC = Electrical conductivity, TN = Total nitrogen, TP = Total Phosphorous, TK = Total potassium, TNa = Total Sodium, TCa = Total calcium, TMg = Total magnesium, TFe = Total iron, Feox = Oxalate extractable iron, Fed = Dithionite extractable iron, Fep = Pyrophosphate extractable iron, ExK = Exchangeable potassium, ExNa = Exchangeable sodium, ExCa = Exchangeable calcium, ExMg = Exchangeable magnesium. CEC = Cation exchange capacity, TOC = Total organic carbon, ML = Mass loss, BOC = Biochemical protected organic carbon, OCa – Oce = Organic carbon fractions, (5mm – 2mm, 2mm – 1mm, 1mm – 0.25mm, 0.25mm -0.05mm, <0.05mm respectively), MWDw = Water stable mean weight diameter, MWDdry = Dry stable aggregate mean weight diameter, AS = Aggregate stability.

Significant if the absolute value of skewness or kurtosis is ≥2X its standard error. The standard error of skewness is $(6/n)^{0.5}$ while the standard error for kurtosis = $(24/n)^{0.5}$. *: Significant, ns: Non significant.

90.83% with the majority exceeding 20% which is an indication of spatial variability. Among these properties, few are ranked low (elevation, ρb, MC, pH and Fe_t), while the majority are ranked medium (clay, silt, sand, TN, TK, TMg, Fe_p, CEC, TOC, BOC, OCb, OCc, OCd, OCe, MWDw, MWDdry and AS), and high (IR, EC, TP, TNa, TCa, Fe_{ox}, Fe_d, ExCa, ExMg, ExNa and OCa).

Bulk density and soil moisture content (SMC) recorded low CV values of (9.33%) and (I8.80%) respectively, indicating certain spatial homogeneity, Timm *et al*. (2006); Duffera *et al.* (2007) and De Oliveira *et al.* (2011), recorded similar results. Tominaga *et al.* (2002) showed that these physical soil attributes can greatly influence important soil processes like water movement (Reichardt and Timm, 2004) and soil compaction (Logsdon and Karlen, 2004). At soil surface significant changes in bulk density for tillage system in humid climate have been detected (Logsdon and Cambardella, 2000). Initial SMC influences the portioning of precipitation/rainfall into infiltration and runoff (Grayson *et al.*, 1997). Hence, small changes in these soil attributes are important. High CV value obtained in infiltration (59.26%) can be attributed to variation in soil moisture content and; to a lesser extent, soil bulk density, soil cracks caused by biological channels and particle size distribution of the study area. These finding are in agreement with the findings by Clemmens (1983); Clemmens and Bautista (2009) and Rahman (2010).

Moderate CV values were obtained for particles size distribution (clay – 26.99%, silt – 35.40% and sand – 20.54%) and MWD (26.74%). These results are in contrast to the work done by Ogunwole *et al*. (2005) on the same study site. They reported low CV values for these soil properties: clay (12.72%), silt (8.35%), sand (8.93) and MWD (6.72). Increase in

the variability of PSD and MWD may be due to accelerated water erosion transport and deposition processes caused by intensive felling of trees in 2001 prior to sampling. Moderate CV values were also obtained from organic carbon fractions (OCb – 32.15%, OCc – 29.01%, OCd − 33.20%, OCe – 27.98% and BOC – 23.03%) except for OCa with high CV value (39.44%). These moderate to high CV values obtained may not be unconnected with the latter distribution of the area.

Other researchers (Zhou *et al.,* 1996; Tsegaye and Hill, 1998; Cemek *et al.,* 2007; Gokalp *et al.,* 2010) have also documented a lower variance of the soil pH compare to other soil chemical properties. This is because pH values are on log scale of proton concentration in soil solution; there would be a higher variability if the soil acidity is expressed in terms of proton concentration directly. However, the larger CV obtained in other soil properties is attributed to the size of the research area spatial variation of the soil texture and micro-topography as supported by Chien *et al.* (1997); Balasundram (2008)

4.2 POINT-TO-POINT DATA DISTRIBUTION THROUGH SPACE

The CV values of investigated soil properties give a relative estimate of the properties' variability. However, it does not provide any information about how that variability is distributed through space. The spatial distributions of soil variables are presented in Figures 4.1 − 4.4. All studied soil variables exhibited large properties point-to-point fluctuations as compared to the overall variation. This is due to soil natural spatial variability (soil heterogeneity), which presents local characteristics and may therefore be better represented, by locally adaptable models; state space model (Timm *et al.,* 2003a; De Oliveira *et al*., 2011). Although, variables such as elevation, bulk density, MC and pH showed relatively

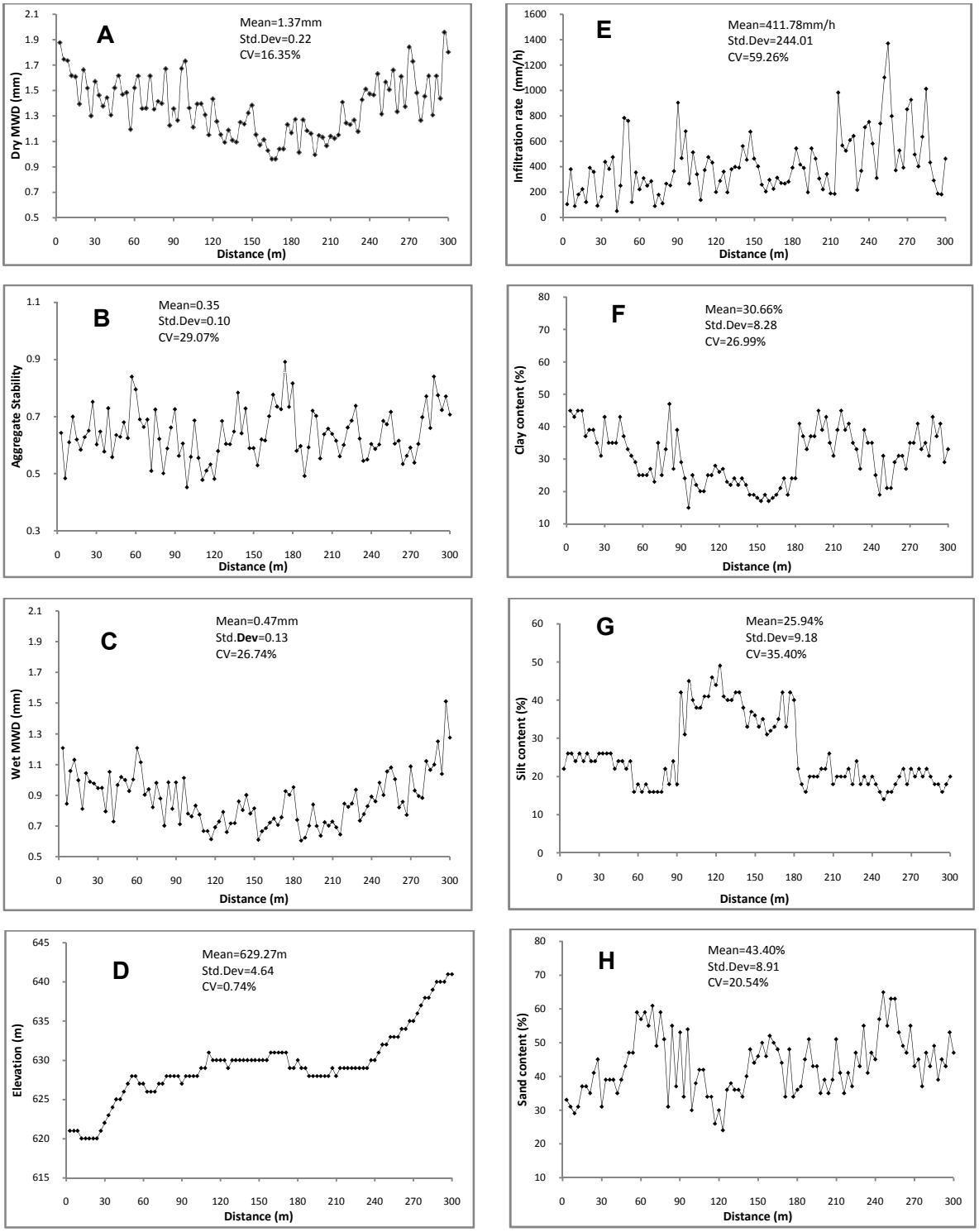
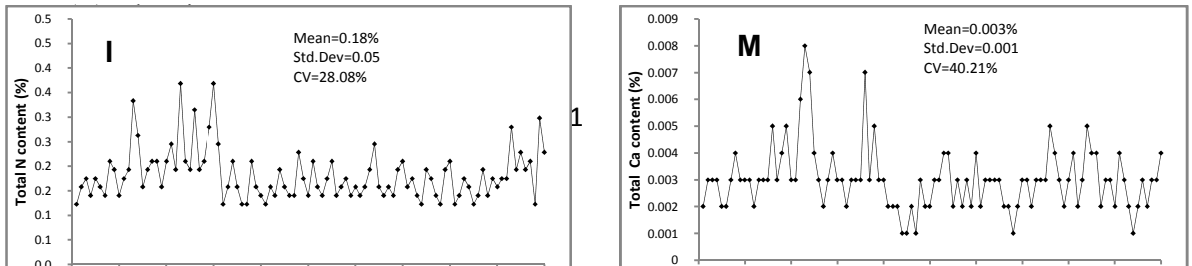


Figure 4.1 Data distribution 3m by 3m along the 300m transect:

(A). Dry mean weight diameter, Dry MWD.
(B). Aggregate stability, AS.
(C). Wet mean weight diameter, Wet MWD.
(E). Infiltration rate, IR.
(F). Clay content, Clay.
(G). Silt content, silt.



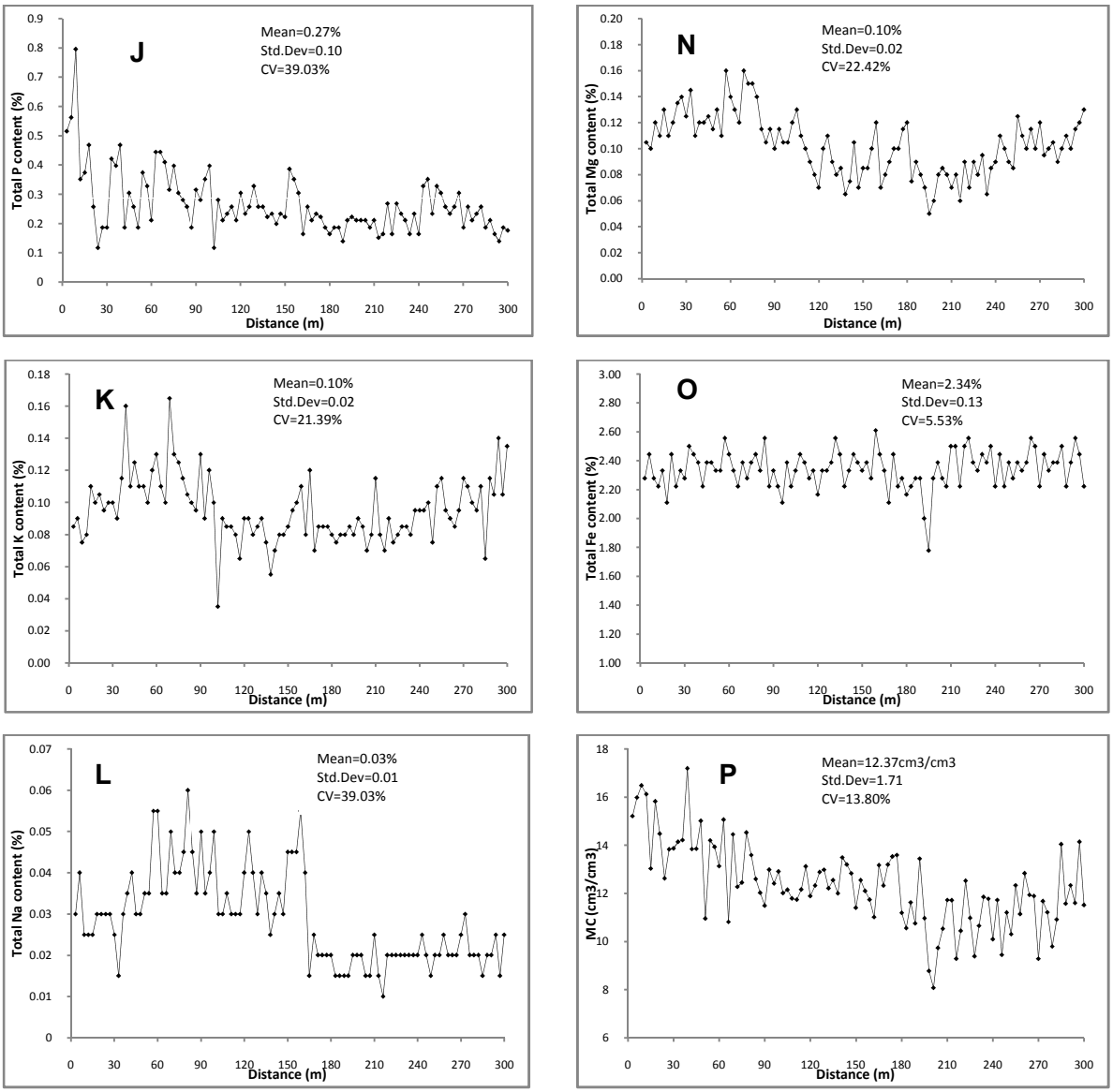
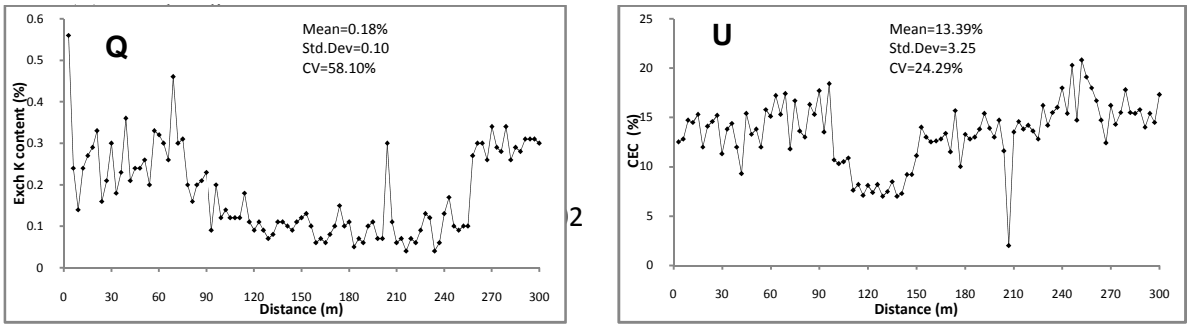


Figure 4.2 Data distribution 3m by 3m along the 300m transect:

(I). Total nitrogen, TN.
(J).Total phosphorous, TP.
(K).Total potassium, TK.
(M). Total calcium, TCa.
(N). Total magnesium, TMg.
(O). Total iron, Fe_t.



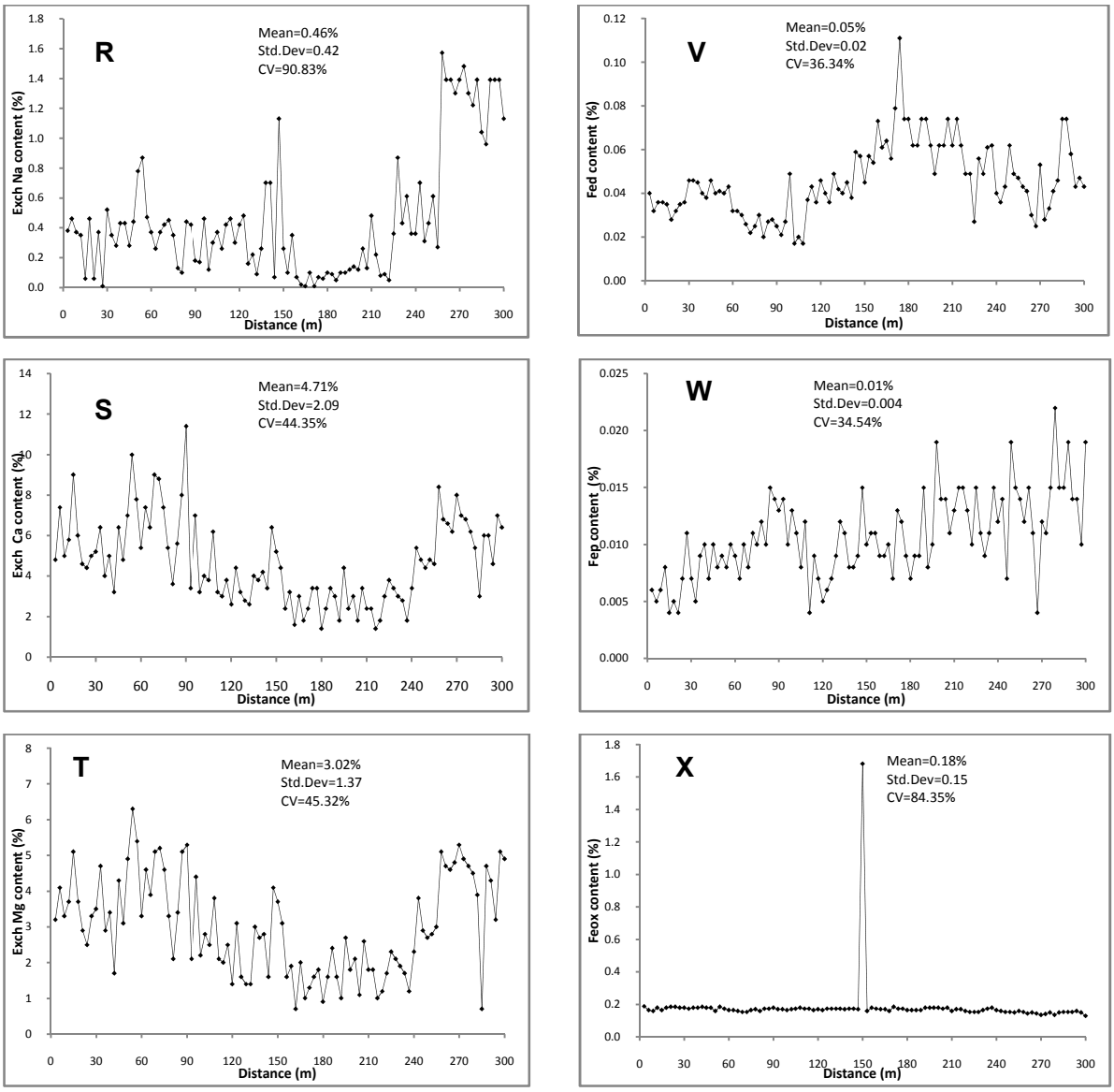
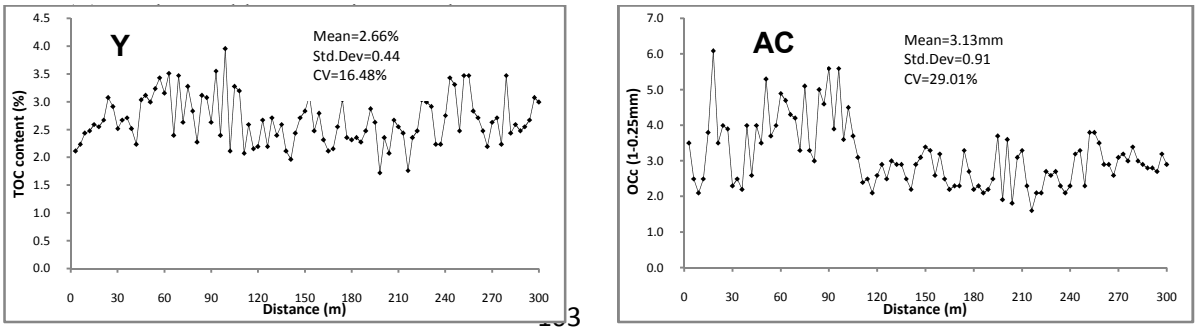


Figure 4.3 Data distribution 3m by 3m along the 300m transect:

(Q). Exchangeable potassium, Exch.K.
(R). Exchangeable soium, Exch.Na.
(S). Exchangeable calcium, Exch.Ca.
(U). Cation Exchangeable capacity, CEC.
(V). Dithionite iron, Fe_d.
(W). Pyrophosphate iron, Fe_p.



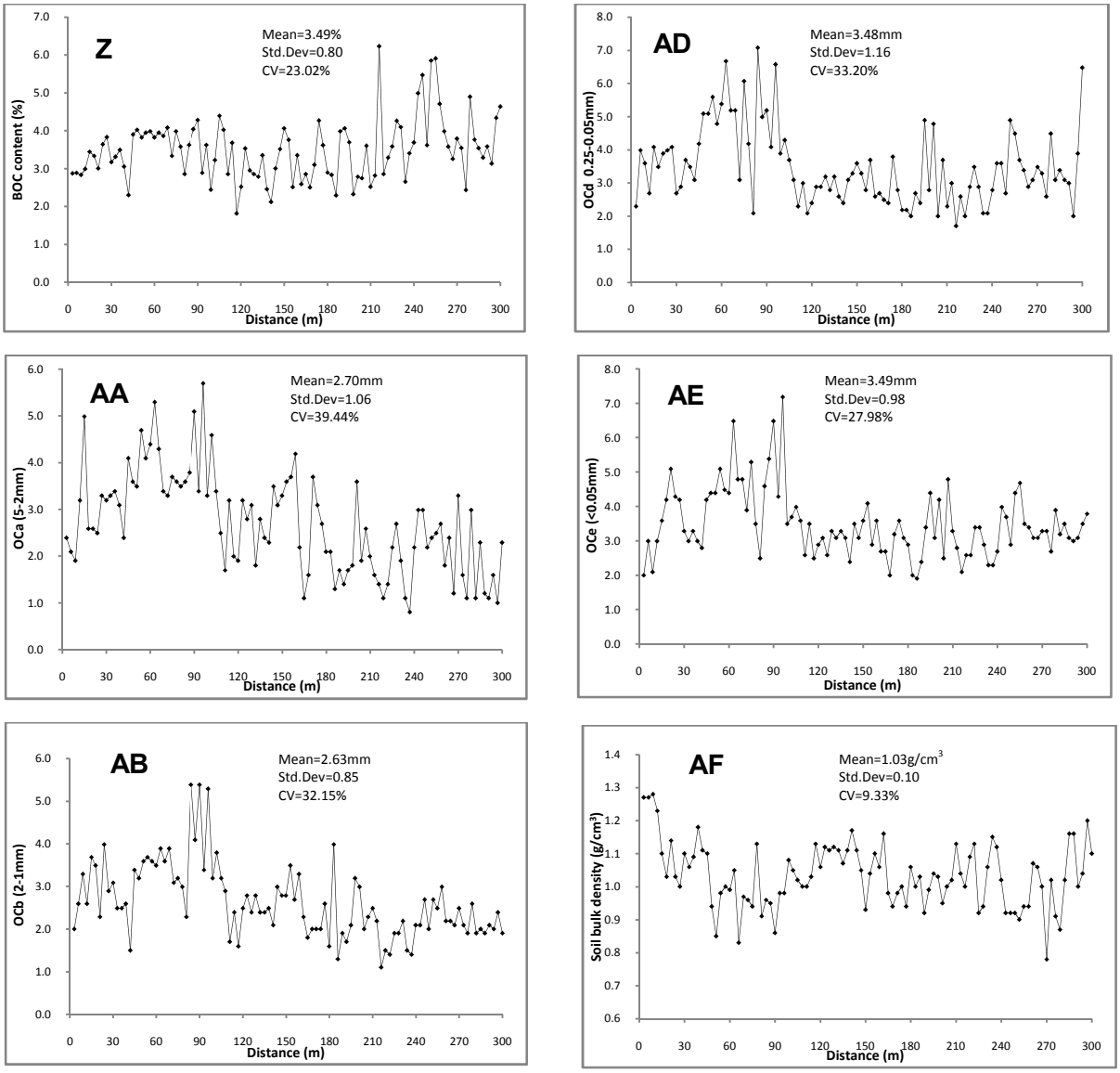


Figure 4.4 Data distribution 3m by 3m along the 300m transect:

(Y). Total organic carbon, TOC.
(Z). Biochemically protected organic carbon, BOC.
(AA). 5-2mm, OCa.
(AB). 2-1mm, OCb.
(AC). 1-0.25mm, OCc..
(AD). 0.25-0.05mm, OCd.
(AE). <0.05mm OCe.
(AF). Soil bulk density, ρb.

low CV values, they exhibited appreciable point-to-point fluctuations along the spatial transect. This behaviours according to Wendroth *et al* (1999), is better identified using statistical tools that consider local behavioral tendencies. Several statistical tools like autocorrelation, cross-correlation, semivariogram and state-space analysis (Morkoc *et al*.,

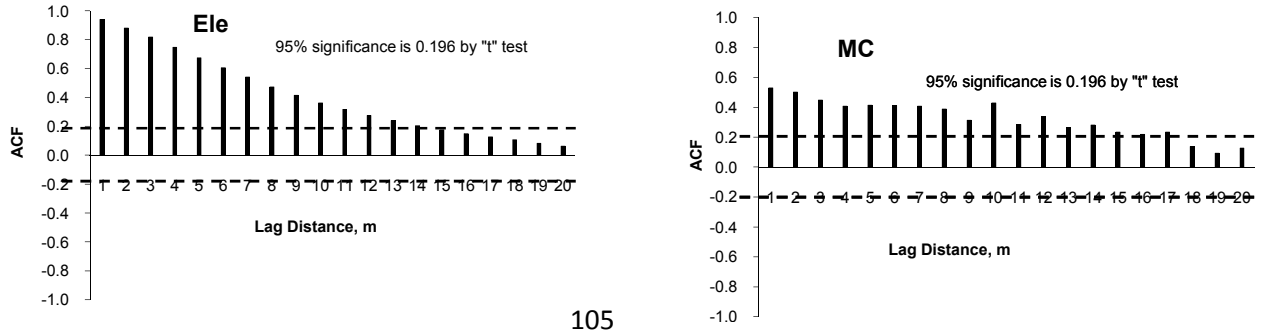
1985; Wendroth *et al.,* 1997; Timm *et al.,* 2006; De Oliveira *et al.,* 2011) have been used to portal this local behaviour.

4.3 AUTOCORRELATION FUNCTION

The calculated ACF for each data set is presented in Figure 4.5 to 4.7 with the objective of evaluating the spatial correlation of the observations i.e if they had been monitored at a distance sufficient for identifying their spatial representation (Timm *et al.*, 2003b). Using a t-test of 5% level of probability, the autocorrelation function of all the soil variables were calculated.

Figure 4.5 presents the autocorrelogram of the investigated soil physical properties (elevation, clay, silt sand, soil moisture content, bulk density and infiltration rate). There is a large spatial dependence of up to 17 lags (MC), 15 lags (elevation) and 13 lags (silt) ie up to a distance of 51 m, 45 m and 39 m respectively between adjacent observations of each variable. For adjacent observations of clay, there was a significant correlation of up to 7 lag (21 m), while sand exhibit a cyclic behaviour with a lag dist up to 5 lags (15 m) between adjacent observations. Spatial structure of up to 2 lags (6 m) and 1 lag (3 m) were observed between adjacent observations of bulk density and infiltration rate.

Strong spatial dependence between adjacent observations of Total Mg (18 lags) and Total



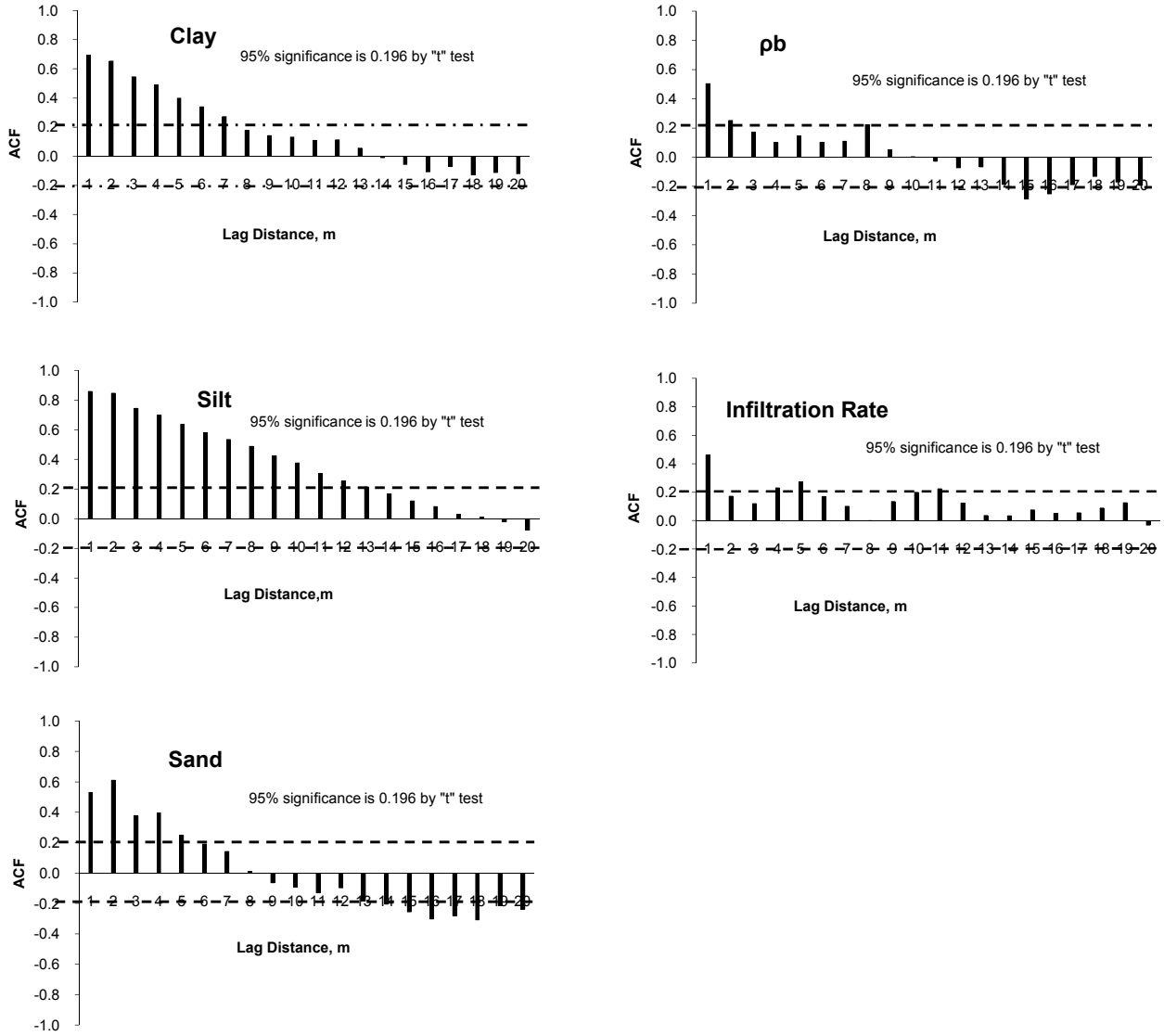


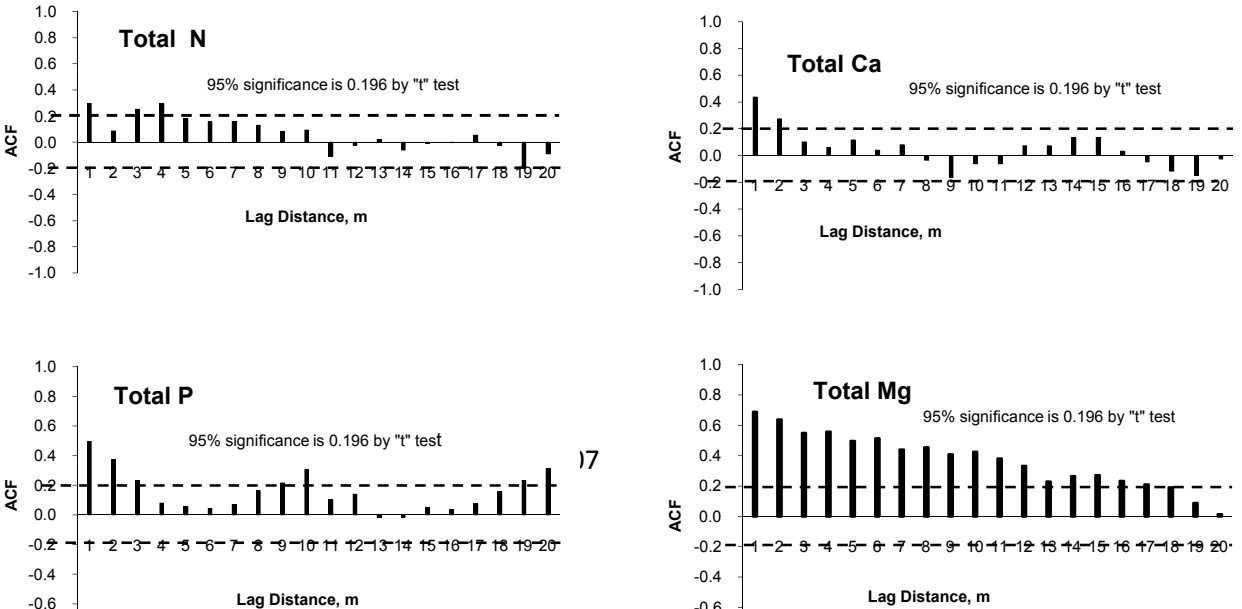
Figure 4.5: Calculated autocorrelation function (ACF) for studied physical properties.

Na (15 lags) data are presented in Figure 4.6. Point-to-point fluctuation of these variables exhibit a trend along the transect causing relatively strong spatial dependence as shown by ACF. Other variables in Figure 4.6 except Total Fe, also manifest a spatial correlation of up to 8 lags (24 m) for Total K, 3 lags (9 m) for Total P, 2 lags (6 m) for Total Ca and 1 lag (3 m) for Total N. No spatial correlation was observed in total iron indicating a random distribution.

Autocorrelation functions for organic carbon (OC) fractions are showed in Figure 4.7. It was observed that the spatial dependence of OC fractions decreased from unprotected to biochemically protected fraction. Organic carbon in the 5−2 mm fraction (OCa) exhibited the highest spatial dependence of 19 lags (57 m), followed by OCb (13 lags – 39 m), OCc (12 lags – 36 m), OCd (7 lags – 21 m), OCe (4 lags – 12 m) while BOC exhibited the less spatial dependence of 1 lag (3 m).

4.4 CROSS-CORRELATION FUNCTION

Based on autocorrelogram of the soil attributes, spatial trends were observed and were expected to be related to each other. To describe the degree of linear association or spatial degree of linkage between two variables, cross-correlation functions (CCF) were calculated. The use of cross-correlation analysis to determine the spatial correlation structure of soil properties as a logical quantitative description of the spatial association between two soil attributes have been reported by Shunway *et al.* (1988); Nielsen *et al.* (1999) and Cassel *et al.* (2001). According to Nielsen *et al.* (1999), analysis of the cross-correlation coefficient between variables that are sampled at neighbouring locations with increasing distance also provides more insight on the spatial covariance structure of the two



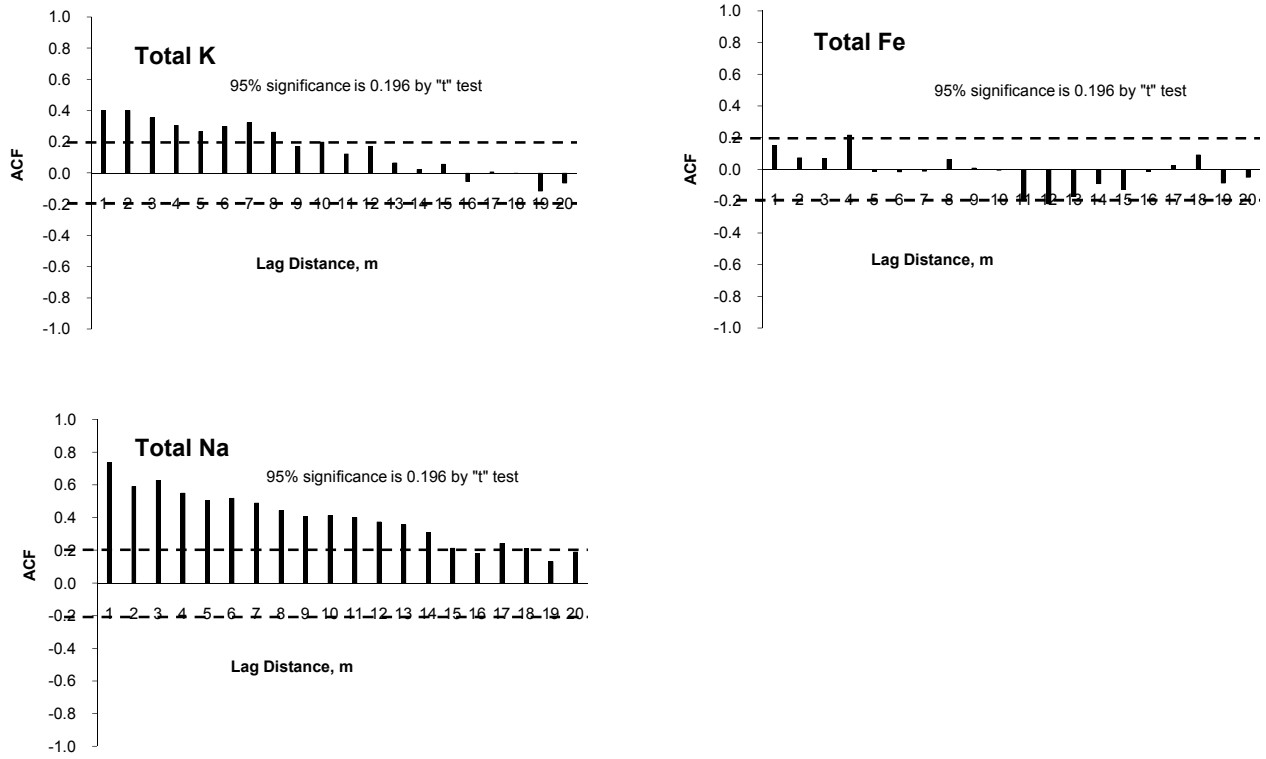
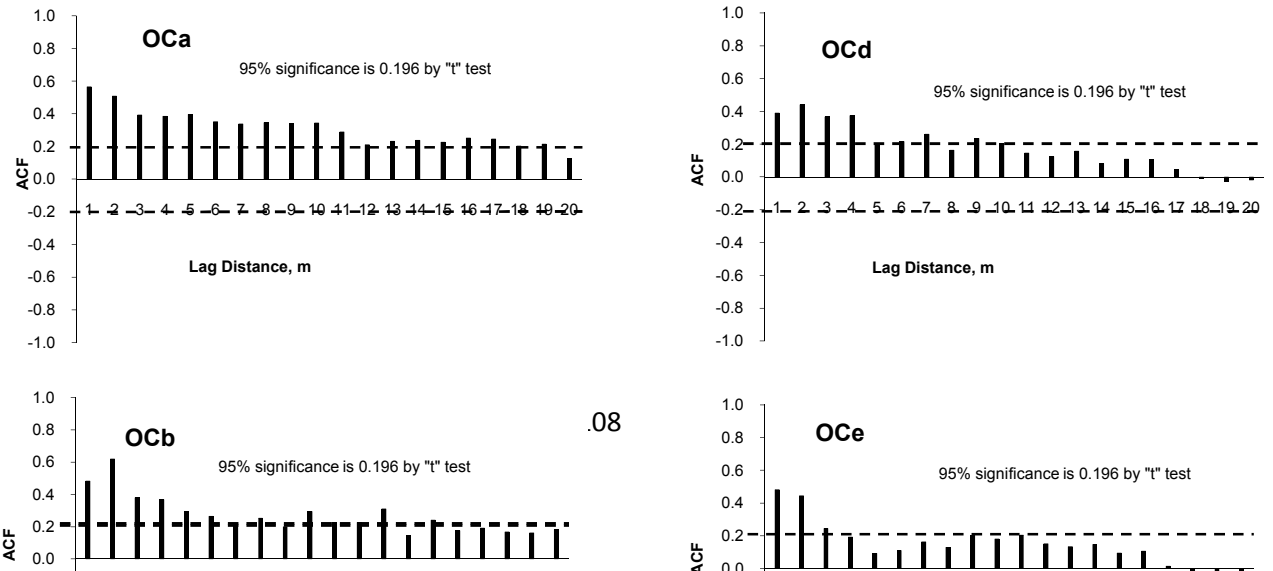


Figure 4.6: Calculated autocorrelation function (ACF) for total elements.



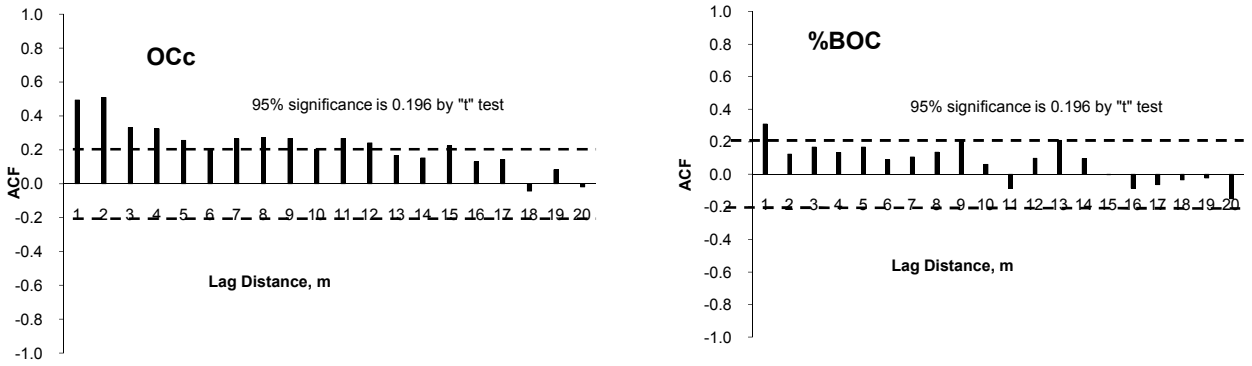


Figure 4.7: Calculated autocorrelation function (ACF) for organic carbon fractions.

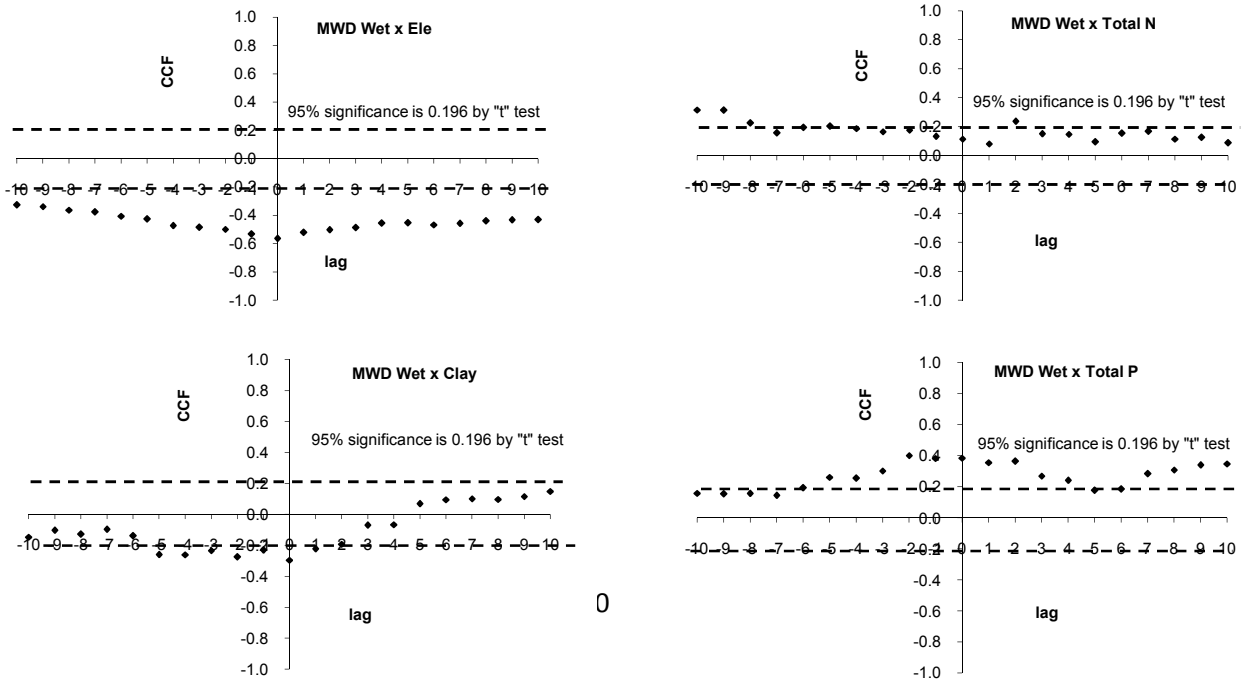
variances. This information can be more useful than the classical correlation coefficient because correlation over several lags are considered and provides a stronger basis for spatial interpolation.

Cross-correlation function was calculated to analyze spatial correlation structures between the investigated soil properties. Using the t-test at the 5% level of probability, the cross-correlogram between MWDw and other soil attributes were calculated. The cross-

correlogram between MWDw and (i) elevation (ii) total sodium showed a stronger spatial dependence (up to 10 lags in both directions) between them than that between MWDw and total P (up to 4 lags) and clay (up to 2 lags) as presented in Figure 4.8. No spatial correlation was observed between MWDw and; (i) silt and (ii) sand. Similar results were also found between MWD wet and; (i) Total N and (ii) Total K (Figure 4.8).

In Figure 4.9 cross-correlograms show strong spatial dependence structure between MWDw and: total Mg (10 lags in both direction) , Exch Na (6 lags) and Fe_d (5 lags); but no spatial dependence structures between MWDw and either total Ca, Exch K, Exch Ca, Exch Mg or CEC. There was a spatial cross- correlation between MWDw and all the organic carbon fractions expect BOC which shows no spatial correlation (Figure 4.10). Similar results were also obtained between MWDw and (i) MC and (ii) Fe_p. Cross-correlogram (Fig. 4.11) showed weak spatial structural dependence between MWDw and (i) ρb and (ii) IR.

From the magnitudes of the CCF between MWDw and other soil properties, there were potential for describing their distributions across transect of observations, suggesting that



0

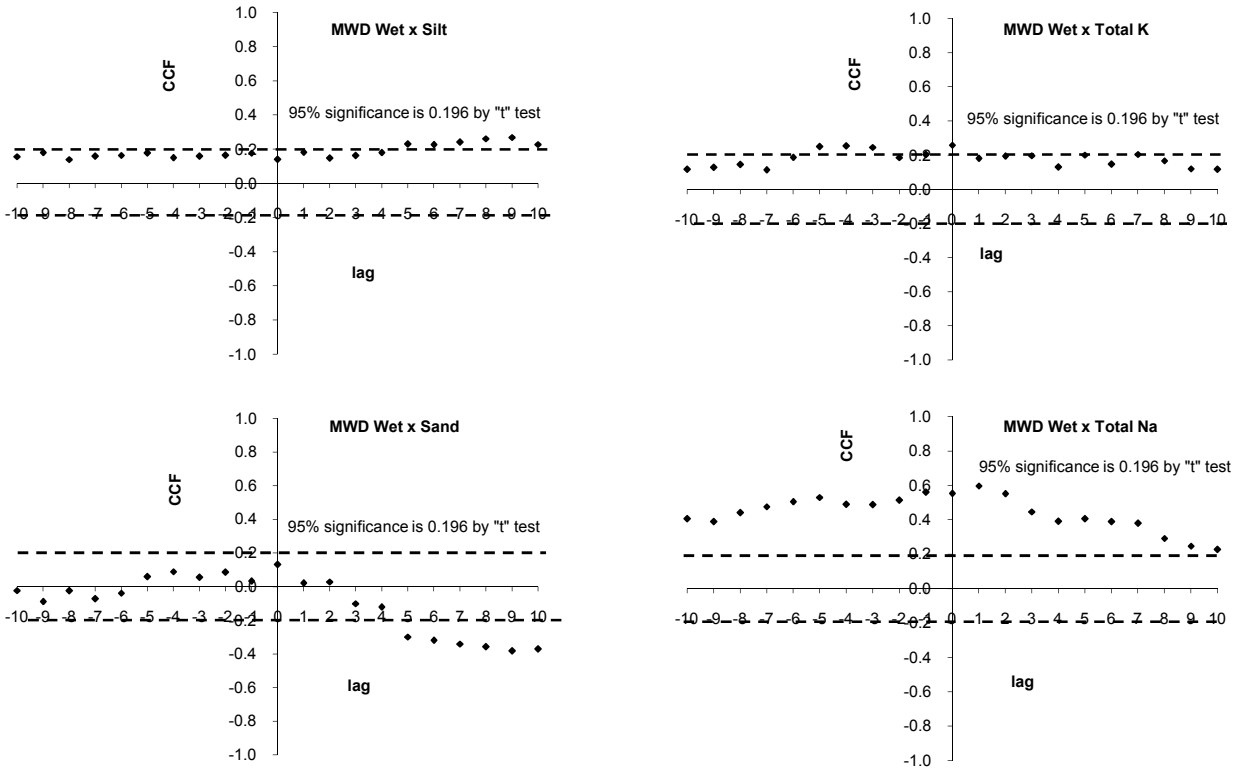
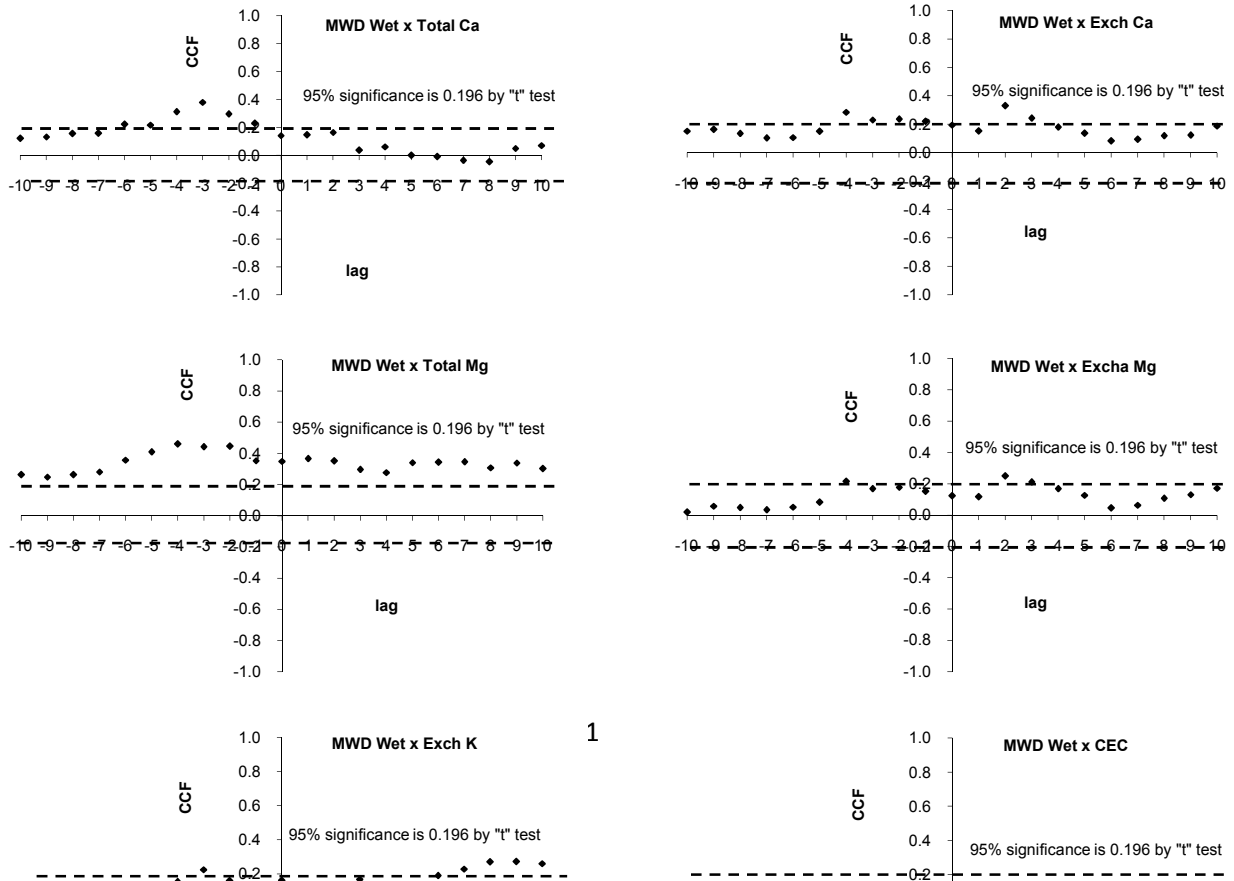


Figure 4.8: Calculated crosscorrelogram function (CCF) between wet mean weight diameter and selected soil variables



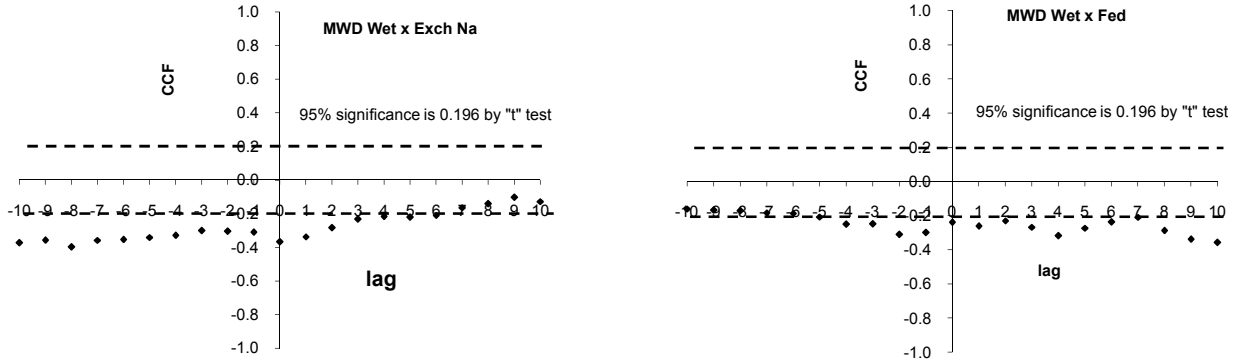
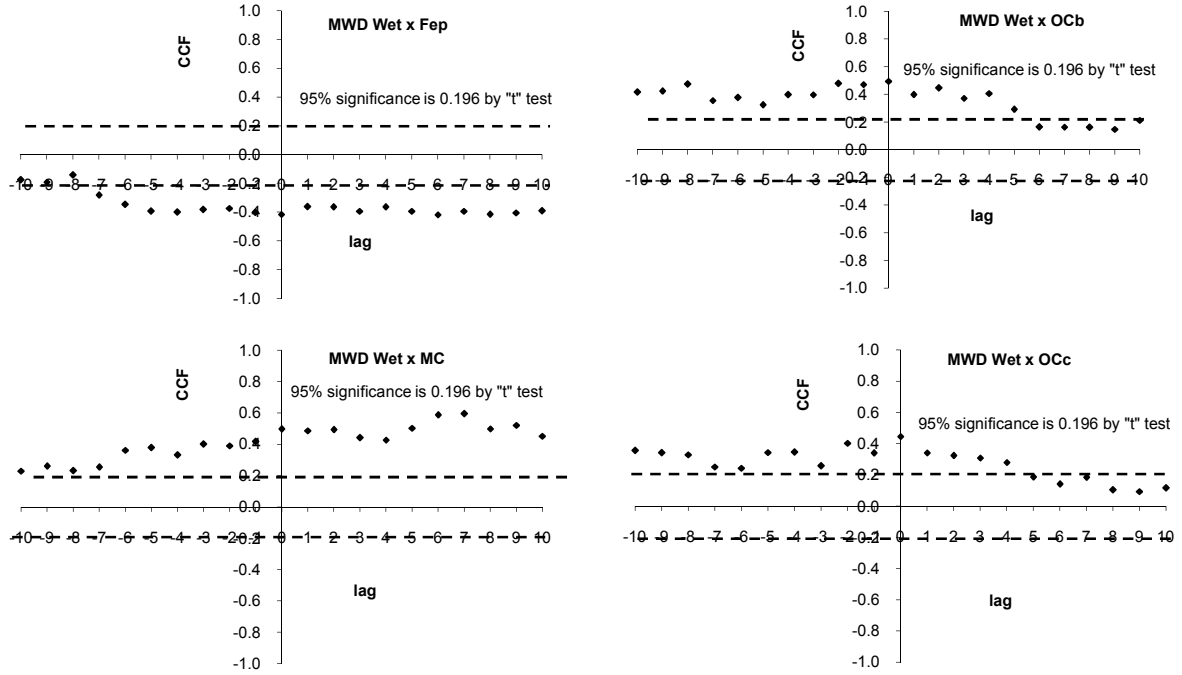


Figure 4.9: Calculated crosscorrelogram function (CCF) between wet mean weight diameter and selected soil variables



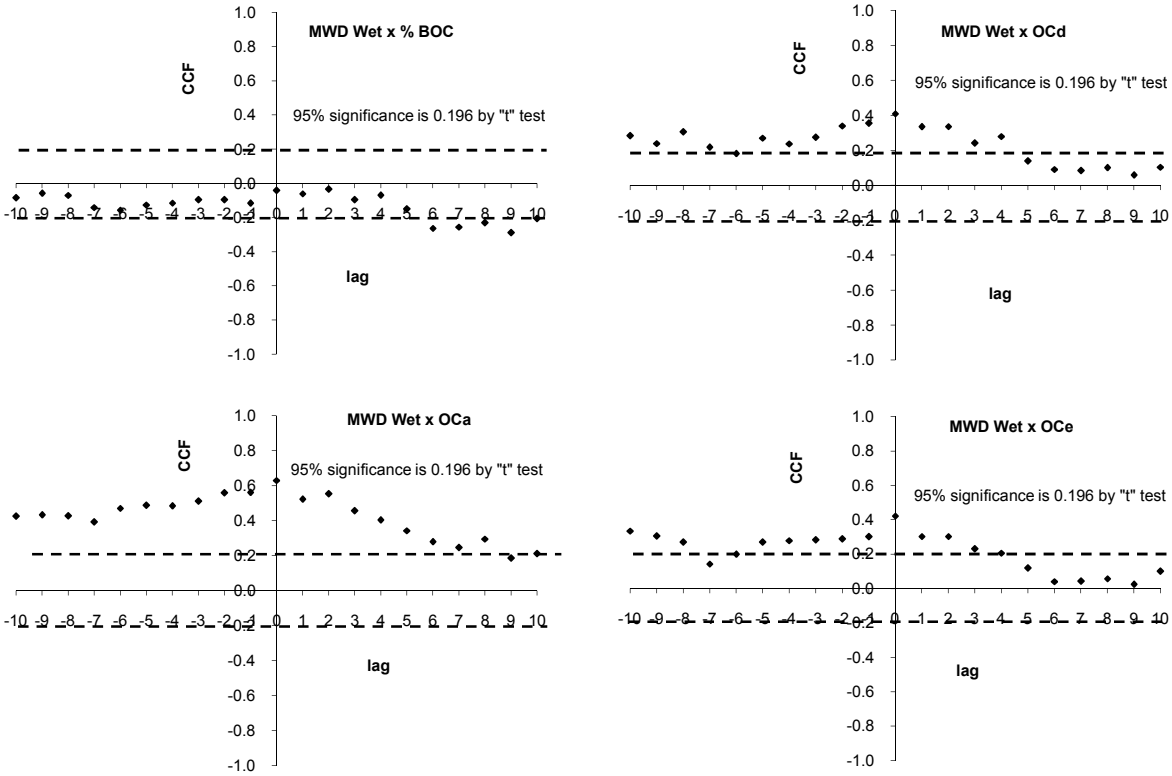


Figure 4.10: Calculated crosscorrelogram function (CCF) between wet mean weight diameter and selected soil variables

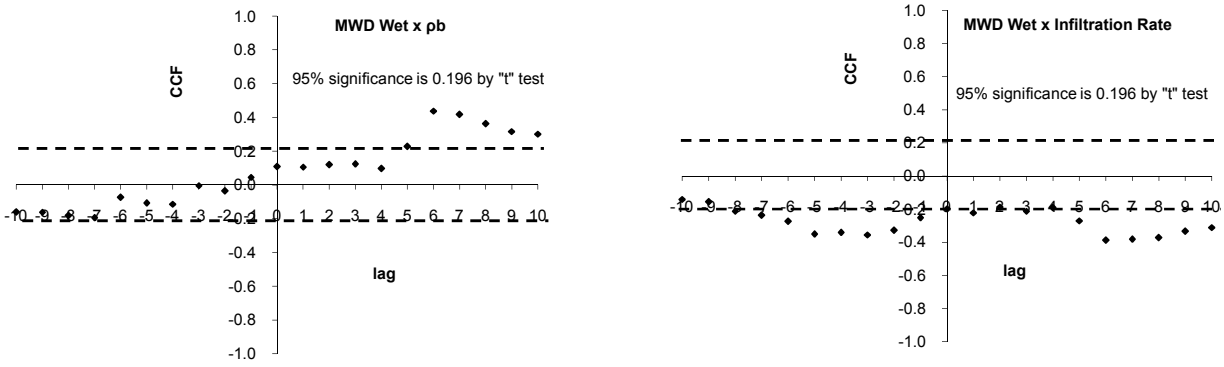


Figure 4.11: Calculated crosscorrelogram function (CCF) between wet mean weight diameter and selected soil variables

CCF could be a useful tool and can lead to additional information on the spatial variability of soil attributes.

4.5 CLASSICAL MULTIPLE REGRESSIONS AND STATE-SPACE ANALYSIS

For a better understanding of the spatial relations between MWDw and other soil variables, the classical multiple regressions and the state-space analysis were compared using the same state variables. Based on the magnitude of the CCF, ten properties were selected and used in various combinations to understand how MWDw is related to itself and to these selected soil variables. Classical multiple regression is based on mean values of each variable across the space under study, in which only the difference between a variable at a given location compared to its respective value at a previous location is considered (De Oliveira *et al*., 2011), assuming independence of the variable (Nielsen and Alemi, 1989).

Ignoring the locations of the observations, simple and multiple linear regression analysis were performed and state-space analysis that allows the study of dynamic processes with local behavioral tendencies (Timm *et al.,* 2003b) were also performed using various combinations of the ten selected soil properties.

Table 4.2 shows the simple linear regression relationships between MWDw and selected soil properties. The result showed that not more than 40% of the variance of the MWDw data could be explained by each property. The poorest simple regression result was obtained using Fe_d (5.7%) while the highest was obtained using OCa (39.7%). Other variables tend to explain MWDw variance to a varying degree; MC (24.7%), OCb (24.5%), OCc (19.1%), OCe (17.8%), Fe_p (17.3%), OCd (16.71%), TP (14.8%) and clay (08.0%).

Table 4.2: Simple linear regression analysis of the ten selected sets of observations versus MWDw and their values of R^2 coefficient

Equation	**Number of samples**	**R^2**
MWDw= 0.017 + 0.037MC	100	0.247
MWDw= 0.606 - 0.004Clay	100	0.088
MWDw= 0.345 + 0.463TP	100	0.148
MWDw= 0.551 - 1.801Fe_d	100	0.057
MWDw= 0.619 - 14.127Fe_p	100	0.173
MWDw= 0.268 + 0.074OCa	100	0.397
MWDw= 0.276 + 0.073OCb	100	0.245
MWDw= 0.276 + 0.062OCc	100	0.199
MWDw= 0.314 + 0.044OCd	100	0.167
MWDw= 0.280 + 0.054OCe	100	0.178

The multiple linear regression analysis (MLRA) revealed that not more than 57.43% of the variance of MWDw data along the spatial transect was explained by the ten variables (Table 4.3a), independent of their location. The state-space analysis performed better by explaining about 90.21% of MWDw data (Table 4.3b). According to McBratney and Webster (1983), using deterministic equations (classical regression equation) information that a variable carries from its neighborhood is often neglected and the additional information from the spatial variability of soil properties is ignored.

Different scenarios were presented to evaluate the results when one, two, three and four out of ten properties were not considered for the estimation. This is because the weight of different variables that contribute to the estimation can change depending on available data (Wendroth *et al.,* 2001). In Tables 4.4a and 4.4b, the analysis of the multiple linear regressions and the state-space using any combination of the nine properties are presented

respectively. Both analyses yielded ten equations or models each. The multiple regression models (Table 4.4a) yielded an R^2 of 0.5127 to 0.5753. The best equation/model (R^2 = 0.5753) was recorded without OCd while the poorest was recorded without OCa. Overall, equations with OCa, MC and Fep contributed over 56% in determining how well the set of MWDw data measured across the transect and described by classical regression equation using this set of properties (clay, Total P, Fed, Fep, OCa, OCb, OCc and OCe).

Table 4.4b, showed state-space models/equations with R^2 values of 0.8039 to 0.9842. The highest R^2 value (0.9842) was recorded when all the carbon fractions were used and the least R^2 (0.8039) recorded when OCe was removed. The analysis further revealed that removal of any of the carbon fractions, adversely affected the R^2 values, with removal of

Table 4.3a: Multiple linear regression equations of wet mean weight diameter for the ten selected variables

Equations	**R^2**
$MWDw_i = 0.\ 1100 - 0.0017(Clay) + 0.0231(Total\ P) + 0.4706(Fed) - 6.5434(Fep) + 0.0500(OCa) + 0.0045(OCb) + 0.0041(OCc) + 0.0060(OCd) + 0.0003(OCe) + 0.0220(MC)$	0.5743

Table 4.3b: State-space equations of wet mean weight diameter for the ten selected variables

Equations	**R^2**
$(MWDw)_i = 0.7589*(MWDw)_{i-1} - 0.0277*(Clay)_{i-1} - 0.2234*(Total\ P)_{i-1} + 0.0272*(Fed)_{i-1} + 0.0260*(Fep)_{i-1} - 0.3721*(OCa)_{i-1} + 0.8966*(OCb)_{i-1} - 0.3309*(OCc)_{i-1} - 0.0363*(OCd)_{i-1} - 0.0816*(OCe)_{i-1} + 0.3480*(MC)_{i-1} + w_i$	0.9021

Table 4.4a: **Multiple linear regression equations of wet mean weight diameter for the nine selected variables**

Equations	**R^2**
$MWDw_i$ = 0. 3558 – 0.0013(Clay) + 0.1583(Total P) + 0.5469(Fed) –10.1013(Fep) + 0.0538(OCa) - 0.0007(OCb) + 0.0124(OCc) + 0.0089(OCd) – 0.0061(OCe)	0.5203
$MWDw_i$ = 0. 1102 – 0.0017(Clay) + 0.0230(Total P) + 0.4709(Fed) – 6.5442(Fep) + 0.0500(OCa) + 0.0045(OCb) + 0.0042(OCc) + 0.0061(OCd) + 0.0220(MC)	0.5743
$MWDw_i$ = 0. 1039 – 0.0017(Clay) + 0.0308(Total P) + 0.4641(Fed) – 6.2590(Fep) + 0.0501(OCa) + 0.0053(OCb) + 0.0056(OCc) + 0.0042(OCe) + 0.0222(MC)	0.5753
$MWDw_i$ = 0. 1116 – 0.0017(Clay) + 0.0216(Total P) + 0.4438(Fed) – 6.5485(Fep) + 0.0499(OCa) + 0.0057(OCb)+ 0.0066(OCd) + 0.0019(OCe) + 0.0222(MC)	0.5741
$MWDw_i$ = 0. 1136 – 0.0017(Clay) + 0.0253(Total P) + 0.4508(Fed) – 6.5564(Fep) + 0.0515(OCa) + 0.0055(OCc) + 0.0064(OCd) + 0.0003(OCe) + 0.0219(MC)	0.5740
$MWDw_i$ = 0. 1115 – 0.0026(Clay) + 0.0504(Total P) + 0.5494(Fed) – 7.6755(Fep) + 0.0357(OCb) + 0.0016(OCc) + 0.0076(OCd) + 0.0165(OCe) + 0.0240(MC)	0.5127
$MWDw_i$ = 0. 0039 – 0.0022(Clay) + 0.0551(Total P) + 0.2283(Fed) + 0.0534(OCa) + 0.0053(OCb) + 0.0045(OCc) – 0.0028(OCd) + 0.0013(OCe) + 0.0275(MC)	0.5499
$MWDw_i$ = 0. 1447 – 0.0019(Clay) + 0.0115(Total P) – 6.1658(Fep) + 0.0503(OCa) + 0.0026(OCb) + 0.0012(OCc) + 0.0057(OCd) + 0.0009(OCe) + 0.0222(MC)	0.5715
$MWDw_i$ = 0. 1096 – 0.0017(Clay) + 0.4508(Fed) – 6.6282(Fep) + 0.0502(OCa) + 0.0048(OCb) + 0.0039(OCc) + 0.0066(OCd) – 0.0002(OCe) + 0.0226(MC)	0.5740
$MWDw_i$ = 0. 0504 + 0.0119(Total P) + 0.6107(Fed) – 7.2858(Fep) + 0.0542(OCa) + 0.0038(OCb) + 0.0047(OCc) + 0.0070(OCd) + 0.0015(OCe) + 0.0208(MC)	0.5637

Table 4.4b: **State-space equations of wet mean weight diameter for the nine selected variables**

Equations	**R^2**
$(MWDw)_i = 0.8593*(MWDw)_{i-1} + 0.0593*(Clay)_{i-1} - 0.0519*(Total\ P)_{i-1} + 0.0962*(Fed)_{i-1} - 0.0950*(Fep)_{i-1} - 0.4911*(OCa)_{i-1} + 1.1604*(OCb)_{i-1} - 0.3531*(OCc)_{i-1} - 0.1473*(OCd)_{i-1} - 0.0552*(OCe)_{i-1} + w_i$	0.9594
$(MWDw)_i = 0.8274*(MWDw)_{i-1} + 0.0390*(Clay)_{i-1} - 0.2067*(Total\ P)_{i-1} + 0.0067*(Fed)_{i-1} - 0.0028*(Fep)_{i-1} - 0.1170*(OCa)_{i-1} + 0.4876*(OCb)_{i-1} - 0.1905*(OCc)_{i-1} - 0.0955*(OCd)_{i-1} + 0.2357*(MC)_{i-1} + w_i$	0.8039
$(MWDw)_i = 0.7801*(MWDw)_{i-1} - 0.0228*(Clay)_{i-1} - 0.1860*(Total\ P)_{i-1} + 0.0389*(Fed)_{i-1} + 0.0118*(Fep)_{i-1} - 0.4758*(OCa)_{i-1} + 1.0184*(OCb)_{i-1} - 0.3960*(OCc)_{i-1} - 0.0916*(OCe)_{i-1} + 0.3088*(MC)_{i-1} + w_i$	0.9319
$(MWDw)_i = 0.6935*(MWDw)_{i-1} - 0.0268*(Clay)_{i-1} - 0.1864*(Total\ P)_{i-1} + 0.0821*(Fed)_{i-1} - 0.0426*(Fep)_{i-1} - 0.3890*(OCa)_{i-1} + 0.8285*(OCb)_{i-1} - 0.2198*(OCd)_{i-1} - 0.0750*(OCe)_{i-1} + 0.3189*(MC)_{i-1} + w_i$	0.8521
$(MWDw)_i = 0.6683*(MWDw)_{i-1} + 0.0471*(Clay)_{i-1} - 0.2284*(Total\ P)_{i-1} + 0.0024*(Fed)_{i-1} - 0.0049*(Fep)_{i-1} + 0.2652*(OCa)_{i-1} - 0.0250*(OCc)_{i-1} + 0.0230*(OCd)_{i-1} - 0.0915*(OCe)_{i-1} + 0.3270*(MC)_{i-1} + w_i$	0.9073
$(MWDw)_i = 0.8010*(MWDw)_{i-1} + 0.0363*(Clay)_{i-1} - 0.2545*(Total\ P)_{i-1} - 0.0221*(Fed)_{i-1} + 0.0439*(Fep)_{i-1} + 0.3416*(OCb)_{i-1} - 0.1261*(OCc)_{i-1} - 0.0883*(OCd)_{i-1} - 0.0361*(OCe)_{i-1} + 0.2895*(MC)_{i-1} + w_i$	0.8307
$(MWDw)_i = 0.6216*(MWDw)_{i-1} - 0.0412*(Clay)_{i-1} - 0.1694*(Total\ P)_{i-1} + 0.0578*(Fed)_{i-1} - 0.2447*(OCa)_{i-1} + .8729*(OCb)_{i-1} - 0.2824*(OCc)_{i-1} - 0.0730*(OCd)_{i-1} - 0.1162*(OCe)_{i-1} + 0.3593*(MC)_{i-1} + w_i$	0.9744
$(MWDw)_i = 0.6968*(MWDw)_{i-1} - 0.0617*(Clay)_{i-1} - 0.2259*(Total\ P)_{i-1} + 0.0841*(Fep)_{i-1} - 0.2541*(OCa)_{i-1} + .8136*(OCb)_{i-1} - 0.2983*(OCc)_{i-1} - 0.1154*(OCd)_{i-1} - 0.0725*(OCe)_{i-1} + 0.4194*(MC)_{i-1} + w_i$	0.9470
$(MWDw)_i = 0.6174*(MWDw)_{i-1} - 0.0560*(Clay)_{i-1} + 0.0549*(Fed)_{i-1} + 0.0029*(Fep)_{i-1} - 0.3012*(OCa)_{i-1} + 0.8673*(OCb)_{i-1} - 0.3035*(OCc)_{i-1} - 0.1040*(OCd)_{i-1} - 0.0604*(OCe)_{i-1} + 0.2706*(MC)_{i-1} + w_i$	0.9842
$(MWDw)_i = 0.7810*(MWDw)_{i-1} - 0.2038*(Total\ P)_{i-1} + 0.0449*(Fed)_{i-1} - 0.0064*(Fep)_{i-1} - 0.3036*(OCa)_{i-1} + 0.8535*(OCb)_{i-1} - 0.3037*(OCc)_{i-1} - 0.0112*(OCd)_{i-1} - 0.1307*(OCe)_{i-1} + 0.2631*(MC)_{i-1} + w_i$	0.9215

OCe being the most affected and OCd the least. The best equation was obtained was with the combination of these properties; clay, Fed, Fep, OCa, OCb, OCc, OCd, OCe and MC.

Appendices B−G show detailed results of different scenarios when eight, seven and six sets of properties out of the ten properties were used for estimation. Multiple linear regression analysis of MWDw against any combination of eight sets of properties showed that the contribution of MC, OCa and Fep is somewhat higher (Appendix B). The removal of any of these properties (MC, OCa and Fep) in combination with any other variable lowers the R^2 values. Removal of OCa and MC from the equation recorded the least R^2 value (0.4483), followed by Fep and MC (R^2 = 0.4533) then Fep and OCa (R^2 = 0.4787). The best R^2 of 0.5740 were obtained with the removal of OCe in combination with (i) OCc (ii) OCb (iii) TP. Again, the equation that best describe the measured set of MWDw data showed that OCa, MC and Fep are important variables and they contributed at least 55%.

Appendix C presents state-space equations using a set of eight variables. The best suited equation of the State-space was determined by an equation involving all the carbon fractions with 0.9968 R^2 value. Furthermore, the removal of any two organic carbon fractions in an equation resulted in an R^2 value of less than 0.9000, except the removal of OCd in combination with (i) OCb and (ii) OCa. The least R^2 value resulted when OCa was removed in combination with OCd. These analyses with combination of eight set of observations produced a total of 45 equations each.

Evaluation of the results when three out of the ten properties were not considered for estimation using multiple linear regression models and state-space models, are presented in Appendices D and E respectively. These three variables (OCa, MC and Fep) still explained

more than 57% of MWDw data variance. Models where the three properties are included in the estimation explained about 58% of the variance, while those with only 2 out of the 3 properties explained between 47-51% followed by those with at least one of the property. Exclusion of three properties from the estimation explained only 36% of the variance. When state space models were used to estimate the same number of properties more than 70% of the MWDw data variable were explained. Unlike, the result obtained using multiple linear regression analysis, Fep seem less important with its exclusion, 97% of the variance were explained. Although removal of OCa from any combination adversely affect the R^2 values, removal of Total P, OCd and MC explained only 72.31% of the variance while the removal of Fep, OCb and MC explained the highest percentage variation (99.85%). Evaluation of all the possible combination of seven out of the ten variables generated 70 equations for each analysis.

Presented in Appendices F and G, are data showing models generated using six of the selected soil attributes, i.e., exclusion of four soil attributes. Estimation of MWDw variation using only six variables in all possible combination generated 116 models for each analysis. The coefficient of determination (R^2) values ranges from 0.2885 to 0.5733. The least R^2 value was observed when Fep, OCa and MC were excluded in combination with Total P from the estimation properties. The highest value of R^2 was obtained when Total P, OCb, OCc and OCe was excluded from the determination. Again, when any one of these three variables (Fep, OCa and MC) is removed R^2 values were affected. With the removal of Fep, OCa or MC in combination with other soil properties, about 55%, 50% or 52% of the variation could be explained. Furthermore, removal of any of the two properties in combination with other soil properties reduces the percentage portion of the explainable

MWDw variation; Fep and OCa (48%), Fep and MC (46%) and OCa and MC (45%). Thirty-six percent of the variation could be explained when these three variables are ccexcluded from the estimations. Exclusion of these three variables in combination with Total P recorded the poorest percentage of explainable portion of the variation (28.85%).

Data in Appendix G shows models using state-space approach with the R^2 values ranging from 0.7238 to 0.9978. The highest R^2 value (0.9978) was recorded when Total P, Fep, OCd and OCe while the least value (0.7238) was recorded with the exclusion of Total P, OCa, OCb and OCe from the determination variables. This implies that clay, Fed, OCa, OCb, OCc and MC are useful in the determination of MWDw spatial variation. As the number of properties excluded from the estimation of MWDw spatial distribution increases, the percentage explainable portion of MWDw variation gradually diminished. This indicates change in the property contribution owning to the available data (Wendroth *et al.,* 2001).

The best result obtained for different scenarios using both MLRA and state-space analyses are presented in Table 4.5. Examining results, the best performance of all the state-space equations was that in which clay, Total P, Fed, OCa, OCc, OCd and OCe were used, with R^2 coefficient of 0.9985. In other words, the local and regional variations of these properties across transect were the most important variation related to the spatial distribution of MWDw. The best performance of all the multiple linear regression equation was given when clay, Total P, Fed, Fep, OCa, OCb, OCc, OCe and MC were used (R^2 coefficient of 0.5753). When both best equations were considered, it was observed that

Table 4.5: Best performance model for each set of soil variables

Models	R^2
State-space	
$(MWDw)_i = 0.7589*(MWDw)_{i-1} - 0.0277*(Clay)_{i-1} - 0.2234*(Total\ P)_{i-1} + 0.0272*(Fed)_{i-1} + 0.0260*(Fep)_{i-1} - 0.3721*(OCa)_{i-1} + 0.8966*(OCb)_{i-1} - 0.3309*(OCc)_{i-1} - 0.0363*(OCd)_{i-1} - 0.0816*(OCe)_{i-1} + 0.3480*(MC)_{i-1} + w_i$	0.9021
$(MWDw)_i = 0.6174*(MWDw)_{i-1} - 0.0560*(Clay)_{i-1} + 0.0549*(Fed)_{i-1} + 0.0029*(Fep)_{i-1} - 0.3012*(OCa)_{i-1} + 0.8673*(OCb)_{i-1} - 0.3035*(OCc)_{i-1} - 0.1040*(OCd)_{i-1} - 0.0604*(OCe)_{i-1} + 0.2706*(MC)_{i-1} + w_i$	0.9842
$(MWDw)_i = 0.7385*(MWDw)_{i-1} - 0.0031*(Clay)_{i-1} + 0.0621*(Total\ P)_{i-1} + 0.0685*(Fed)_{i-1} - 0.3957*(OCa)_{i-1} + 1.1545*(OCb)_{i-1} - 0.3211*(OCc)_{i-1} - 0.2283*(OCd)_{i-1} - 0.0911*(OCe)_{i-1} + w_i$	0.9968
$(MWDw)_i = 0.6144*(MWDw)_{i-1} + 0.0592*(Clay)_{i-1} + 0.1126*(Total\ P)_{i-1} + 0.0236*(Fed)_{i-1} + 0.3747*(OCa)_{i-1} + 0.0602*(OCc)_{i-1} - 0.1078*(OCd)_{i-1} - 0.1558*(OCe)_{i-1} + w_i$	0.9985
$(MWDw)_i = 0.4746*(MWDw)_{i-1} - 0.0914*(Clay)_{i-1} + 0.0525*(Fed)_{i-1} - 0.1511*(OCa)_{i-1} + 0.7506*(OCb)_{i-1} - 0.4455*(OCc)_{i-1} + 0.3993*(MC)_{i-1} + w_i$	0.9978
Multiple linear regression	
$MWDw_i = 0.1100 - 0.0017(Clay) + 0.0231(Total\ P) + 0.4706(Fed) - 6.5434(Fep) + 0.0500(OCa) + 0.0045(OCb) + 0.0041(OCc) + 0.0060(OCd) + 0.0003(OCe) + 0.0220(MC)$	0.5743
$MWDw_i = 0.1039 - 0.0017(Clay) + 0.0308(Total\ P) + 0.4641(Fed) - 6.2590(Fep) + 0.0501(OCa) + 0.0053(OCb) + 0.0056(OCc) + 0.0042(OCe) + 0.0222(MC)$	0.5753
$MWDw_i = 0.1143 - 0.0017(Clay) + 0.0199(Total\ P) + 0.4410(Fed) - 6.5575(Fep) + 0.0502(OCa) + 0.0060(OCb) + 0.0076(OCd) + 0.0222(MC)$	0.5740
$MWDw_i = 0.1139 - 0.0017(Clay) + 0.0251(Total\ P) + 0.4512(Fed) - 6.5574(Fep) + 0.0515(OCa) + 0.0057(OCc) + 0.0065(OCd) + 0.0219(MC)$	0.5740
$MWDw_i = 0.1093 - 0.0017(Clay) + 0.4503(Fed) - 6.6279(Fep) + 0.0501(OCa) + 0.0049(OCb) + 0.0038(OCc) + 0.0065(OCd) + 0.0226(MC)$	0.5740
$MWDw_i = 0.1131 - 0.0017(Clay) + 0.4259(Fed) - 6.6297(Fep) + 0.0503(OCa) + 0.0062(OCb) + 0.0079(OCd) + 0.0227(MC)$	0.5738
$MWDw_i = 0.1208 - 0.0017(Clay) + 0.3785(Fed) - 6.6632(Fep) + 0.0528(OCa) + 0.0094(OCd) + 0.0226(MC)$	0.5733

clay, Total P, Fed, Fep, OCa, OCc and OCe were important soil attributes in the determination of spatial distribution of MWDw. Description of MWDw variation across different number of selected soil variables showed that clay, Fed, OCa and OCc (state-space model); and clay, Fed, Fep, OCa and MC (multiple linear regression model) were essential. Also, it was identified that clay, Fed and OCa have effective contribution to describe MWDw variation in this study because they were related to the best performance of each different scenarios (Table 4.5).

However, comparing the results from the two scenarios presented in Table 4.8, State-space model using all of ten variables describes the MWDw (R^2 = 0.9021) better than the equivalent multiple linear regression equation (R^2 = 0.5743). Using nine of all the soil variables, state-space model describes MWDw with R^2 coefficient of 0.9824 and the equivalent multiple regression equation with R^2 coefficient of 0.5753. Again, state-space model describes MWDw better than the equivalent multiple regression equation using eight, seven and six of all the selected soil variables. In this study all of state-space equations describes MWDw better than the equivalent multiple regression equations. The better performance of state-space models compared to classical multiple regression models was also reported by Timm *et al*. (2003a; 2004); De Oliveira *et al.* (2011). These authors observed a better estimation of the soil water content by state-space than by the equivalent linear regression equations. The benefit of a state-space analysis of the state variables is that each variable is treated statistically as random and the spatial variation as a function of the distance between measurements.

4.6 SPATIAL STRUCTURE AND ATTRIBUTES

To characterize spatial structure or variations of soil properties, data were analyzed by semivariograms underlying geostatistical methods, according to Vieira and Gonzalez (2003), based on the assumption of an invariable intrinsic hypothesis. Geostatistical method assumes that variables in an area exhibit both random and spatially structured properties. The semivariogram determines the increase in variance between samples collected at increasing separation distances from one another (Burgess and Webster, 1980a), and is a graphical representation of the relationship between semivariances and separation distances. Semivariance ideally increases with distance between sample locations, to a more or less constant value (total semivariance) at a given separation distance, i.e. the range of spatial dependence. Samples separated by the distances closer than the range are related spatially, and those separated by the distance greater than the range are not spatially related. According to Vieira and Gonzalez (2003), measurements carried out in areas that are close to one another are expected to be more similar to each other than those further apart.

4.6.1 Semivariogram model

The most common semivariogram models used to fit experimental semivariograms and therefore used to describe spatial variability of the properties under study were spherical, exponential, gaussian and linear (Webster and Oliver, 2007). Parameters that characterize these models are the nugget, sill, and range and are calculated through the fitting process. Fitting models to the experimental semivariograms to theoretical models were based on cross-validation procedure to check validity of the models and to compare values estimated from the semivariogram model with actual values (Utset *et al.,* 2000). Selection of the best-fitting model was based on regression statistics such as minimum residual sum of square

(RSS) and maximum determination coefficient (R^2) values. These models provide information about the spatial structure as well as the spatial attributes.

The semivariogram structure and the corresponding nugget, sill and range values of the best fitted model based on the least RSS and maximum R^2 values are presented in Figures 4.12 to 4.15 and Table 4.6 respectively. Spherical models were defined for MC, silt and sand; exponential for MWDw, IR, ρb and clay while Gaussian model was defined for MWDdry (Figure 4.12). The results obtained for silt was consistent with the report from Ayoubi *et al.* (2007) but contradict the result obtained for clay and sand. They defined spherical and Gaussian models for clay and sand respectively. All the exchangeable bases analyzed (K^+, Na^+, Mg^{2+} and Ca^{2+}) exhibited a definable spatial structure and were described by spherical models (Table 4.13), while forms of iron (Fe_d, Fe_p and Fe_{ox}) subscribe to different models: gaussian (Fe_d), exponential (Fe_p) and linear (Fe_{ox}). There was no definable structure for total iron. Total iron exhibit pure nugget (DD = 100%) i.e. non-spatially correlated because slope of the semivariogram was close to zero. Instead of the semivariogram to increase and depend on distance, there was no baseline, total absence of spatial dependence, making it impossible to fit a model (Vieira and Gonzalez, 2003).

The best fitted models for TOC, OC fractions and CEC are showed in Table 4.14. The semivariograms of TOC and all OC fractions except OCd (0.25 - 0.05 mm) and OCe (< 0.05 mm) were fitted to exponential model including CEC. OC fraction of 0.25 - 0.05 mm and < 0.05 mm fitted to spherical. The four identified models under this study were used to describe the total elements (Table 4.15). Exponential models were used to describe Total N,

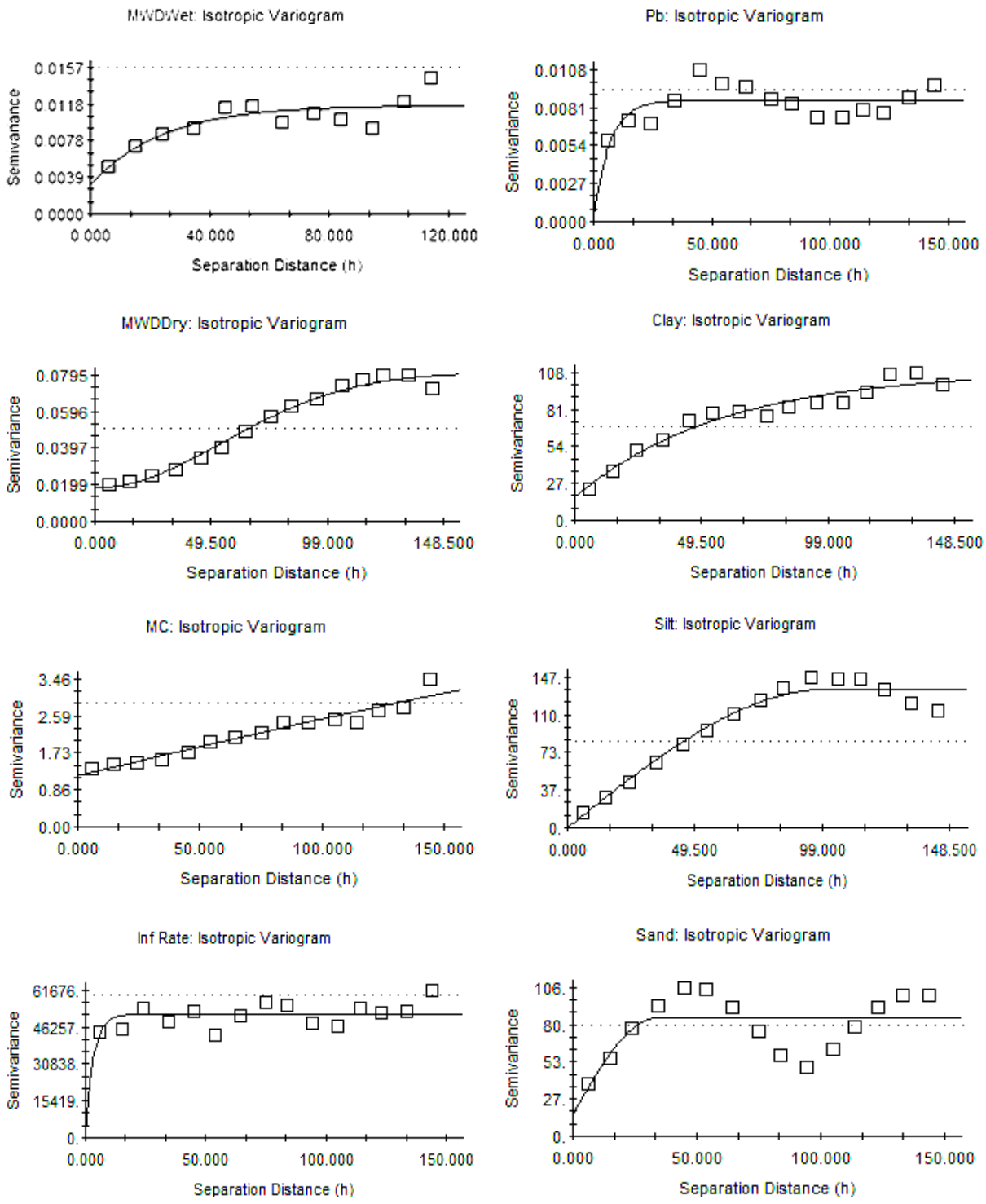


Figure 4.12: Experimental and best-fitted mathematical semivariogram models based on the least Residual Sum of Squares (RSS) and the maximum coefficient of determination (R^2) value.

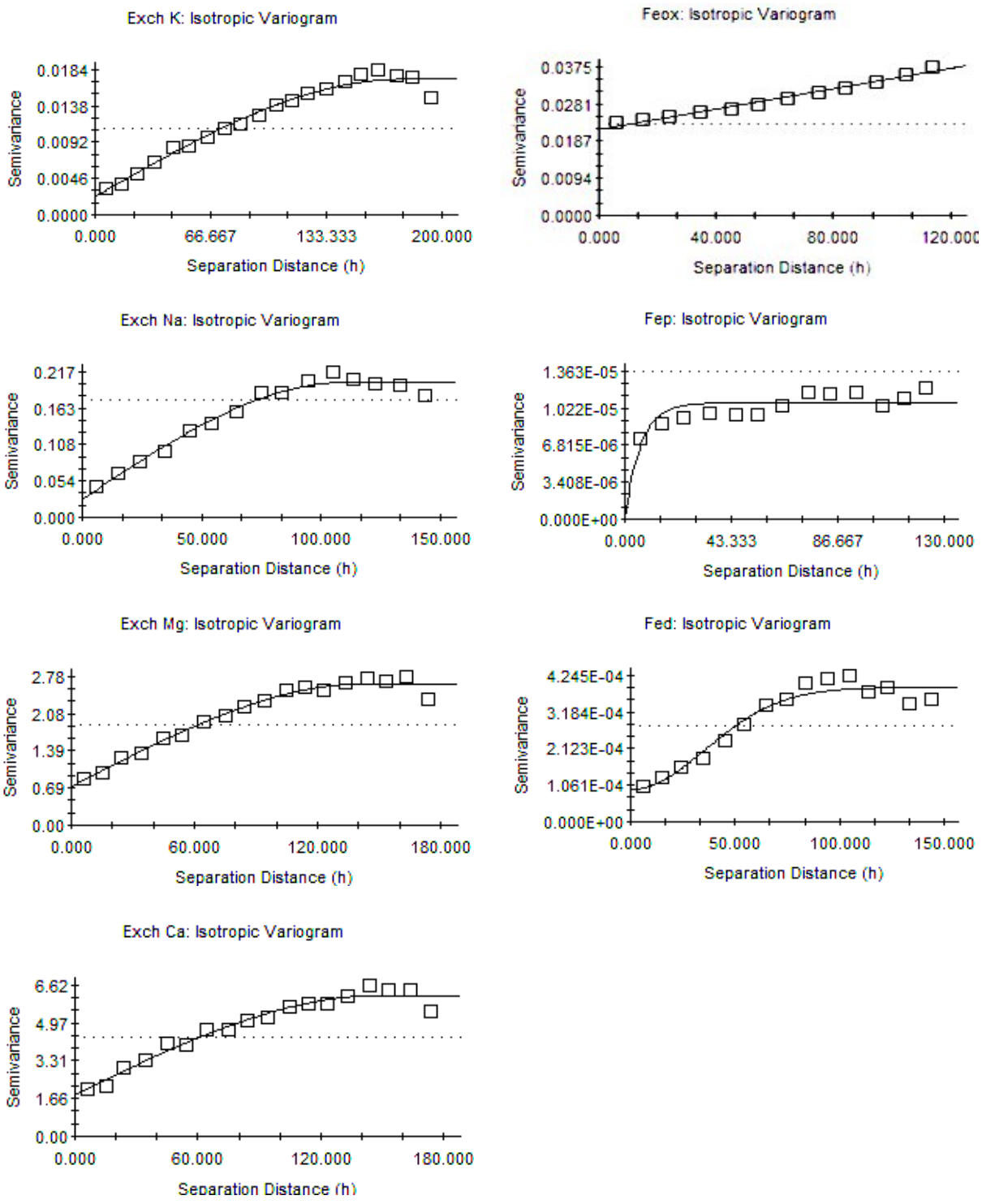


Figure 4.13: Experimental and best-fitted mathematical semivariogram models based on the least Residual Sum of Squares (RSS) and the maximum coefficient of determination (R^2) value.

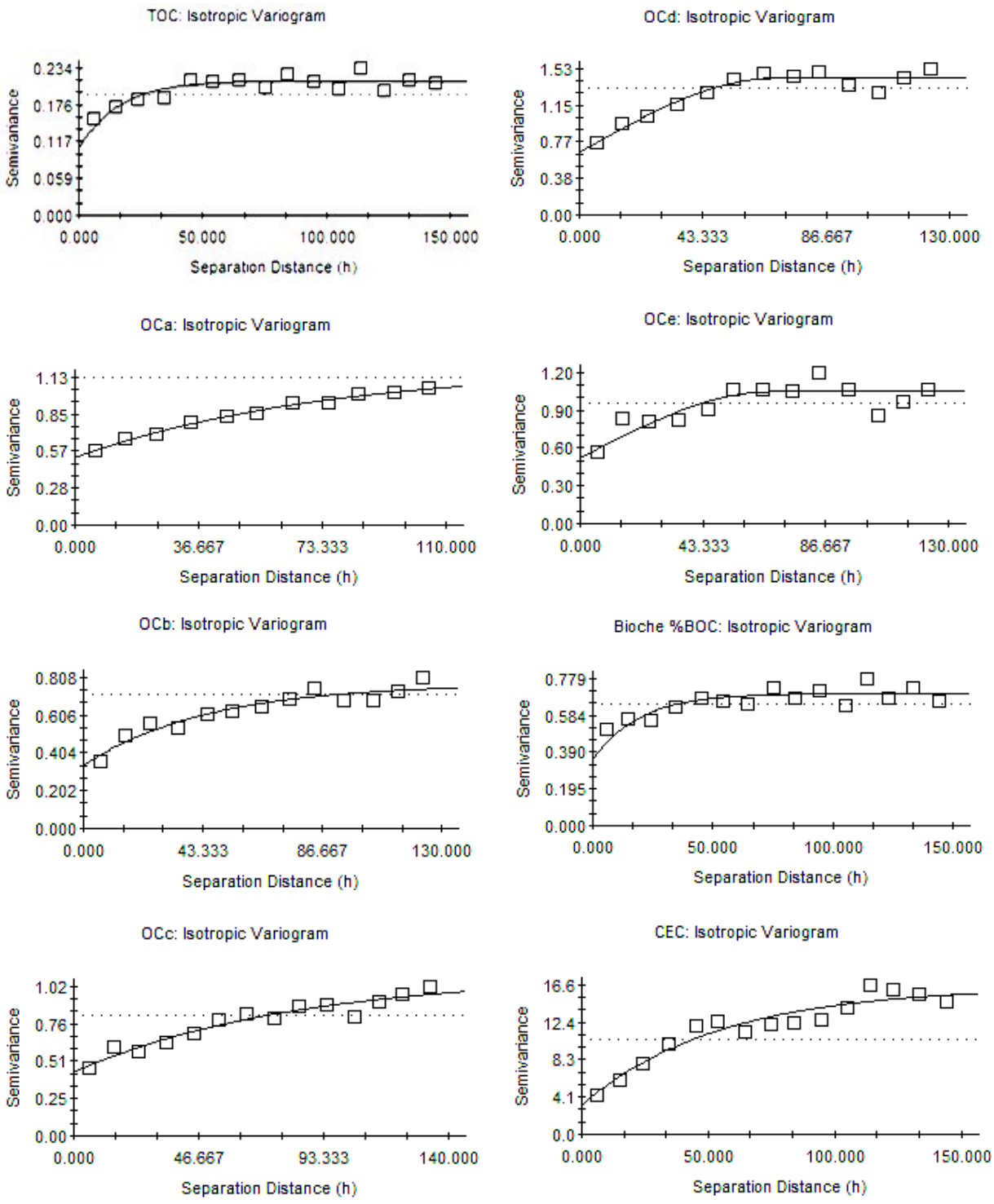


Figure 4.14: Experimental and best-fitted mathematical semivariogram models based on the least Residual Sum of Squares (RSS) and the maximum coefficient of determination (R^2) value.

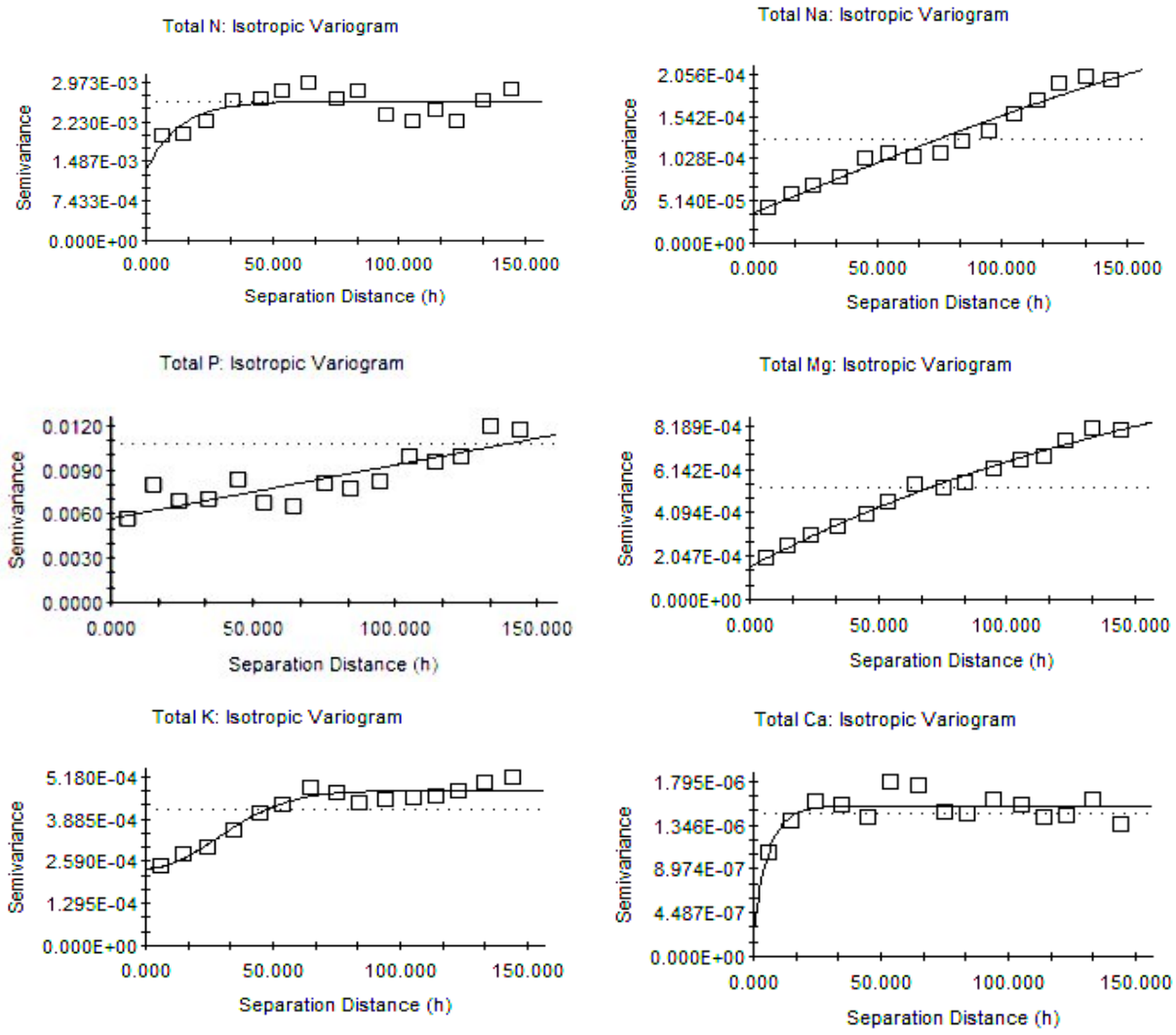


Figure 4.15: Experimental and best-fitted mathematical semivariogram models based on the least Residual Sum of Squares (RSS) and the maximum coefficient of determination (R^2) value.

Total Mg and Total Ca, spherical for describing Total Na, linear for Total P while gaussian was used for Total K.

Exponential and spherical models were predominant models under this study, confirming the predominance of these models in soil science research (Cambardella *et al.,* 1994; Jusoff *et al.,* 2004; Liu *et al.,* 2007; Law *et al.,* 2009; Gokalp *et al.,* 2010; Filho *et al.,* 2010; Yang *et al.,* 2011). Considering each soil property, however, the results obtained are inconsistent with the reports of other authors. Clay and bulk density data were described by spherical model (Filho *et al.,* 2010), silt by exponential and MWDw by spherical model (Gokalp *et al.,* 2010), Exch Na by exponential (Liu *et al.,* 2007), TOC by spherical (Law *et al.,* 2009; Gokalp *et al.,* 2010) while Jusoff *et al.* (2004) fitted Total N to spherical model and Total P to exponential. These differences could probably be due to differences in landuse systems of the study sites. All the studies mentioned were conducted on agricultural soils. Therefore, tillage and other farming practices may have induced these differences.

4.6.2 Nugget effect

Nugget effect (C_o) represents field and experimental variability, or random variability that is undetectable at the sampling distances (Webster and Oliver, 1992). It is an expression of the unexplained variations due to sampling distance, area variations, analysis errors, and sampling errors (Trangmar *et al.,* 1985). Nugget semivariance is the variance at zero distance. The nugget effect reveals discontinuity of the semivariogram or spatial variability than the distance between samples (Webster, 1985).

Nugget effect values (Table 4.6) obtained ranged from 0.000 to 100.000. The lowest C_o values were observed for ρb, Total K, Na, Mg and Ca, Fe_d and Fe_p, were equal to zero,

Table 4.6: Best fitted models and the corresponding parameters describing soil attributes of the study area.

Variables	Models	Nugget C_o	Sill $C_o + C$	Range(m) A_o	Spatial ratio (%)	Spatial dependence	R^2	RSS
MWDw	Exponential	0.003	0.012	24.000	25.00	Strong	0.692	2.009E-05
MWDdry	Gaussian	0.018	0.081	77.000	22.22	Strong	0.987	9.309E-05
MC (cm^3/cm^3)	Spherical	1.200	4.628	379.000	25.93	Strong	0.939	0.300
IR (mm/hr)	Exponential	100.000	51710.000	3.300	0.19	Strong	0.161	3.10E+08
Pb (g/cm^3)	Exponential	0.000	0.009	7.000	0.00	Strong	0.375	1.514E-05
Clay (%)	Exponential	17.100	109.400	57.90	15.63	Strong	0.952	404.
Silt (%)	Spherical	0.100	134.900	101.000	0.07	Strong	0.960	1073.
Sand (%)	Spherical	15.400	84.500	33.700	18.22	Strong	0.379	4247.
Exch K (%)	Spherical	0.002	0.017	177.100	11.76	Strong	0.977	1.026E-05
Exch Na (%)	Spherical	0.027	0.201	110.100	13.43	Strong	0.979	9.289E-04
Exch Mg (%)	Spherical	0.724	2.647	144.700	27.35	Moderate	0.978	0.148
Exch Ca (%)	Spherical	1.840	6.186	149.400	29.74	Moderate	0.966	1.17
Fe_{ox} (%)	Linear	0.022	0.036	113.968	61.11	Moderate	0.983	3.993E-06
Fe_p (%)	Exponential	0.000	0.000	6.500	0.00	Strong	0.536	1.090E-11
Fe_d (%)	Gaussian	0.000	0.000	50.800	0.00	Strong	0.952	8.147E-09
Fe_t (%)	PURE NUGGET EFFECT							
TOC (%)	Exponential	0.107	0.214	16.300	50.00	Moderate	0.775	1.504E-03
OCa (%)	Exponential	0.517	1.208	73.800	42.80	Moderate	0.992	1.972E-03
OCb (%)	Exponential	0.339	0.774	45.300	43.80	Moderate	0.909	0.0155
OCc (%)	Exponential	0.434	1.093	82.100	39.71	Moderate	0.932	0.0232
OCd (%)	Spherical	0.658	1.436	69.300	45.82	Moderate	0.928	0.0502
OCe (%)	Spherical	0.523	1.047	67.500	49.95	Moderate	0.720	0.0948
CEC (%)	Exponential	3.270	16.360	54.200	19.99	Strong	0.923	13.6
BOC (%)	Exponential	0.350	0.701	19.200	49.93	Moderate	0.703	0.0244
Total N (%)	Exponential	0.001	0.003	13.000	33.33	Moderate	0.441	7.603E-07
Total P (%)	Linear	0.006	0.011	143.962	54.55	Moderate	0.753	1.202E-05
Total K (%)	Gaussian	0.000	0.000	39.800	0.00	Strong	0.936	6.310E-09
Total Na (%)	Spherical	0.000	0.000	287.600	0.00	Strong	0.963	1.390E-09
Total Mg (%)	Exponential	0.000	0.001	193.300	0.00	Strong	0.988	6.259E-09
Total Ca (%)	Exponential	0.000	0.000	6.000	0.00	Strong	0.513	2.033E-13

followed by Total N (0.001), Exch K (0.002), MWDw (0.003), Total P (0.006), MWDdry (0.018), Exch Na (0.027), Feox (0.036), silt (0.100), TOC (0.214), OCb (0.339), BOC (0.350), OCc (0.434), OCa (0.517), OCe (0.523), OCd (0.658), Exch Mg (0.724), MC (1.200), OCa (1.840) and CEC (3.270). These properties were spatially continuous than sand, clay and IR, with C_o values of 15.400, 17.100 and 100.000 respectively.

The zero and almost zero nugget effect values indicate a very smooth spatial continuity between neighbouring points. Low nugget values (0.000 – 3.270) indicate small error of estimation process probably due to chemical analysis, data recording and the soil properties while large values (15.400 – 100.000) obtained may be related to sampling distances and density, positioning and the soil properties. Therefore, additional sampling of these properties (sand, clay and IR) at smaller distances and greater sampling density might be needed to detect spatial dependence. On the other hand, the sampling density and sampling distances for other investigated soil parameters were rational. This is because their nugget effect values are lower than the sampled distance of 3 m by 3 m used in this study, implying adequate sampling distances and proper handling of the samples during laborary analysis.

4.6.3 Total variance (Sill)

The sill (C_o + C) is the the total vertical scale of the semivariogram whereby the semivariance becomes constant when the distance between sample locations increases. Sill is the distance between measurements at which one value for a variable does not influence neighboring values (Lopez-Granadoz *et al.,* 2002). The observed sill values vary from 0.000 to 51,710.000 (Table 4.6). The sill values of most of the soil attributes were low

indicating that these attributes had great magnitude of spatial variability. The high values observed in the particle size distribution; sand (84.500), clay (109.400) and silt (134.900), may not be unconnected with the variation in the microtopography of the study site. The elevation of the site varies from 620 m to 641 m above the sea level, creating a gentle slope that enhances attachment, transportion and deposition of soil particles by the action of water. The high value recorded by IR can be related to the nature of the soil pores. The soil pores are discontinuous, associated to chanells caused by tree roots, rock outcrop and various soil fauna.

4.6.4 Effective range

Range (A_o) refers to the distance at which the samples become spatially independent and uncorrelated with one another. This indicates that at separation distances greater than the range, sampled points become spatially independent of each another (Lopez-Granadoz *et al.,* 2002). Semivariogram ranges depend on the spatial interaction of soil processes affecting each property at the sampling distance used (Trangmar *et al.,* 1985), thus range provides an estimated area of similarity.

The range values showed considerable variability among the parameters (Table 4.6). There were great differences between ranges of the different soil variables, as had been already reported in several studies (Weitz *et al.,* 1993; Doberman, 1994; Cambardella *et al.,* 1994; Ayoubi *et al.,* 2007). The range values showed that the patch of largest spatial variation is represented by MC with a 379.000 m range while the least is represented by IR with a 3.300 m range. Among the forms of iron, Fe_p had the smallest range value (6.500 m), followed by Fe_d (50.800 m) and then Fe_{ox} (113.968 m). The least value recorded for Fe_p

confirm that this form of iron could be organically-bounded while the highest value in Fe_{ox} can be attributed to the age of the plantation. The TOC and BOC data had low range of 16.3 m and 19.2 m respectively, which is relatively low spatial correlation range as compared to other carbon fractions; OCb (43.3 m), OCe (67.5 m), OCd (69.3m), OCa (73.8 m) and OCc (82.1 m). The ranges of primary soil nutrient (Total N, P and K) show a large variation (from 13.000 m for total N up to 143.962 m for total P). The different ranges of spatial correlation for these nutrients may be related to the mobility of the ions. In the present study, total N, the most mobile of the three ions studied, had the shortest range (13.000 m) of spatial correlation, followed by total K whereas P, presumably the least mobile, were spatially correlated across the longest distance (143.962 m). Spatial distribution of total N appeared to be correlated with TOC. The ranges of Total N and TOC were relatively similar (Table 4.6). These results are in accordance with the results of Cahn *et al.* (1994) and Ayoubi *et al*. (2007).

Large range values (> 25 m) indicates that observed values of a soil property could be influenced by other values of that variable over greater distances than soil variables which have smaller ranges (Lopez–Granadoz *et al.,* 2002). For example a range of 77 m for MWDdry indicate that MWDdry values influenced neighboring values of MWDdry over greater distances than other soil variable. Thus, variables such as MWDw, IR, ρb, Total N, Total Ca, Fe_p, TOC and BOC were greatly influenced by other soil variables. On the other hand, soil attributes that showed almost zero nugget effect value and a low range of spatial correlation could imply that the continuity disappear very fast (Vieira and Gonzalez, 2003). At separation distance greater than the range, sampling points will not be subjected to spatial correlation. This has great implication on sampling design. Sampling design should

use separation distances shorter than the range in order to understand the spatial pattern of a given property. In addition, spacing between sampling points should be from 0.25 to 0.5 of the range (Flatman and Yfantis, 1984; Mulla and McBratney, 1999).

4.6.5 Spatial Dependence Degree

Since it is impossible to quantify the individual contribution of field and experimental errors, the nugget effect could be expressed as percentage of the sill, thus facilitating a comparison of the spatial dependence degree (DD) of soil properties. By analysis of $C_o/(C_o + C)$ ratio, the proportion of random component (C_o) in total variance ($C_0 + C$) was quantified. In this analysis DD was classified according Cambardella *et al.* (1994); strong spatial dependence (< 25%), moderate spatial dependence (26% < DD < 75%) and weak spatial dependence (DD > 75%).

Thus, the semivariograms of all chemical propertie indicated spatial dependence (Table 4.6). Analyzed soil properties exhibited strong or moderate spatial dependence degree that vary from 0% for ρb, Fe_p, Fe_d, Total K, Na, Mg and Ca to 61.11% for Fe_{ox}. These infer that the explainable proportion of the total variation of the investigated soil attributes ranges from relatively 100% to 38.89%, with the remaining variations attributed to random sources. Strongly or moderately spatial dependence observed in these properties may be controlled by intrinsic variations in soil characteristics, such as texture, mineralogy and structural factors which might include topography and climatic condition (Zheng *et al.,* 2009; Yang *et al.,* 2011).

CHAPTER FIVE

SUMMARY AND CONCLUSION

Classical and spatial statistical tools were employed to investigate the field-scale horizontal spatial variability and, the degree of linear association within and between the soil physio-chemical properties, and to develop models for predicting the soil aggregate stability from other soil properties in one block of the Nimbia forest in Southern Guinea Savannah of Nigeria. Descriptive statistics for the study area revealed differences in the amount of the variability of the soil property. Some of the measured properties were significantly skewed or kurtotic but with the median either equal to or less than the mean showing that outliers did not dominate the measure of central tendency. The calculated coefficient of variation (CV) ranged from 0.74% (elevation) to 90.83% (Exch Na) indicating low to high spatial variation patterns. Although, the classical statistics showed the spatial variation pattern of soil property; they failed to point out the distribution of these spatial variations through space.

Point to point analysis of properties showed spatial trend or fluctuation of the properties along the 300 m transect. Both autocorrelation function (ACF) and cross-correlation functions (CCF) were calculated using a t-test at 5% level of probability. Autocorrelation function that reflects the local variation between samples for different separation distance exhibited strong (OCa-19 lags) to no (Total Fe) spatial dependence. To describe the degree of linear association between MWDw and other properties, cross-correlation function (CCF) were calculated. Based on the degree of correlation, 10 soil properties (clay, Total P, Fed, Fep, OCa, OCb, OCc, OCd, OCe and MC) were selected and used to describe how MWDw is related to itself and to various combinations of these properties in the spatial

neighborhood. The various combinations analyzed through state-space models and multiple linear regression models, revealed that all the state-space models described the spatial distribution of MWDw better than the equivalent multiple linear regression equations. Effective contribution of clay, Fed and OCa in describing MWDw were also identified because they relate to all the best performance in both analyses.

The spatial behaviour of soil attributes was evaluated through their semivariograms along with the best fitted models based on regression statistics such as minimum residual sum of square (RSS) and maximum determination coefficient (R^2) values. All the investigated soil properties except Total Fe exhibited a definable spatial structure which was described by exponential, spherical, gaussian or linear models. Knowledge of the range of influence for various soil properties allows one to construct independent datasets to perform classical statistical analysis. Furthermore, it aids in determining where to resample if necessary, and in the design of future field experiments to avoid spatial dependency.

In conclusion, classical statistical method allows the identification of variations in soil properties but does not provide information on how these variations are distributed in space. Geostatistical based tools on the other hand, offer alternative methods to classical statistics for the estimation of soil properties and their associated variability. MWDw was better defined stochastically rather than deterministically. This is due both to intrinsic and extrinsic heterogeneities of contributory factors which are essentially stochastic. Adoption of alternative analytical tools like state-space, semivariogram etc, under forest conditions, consider the underlying processes of soil properties in every local neighborhood along transect. It was also possible to identify the local relations between MWDw and selected properties and quantify this relationship, stochastically, taking measurement and model

errors into account. The model represents a possibility of investigating the variation in soil properties from adjacent sampling points in heterogeneous fields and allows optimization of forest soil resources for site-specific management.

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APPENDIX A: Point-to-point coordinates and infiltration rate data of the study area

			Infiltration Rate (cm/hr)				
S/No	**X - Coordinate (N)**	**Y - Coordinate (E)**	**0.083h**	**0.25h**	**0.5hr**	**1hr**	**2hrs**
P1	9°30.162	8°34.308	24	14.4	12.4	10	10.4
P2	9°30.165	8°34.306	102	70	56.2	45.8	37.95
P3	9°30.169	8°34.309	21.6	16	12.2	10.3	9.05
P4	9°30.166	8°34.310	51.6	34.8	31.4	23.8	18.25
P5	9°30.170	8°34.308	176.4	91.2	56.6	35.2	22.3
P6	9°30.170	8°34.311	40.8	24.8	18.8	14.7	12.15
P7	9°30.166	8°34.314	99.6	69.6	63.2	52	39.3
P8	9°30.171	8°34.312	165.6	108	78.2	53.6	35.9
P9	9°30.172	8°34.316	33.6	22.4	16.2	12.1	9.2
P10	9°30.169	8°34,316	55.2	40.4	31.6	23	16.6
P11	9°30.171	8°34.316	248.4	154.8	99.4	60.9	43.75
P12	9°30.174	8°34.318	194.4	113.2	71.6	48.1	38.15
P13	9°30.176	8°34.320	207.6	135.2	98.4	65.5	47.5
P14	9°30.180	8°34.321	31.2	12.4	8	6.3	5.05
P15	9°30.180	8°34.320	174	104.4	65.6	40	25
P16	9°30.180	8°34.322	258	197.6	154.8	113.1	78.35
P17	9°30.179	8°34.325	295.2	229.6	172	113.2	75.95
P18	9°30.182	8°34.334	72	41.2	29	18.8	12.2
P19	9°30.184	8°34.331	105.6	75.6	66.8	50.7	35.35
P20	9°30.186	8°34.334	78	49.2	38.2	30.3	22.15
P21	9°30.184	8°34.333	183.6	105.2	65.2	47	31.15
P22	9°30.187	8°34.328	76.8	50	41.6	34.5	25
P23	9°30.184	8°34.330	117.6	68.4	57.6	41.7	28.6
P24	9°30.189	8°34.331	42	24.8	18.2	13.2	9.1
P25	9°30.188	8°34.333	50.4	37.6	28.4	22.9	18
P26	9°30.189	8°34.335	24	18.4	16.2	14.7	11
P27	9°30.189	8°34.338	168	97.6	65.2	41.3	26.8
P28	9°30.193	8°34.337	146.4	86	61.2	40.9	25.3
P29	9°30.190	8°34.340	138	97.6	74.4	54.2	36.4
P30	9°30.195	8°34.337	270	204.4	168.8	132.8	90.45
P31	9°30.193	8°34.343	194.4	131.2	99.4	70.9	46.6
P32	9°30.198	8°34.340	258	175.2	133.8	99.4	68
P33	9°30.196	8°34.343	87.6	67.2	52.2	38.4	26.7
P34	9°30.201	8°34.343	150	113.2	86.8	66.1	51.3
P35	9°30.202	8°34.340	144	100	73	47.9	33.95
P36	9°30.201	8°34.348	90	55.2	33.8	20.3	13.8
P37	9°30.202	8°34.346	147.6	110	86.2	59.2	37.25
P38	9°30.204	8°34.351	153.6	118.4	99	75.9	47.45
P39	9°30.205	8°34.353	100.8	73.2	66.4	55.4	43.1
P40	9°30.207	8°34.354	40.8	32	26.4	23.9	20.15
P41	9°30.208	8°34.354	134.4	87.6	58	42	28.75

P42	9°30.205	8°34.357	157.2	121.2	85.4	56.9	36
P43	9°30.208	8°34.356	99.6	60.4	42.6	29.7	19.9
P44	9°30.209	8°34.355	134.4	96.8	76.2	55.3	37.95
P45	9°30.212	8°34.358	96	77.6	67.2	52	39.8
P46	9°30.212	8°34.359	93.6	74.4	62.8	50	39.1
P47	9°30.214	8°34.361	220.8	154.8	113	80.4	56.35
P48	9°30.215	8°34.364	124.8	92.4	78.8	61.3	45.5
P49	9°30.215	8°34.362	219.6	160.4	126.8	98.1	67.5
P50	9°30.217	8°34.364	136.8	103.6	84	62.9	46.25
P51	9°30.218	8°34.364	115.2	82.4	68	50.3	40.15
P52	9°30.220	8°34.366	102	70.8	55.6	38.8	25.95
P53	9°30.220	8°34.369	63.6	40	31	25.2	20.45
P54	9°30.222	8°34.370	91.2	58.8	49.2	38.7	29.55
P55	9°30.223	8°34.371	76.8	46	37.2	29	22.6
P56	9°30.224	8°34.374	86.4	54	48.8	40.4	31.25
P57	9°30..223	8°34.372	100.8	72	57	40.3	27.2
P58	9°30.224	8°34.373	86.4	67.6	54.4	39.8	26.7
P59	9°30.225	8°34.374	135.6	96	66.6	43.8	28.2
P60	9°30.226	8°34.376	165.6	117.2	86.8	59.9	39.2
P61	9°30.228	8°34.379	147.6	107.2	90.2	73.1	54.35
P62	9°30.230	8°34.379	115.2	86.4	72.2	52.6	41.8
P63	9°30.232	8°34.380	93.6	66	61.8	54.1	38.9
P64	9°30.233	8°34.381	46.8	39.6	34	27.1	19.8
P65	9°30.233	8°34.382	126	102.8	89	73.3	54.3
P66	9°30.234	8°34.383	126	96	79	63	46.3
P67	9°30.236	8°34.385	84	54	48.8	39.4	30.6
P68	9°30.237	8°34.385	67.2	46	38	28	22.05
P69	9°30.238	8°34.387	91.2	62.8	56.6	46.2	34.15
P70	9°30.238	8°34.390	67.2	49.6	39.8	26.9	19.05
P71	9°30.242	8°34.387	74.4	45.2	32.4	26.2	18.6
P72	9°30.242	8°34.392	174	155.6	142	121.2	98.35
P73	9°30.242	8°34.393	147.6	107.2	90.2	73.2	56.65
P74	9°30.244	8°34.394	165.6	121.2	93.4	74.8	52.5
P75	9°30.247	8°34.395	216	168	121.2	85.4	60.85
P76	9°30.245	8°34.394	150	119.2	98.6	82.1	64.2
P77	9°30.246	8°34.395	78	51.2	40	28	21.75
P78	9°30.248	8°34.398	114	75.6	63.6	48.1	36.65
P79	9°30.250	8°34.399	150	118.8	112.4	92.1	70.95
P80	9°30.251	8°34.401	172.8	130.4	119	100.3	75.25
P81	9°30.251	8°34.402	186	147.2	112	81.8	58.1
P82	9°30.254	8°34.403	147.6	99.2	71.2	47.8	31.1
P83	9°30.251	8°34.405	201.6	146.4	130.2	101.9	73.95
P84	9°30.250	8°34.406	192	137.2	141.4	118.2	110.15
P85	9°30.254	8°34.407	272.4	214	190.4	165	137.15
P86	9°30.256	8°34.406	282	219.6	172.8	123.8	79.8
P87	9°30.256	8°34.410	151.2	104.8	78.6	54.6	37.05
P88	9°30.257	8°34.410	255.6	184	123.2	79	52.75

P89	9°30.257	8°34.412	162	111.6	83.2	57.8	39.15
P90	9°30.258	8°34.411	246	216	172.6	124.4	85.25
P91	9°30.260	8°34.413	228	200.8	168.4	131.6	92.75
P92	9°30.264	8°34.416	138	103.6	80.8	64.8	49.65
P93	9°30.268	8°34.419	190.8	130	93.4	63	40.15
P94	9°30.264	8°34.418	198	152.8	118.2	85.9	63.6
P95	9°30.265	8°34.419	175.2	151.2	141.6	125.7	101.2
P96	9°30.267	8°34.420	163.2	124.4	96.2	67.4	43.4
P97	9°30.270	8°34.422	108	70	56	42.2	29.25
P98	9°30.271	8°34.423	66	47.2	36.2	26.4	18.9
P99	9°30.270	8°34.424	76.8	53.2	38.2	25.6	18.1
P100	9°30.270	8°34.429	154.8	120.8	76.4	61.3	46.25

APPENDIX B: Multiple linear regression equations of wet mean weight diameter for the eight selected soil properties

Equations	R^2
$MWDw_i$ = 0. 3515 – 0.0012(Clay) + 0.1633(Total P) + 0.5395(Fed) – 10.1118(Fep) + 0.0529(OCa) - 0.0008(OCb) + 0.0100(OCc)+ 0.0065(OCd)	0.5199
$MWDw_i$ = 0. 3491 – 0.0013(Clay) + 0.1711(Total P) + 0.5380(Fed) – 9.7104(Fep) + 0.0541(OCa)+ 0.0005(OCb) + 0.0146(OCc) – 0.0003(OCe)	0.5187
$MWDw_i$ = 0. 3665 – 0.0013(Clay) + 0.1570(Total P) + 0.4675(Fed) –10.2028(Fep) + 0.0536(OCa)+ 0.0029(OCb) + 0.0109(OCd) – 0.0012(OCe)	0.5184
$MWDw_i$ = 0. 3554 – 0.0013(Clay) + 0.1581(Total P) + 0.5501(Fed) –10.1025(Fep) + 0.0536(OCa)+0.0121(OCc) + 0.0088(OCd) – 0.0061(OCe)	0.5203
$MWDw_i$ = 0. 3812 – 0.0021(Clay) + 0.2009(Total P) + 0.6398(Fed) –11.6729(Fep) + 0.0327(OCb)+0.0104(OCc)+ 0.0109(OCd) + 0.0109(OCe)	0.4483
$MWDw_i$ = 0. 2743 – 0.0018(Clay) + 0.2746(Total P) + 0.1487(Fed) + 0.0616(OCa) - 0.0015(OCb) +0.0166(OCc) - 0.0055(OCd) – 0.0071(OCe)	0.4533
$MWDw_i$ = 0. 3986 – 0.0014(Clay) + 0.1461(Total P) – 9.6959(Fep) + 0.0543(OCa) - 0.0030(OCb) + 0.0090(OCc) + 0.0086(OCd) – 0.0055(OCe)	0.5166
$MWDw_i$ = 0. 4013 – 0.0010(Clay) + 0.4036(Fed) –11.4849(Fep) + 0.0564(OCa) + 0.0011(OCb) + 0.0117(OCc) + 0.0145(OCd) – 0.0114(OCe)	0.5078
$MWDw_i$ = 0. 3071 + 0.1447(Total P) + 0.6467(Fed) –10.5039(Fep) + 0.0568(OCa) - 0.0010(OCb) + 0.0125(OCc) + 0.0095(OCd) – 0.0049(OCe)	0.5147
$MWDw_i$ = 0. 1075 – 0.0018(Clay) + 0.0302(Total P) + 0.4691(Fed) – 6.1712(Fep) + 0.0511(OCa)+ 0.0057(OCb) + 0.0084(OCc) + 0.0221(MC)	0.5733
$MWDw_i$ = 0. 1143 – 0.0017(Clay) + 0.0199(Total P) + 0.4410(Fed) – 6.5575(Fep) + 0.0502(OCa)+ 0.0060(OCb) + 0.0076(OCd) + 0.0222(MC)	0.5740
$MWDw_i$ = 0. 1139 – 0.0017(Clay) + 0.0251(Total P) + 0.4512(Fed) – 6.5574(Fep) + 0.0515(OCa) + 0.0057(OCc) + 0.0065(OCd) + 0.0219(MC)	0.5740
$MWDw_i$ = 0. 1298 – 0.0027(Clay) + 0.0413(Total P) + 0.5764(Fed) – 7.7983(Fep)+ 0.0376(OCb) + 0.0083(OCc) + 0.0146(OCd) + 0.0236(MC)	0.5092
$MWDw_i$ = 0. 0052 – 0.0022Clay) + 0.0544(Total P) + 0.2299(Fed) + 0.0536(OCa) + 0.0053(OCb) + 0.0050(OCc) - 0.0023(OCd) + 0.0274(MC)	0.5499
$MWDw_i$ = 0. 1457 – 0.0019(Clay) + 0.0109(Total P) – 6.1679(Fep) + 0.0505(OCa)+ 0.0026(OCb) + 0.0015(OCc) + 0.0060(OCd) + 0.0222(MC)	0.5715
$MWDw_i$ = 0. 1093 – 0.0017(Clay) + 0.4503(Fed) – 6.6279(Fep) + 0.0501(OCa) + 0.0049(OCb) + 0.0038(OCc) + 0.0065(OCd) + 0.0226(MC)	0.5740
$MWDw_i$ = 0.0585 + 0.0110(Total P) + 0.6130(Fed) – 7.2927(Fep) + 0.0545(OCa) + 0.0038(OCb) + 0.0053(OCc) + 0.0076(OCd) + 0.0208(MC)	0.5636
$MWDw_i$ = 0.1052 – 0.0018(Clay) + 0.0298(Total P) + 0.4255(Fed) – 6.2237(Fep) + 0.0500(OCa)+ 0.0072(OCb) + 0.0071(OCe) + 0.0225(MC)	0.5731
$MWDw_i$ = 0. 1078 – 0.0017(Clay) + 0.0340(Total P) + 0.4398(Fed) – 6.2511(Fep) + 0.0519(OCa) + 0.0074(OCc) + 0.0046(OCe) + 0.0220(MC)	0.5732
$MWDw_i$ = 0. 1038 – 0.0026(Clay) + 0.0602(Total P) + 0.5415(Fed) – 7.3183(Fep) + 0.0369(OCb) + 0.0034(OCc) + 0.0215(OCe) + 0.0242(MC)	0.5115
$MWDw_i$ = 0. 0046 – 0.0022(Clay) + 0.0520(Total P) + 0.2263(Fed) + 0.0534(OCa) + 0.0049(OCb) + 0.0038(OCc) - 0.0007(OCe) + 0.0275(MC)	0.5497
$MWDw_i$ = 0. 1385 – 0.0019(Clay) + 0.0189(Total P) – 5.9009(Fep) + 0.0505(OCa)+ 0.0034(OCb) + 0.0026(OCc) + 0.0046(OCe) + 0.0224(MC)	0.5709
$MWDw_i$ = 0. 1025 – 0.0017(Clay) + 0.4359(Fed) – 6.3348(Fep) + 0.0504(OCa) + 0.0059(OCb) + 0.0054(OCc) + 0.0041(OCe) + 0.0230(MC)	0.5731
$MWDw_i$ = 0. 0492 + 0.0207(Total P) + 0.6050(Fed) – 6.9625(Fep) + 0.0545(OCa) + 0.0048(OCb) + 0.0064(OCc) + 0.0061(OCe) + 0.0210(MC)	0.5627
$MWDw_i$ = 0. 1174 – 0.0017(Clay) + 0.0239(Total P) + 0.4033(Fed) – 6.5692(Fep) + 0.0519(OCa) + 0.0075(OCd) + 0.0028(OCe) + 0.0221(MC)	0.5736
$MWDw_i$ = 0. 1122 – 0.0026(Clay) + 0.0498(Total P) + 0.5390(Fed) – 7.6766(Fep) + 0.0361(OCb) + 0.0078(OCd) + 0.0171(OCe) + 0.0241(MC)	0.5126
$MWDw_i$ = 0. 0055 – 0.0022(Clay) + 0.0535(Total P) + 0.1990(Fed) + 0.0533(OCa) + 0.0067(OCb) - 0.0022(OCd) + 0.0031(OCe) + 0.0276(MC)	0.5496
$MWDw_i$ = 0. 1446 – 0.0019(Clay) + 0.0112(Total P) – 6.1736(Fep) + 0.0503(OCa) + 0.0030(OCb) + 0.0058(OCd) + 0.0014(OCe) + 0.0223(MC)	0.5715
$MWDw_i$ = 0. 1111 – 0.0017(Clay) + 0.4269(Fed) – 6.6278(Fep) + 0.0501(OCa) + 0.0060(OCb) + 0.0071(OCd) + 0.0014(OCe) + 0.0227(MC)	0.5739
$MWDw_i$ = 0. 0587 + 0.0102(Total P) + 05807(Fed) –7.2940(Fep) + 0.0541(OCa) + 0.0052(OCb) + 0.0077(OCd) + 0.0034(OCe) + 0.0210(MC)	0.5634
$MWDw_i$ = 0. 1487 – 0.0028(Clay) + 0.0802(Total P) + 0.3744(Fed) – 8.1497(Fep) + 0.0149(OCc) + 0.0122(OCd) + 0.0218(OCe) + 0.0233(MC)	0.4913
$MWDw_i$ = 0. 0079 – 0.0022(Clay) + 0.0578(Total P) + 0.2044(Fed) + 0.0552(OCa) + 0.0062(OCc) - 0.0024(OCd) + 0.0014(OCe) + 0.0273(MC)	0.5495
$MWDw_i$ = 0. 1460 – 0.0019(Clay) + 0.0130(Total P) – 6.1826(Fep) + 0.0512(OCa) + 0.0021(OCc) + 0.0059(OCd) + 0.0009(OCe) + 0.0221(MC)	0.5714
$MWDw_i$ = 0. 1135 – 0.0017(Clay) + 0.4273(Fed) – 6.6510(Fep) + 0.0518(OCa) + 0.0054(OCc) + 0.0071(OCd) - 0.0025(OCe) + 0.0225(MC)	0.5737

$MWDw_i$ = 0. 0603 + 0.0138(Total P) + 0.5935(Fed) – 7.2945(Fep) + 0.0555(OCa) + 0.0059(OCc) + 0.0073(OCd) + 0.0016(OCe) + 0.0207(MC)	0.5635
$MWDw_i$ = - 0. 0143 – 0.0032(Clay) + 0.0906(Total P) + 0.2682(Fed) + 0.0392(OCb) + 0.0018(OCc) - 0.0027(OCd) + 0.0190(OCe) + 0.0306(MC)	0.4787
$MWDw_i$ = 0. 1522 – 0.0027(Clay) + 0.0370(Total P) – 7.2440(Fep) + 0.0337(OCb) - 0.0019(OCc) + 0.0072(OCd) + 0.0173(OCe) + 0.0242(MC)	0.5089
$MWDw_i$ = 0. 1107 – 0.0026(Clay) + 0.5068(Fed) – 7.8722(Fep) + 0.0368(OCb) + 0.0009(OCc) + 0.0090(OCd) + 0.0156(OCe) + 0.0252(MC)	0.5116`
$MWDw_i$ = 0. 0291 + 0.0365(Total P) + 0.7786(Fed) – 8.9850(Fep) + 0.0388(OCb) + 0.0021(OCc) + 0.0094(OCd) + 0.0206(OCe) + 0.0224(MC)	0.4879
$MWDw_i$ = 0. 0243 – 0.0022(Clay) + 0.0484(Total P) + 0.0535(OCa) + 0.0043(OCb) + 0.0030(OCc) - 0.0027(OCd) + 0.0016(OCe) + 0.0274(MC)	0.5492
$MWDw_i$ = - 0.0004 – 0.0021(Clay) + 0.1726(Fed) + 0.0540(OCa) + 0.0062(OCb) + 0.0038(OCc) - 0.0016(OCd) + 0.0001(OCe) + 0.0289(MC)	0.5486
$MWDw_i$ = - 0. 0805 + 0.0453(Total P) + 0.3747(Fed) + 0.0594(OCa) + 0.0046(OCb) + 0.0053(OCc) - 0.0028(OCd) + 0.0031(OCe) + 0.0267(MC)	0.5325
$MWDw_i$ = 0. 1438 – 0.0018(Clay) – 6.2169(Fep) + 0.0504(OCa) + 0.0028(OCb) + 0.0011(OCc) + 0.0060(OCd) + 0.0006(OCe) + 0.0225(MC)	0.5715
$MWDw_i$ = 0. 0978 - 0.0047(Total P) – 6.8600(Fep) + 0.0551(OCa) + 0.0012(OCb) + 0.0008(OCc) + 0.0067(OCd) + 0.0025(OCe) + 0.0210(MC)	0.5590
$MWDw_i$ = 0. 0571 + 0.5997(Fed) – 7.3258(Fep) + 0.0543(OCa) + 0.0040(OCb) + 0.0046(OCc) + 0.0073(OCd) + 0.0013(OCe) + 0.0211(MC)	0.5636

APPENDIX C: State-space equations of wet mean weight diameter for the eight selected soil properties

Equations	**R^2**

$(MWDw)_i = 1.0468*(MWDw)_{i-1} + 0.0520*(Clay)_{i-1} - 0.0943*(Total\ P)_{i-1} - 0.00098*(Fed)_{i-1} + 0.0214*(Fep)_{i-1} - 0.4137*(OCa)_{i-1} + 0.9669*(OCb)_{i-1} - 0.3943*(OCc)_{i-1} - 0.2007*(OCd)_{i-1} + w_i$	0.8218
$(MWDw)_i = 0.9602*(MWDw)_{i-1} + 0.0610*(Clay)_{i-1} - 0.1299*(Total\ P)_{i-1} + 0.0789*(Fed)_{i-1} - 0.0769*(Fep)_{i-1} - 0.5755*(OCa)_{i-1} + 1.2689*(OCb)_{i-1} - 0.4253*(OCc)_{i-1} - 0.1792*(OCe)_{i-1} + w_i$	0.8868
$(MWDw)_i = 0.8559*(MWDw)_{i-1} + 0.0512*(Clay)_{i-1} - 0.0700*(Total\ P)_{i-1} + 0.1287*(Fed)_{i-1} - 0.1334*(Fep)_{i-1} - 0.5695*(OCa)_{i-1} + 1.1158*(OCb)_{i-1} - 0.3245*(OCd)_{i-1} - 0.0749*(OCe)_{i-1} + w_i$	0.9004
$(MWDw)_i = 0.6014*(MWDw)_{i-1} + 0.1483*(Clay)_{i-1} - 0.0050*(Total\ P)_{i-1} + 0.1172*(Fed)_{i-1} - 0.1951*(Fep)_{i-1} + 0.3973*(OCa)_{i-1} + 0.0658*(OCc)_{i-1} + 0.0055*(OCd)_{i-1} - 0.1591*(OCe)_{i-1} + w_i$	0.9918
$(MWDw)_i = 0.8850*(MWDw)_{i-1} + 0.1516*(Clay)_{i-1} - 0.2427*(Total\ P)_{i-1} + 0.0195*(Fed)_{i-1} - 0.0404*(Fep)_{i-1} + 0.8042*(OCb)_{i-1} - 0.2739*(OCc)_{i-1} - 0.1903*(OCd)_{i-1} - 0.1330*(OCe)_{i-1} + w_i$	0.8925
$(MWDw)_i = 0.7385*(MWDw)_{i-1} - 0.0031*(Clay)_{i-1} + 0.0621*(Total\ P)_{i-1} + 0.0685*(Fed)_{i-1} - 0.3957*(OCa)_{i-1} + 1.1545*(OCb)_{i-1} - 0.3211*(OCc)_{i-1} - 0.2283*(OCd)_{i-1} - 0.0911*(OCe)_{i-1} + w_i$	0.9968
$(MWDw)_i = 0.8760*(MWDw)_{i-1} + 0.0441*(Clay)_{i-1} - 0.0182*(Total\ P)_{i-1} + 0.0072*(Fep)_{i-1} - 0.5060*(OCa)_{i-1} + 1.2710*(OCb)_{i-1} - 0.3888*(OCc)_{i-1} - 0.2116*(OCd)_{i-1} - 0.0955*(OCe)_{i-1} + w_i$	0.9781
$(MWDw)_i = 0.9496*(MWDw)_{i-1} + 0.0747*(Clay)_{i-1} - 0.0265*(Fed)_{i-1} + 0.0092*(Fep)_{i-1} + 0.0105*(OCa)_{i-1} + 0.1971*(OCb)_{i-1} - 0.0340*(OCc)_{i-1} - 0.1621*(OCd)_{i-1} - 0.0337*(OCe)_{i-1} + w_i$	0.7966
$(MWDw)_i = 0.8013*(MWDw)_{i-1} + 0.0194*(Total\ P)_{i-1} + 0.0676*(Fed)_{i-1} - 0.0155*(Fep)_{i-1} - 0.3281*(OCa)_{i-1} + 0.9583*(OCb)_{i-1} - 0.2812*(OCc)_{i-1} - 0.1922*(OCd)_{i-1} - 0.0500*(OCe)_{i-1} + w_i$	0.9801
$(MWDw)_i = 0.7382*(MWDw)_{i-1} - 0.0376*(Clay)_{i-1} - 0.2046*(Total\ P)_{i-1} - 0.0304*(Fed)_{i-1} + 0.0735*(Fep)_{i-1} - 0.1612*(OCa)_{i-1} + 0.5346*(OCb)_{i-1} - 0.3171*(OCc)_{i-1} + 0.3916*(MC)_{i-1} + w_i$	0.8070
$(MWDw)_i = 0.7964*(MWDw)_{i-1} + 0.0076*(Clay)_{i-1} - 0.1475*(Total\ P)_{i-1} + 0.1194*(Fed)_{i-1} - 0.1069*(Fep)_{i-1} - 0.5404*(OCa)_{i-1} + 0.9718*(OCb)_{i-1} - 0.2881*(OCd)_{i-1} + 0.1717*(MC)_{i-1} + w_i$	0.8924
$(MWDw)_i = 0.7835*(MWDw)_{i-1} + 0.1081*(Clay)_{i-1} - 0.2123*(Total\ P)_{i-1} + 0.0160*(Fed)_{i-1} - 0.0620*(Fep)_{i-1} + 0.2689*(OCa)_{i-1} - 0.0575*(OCc)_{i-1} - 0.0387*(OCd)_{i-1} + 0.1783*(MC)_{i-1} + w_i$	0.8197
$(MWDw)_i = 0.8760*(MWDw)_{i-1} + 0.0701*(Clay)_{i-1} - 0.1720*(Total\ P)_{i-1} + 0.0045*(Fed)_{i-1} + 0.0012*(Fep)_{i-1} + 0.4096*(OCb)_{i-1} - 0.1346*(OCc)_{i-1} - 0.1945*(OCd)_{i-1} + 0.1257*(MC)_{i-1} + w_i$	0.7759
$(MWDw)_i = 0.4657*(MWDw)_{i-1} + 0.0208*(Clay)_{i-1} - 0.1201*(Total\ P)_{i-1} + 0.0258*(Fed)_{i-1} + 0.4284*(OCa)_{i-1} + 0.0408*(OCb)_{i-1} - 0.0545*(OCc)_{i-1} - 0.1606*(OCd)_{i-1} + 0.3401*(MC)_{i-1} + w_i$	0.9934
$(MWDw)_i = 0.5436*(MWDw)_{i-1} + 0.0340*(Clay)_{i-1} - 0.1874*(Total\ P)_{i-1} + 0.0054*(Fep)_{i-1} + 0.3674*(OCa)_{i-1} + 0.0967*(OCb)_{i-1} - 0.1226*(OCc)_{i-1} - 0.1111*(OCd)_{i-1} + 0.3583*(MC)_{i-1} + w_i$	0.9592
$(MWDw)_i = 0.5274*(MWDw)_{i-1} - 0.0636*(Clay)_{i-1} + 0.0519*(Fed)_{i-1} - 0.0048*(Fep)_{i-1} - 0.0919*(OCa)_{i-1} + 0.5785*(OCb)_{i-1} - 0.2466*(OCc)_{i-1} - 0.1077*(OCd)_{i-1} + 0.3431*(MC)_{i-1} + w_i$	0.9930
$(MWDw)_i = 0.8020*(MWDw)_{i-1} - 0.2058*(Total\ P)_{i-1} + 0.0324*(Fed)_{i-1} + 0.0149*(Fep)_{i-1} - 0.3647*(OCa)_{i-1} + 0.9358*(OCb)_{i-1} - 0.3133*(OCc)_{i-1} - 0.1900*(OCd)_{i-1} + 0.2715*(MC)_{i-1} + w_i$	0.9329
$(MWDw)_i = 0.6846*(MWDw)_{i-1} - 0.0029*(Clay)_{i-1} - 0.1972*(Total\ P)_{i-1} + 0.0677*(Fed)_{i-1} - 0.0522*(Fep)_{i-1} - 0.1755*(OCa)_{i-1} + 0.4542*(OCb)_{i-1} - 0.1300*(OCe)_{i-1} + 0.3348*(MC)_{i-1} + w_i$	0.9108
$(MWDw)_i = 0.4742*(MWDw)_{i-1} + 0.0136*(Clay)_{i-1} - 0.1662*(Total\ P)_{i-1} + 0.0182*(Fed)_{i-1} - 0.0139*(Fep)_{i-1} + 0.3485*(OCa)_{i-1} - 0.0332*(OCc)_{i-1} - 0.0913*(OCe)_{i-1} + 0.4343*(MC)_{i-1} + w_i$	0.9891
$(MWDw)_i = 0.5976*(MWDw)_{i-1} - 0.0488*(Clay)_{i-1} - 0.2503*(Total\ P)_{i-1} - 0.0126*(Fed)_{i-1} + 0.0885*(Fep)_{i-1} + 0.5751*(OCb)_{i-1} - 0.2338*(OCc)_{i-1} - 0.1922*(OCe)_{i-1} + 0.4634*(MC)_{i-1} + w_i$	0.7417

$(MWDw)_i = 0.5628*(MWDw)_{i-1} - 0.0589*(Clay)_{i-1} - 0.1523*(Total\ P)_{i-1} + 0.0675*(Fed)_{i-1} - 0.2394*(OCa)_{i-1} + 0.9258*(OCb)_{i-1} - 0.3071*(OCc)_{i-1} - 0.1840*(OCe)_{i-1} + 0.3723*(MC)_{i-1} + w_i$	0.9856
$(MWDw)_i = 0.5795*(MWDw)_{i-1} - 0.0549*(Clay)_{i-1} - 0.1770*(Total\ P)_{i-1} + 0.0583*(Fep)_{i-1} - 0.1551*(OCa)_{i-1} + 0.7720*(OCb)_{i-1} - 0.3156*(OCc)_{i-1} - 0.1465*(OCe)_{i-1} + 0.4249*(MC)_{i-1} + w_i$	0.9777
$(MWDw)_i = 0.6629*(MWDw)_{i-1} - 0.0360*(Clay)_{i-1} + 0.0752*(Fed)_{i-1} - 0.0307*(Fep)_{i-1} - 0.3766*(OCa)_{i-1} + 0.9856*(OCb)_{i-1} - 0.3718*(OCc)_{i-1} - 0.1319*(OCe)_{i-1} + 0.2098*(MC)_{i-1} + w_i$	0.9869
$(MWDw)_i = 0.7756*(MWDw)_{i-1} - 0.1841*(Total\ P)_{i-1} + 0.0500*(Fed)_{i-1} - 0.0020*(Fep)_{i-1} - 0.3760*(OCa)_{i-1} + 0.9950*(OCb)_{i-1} - 0.3561*(OCc)_{i-1} - 0.1671*(OCe)_{i-1} + 0.2484*(MC)_{i-1} + w_i$	0.9669
$(MWDw)_i = 0.4611*(MWDw)_{i-1} - 0.0136*(Clay)_{i-1} - 0.2338*(Total\ P)_{i-1} + 0.0441*(Fed)_{i-1} - 0.0255*(Fep)_{i-1} + 0.3618*(OCa)_{i-1} - 0.0559*(OCd)_{i-1} - 0.0475*(OCe)_{i-1} + 0.4932*(MC)_{i-1} + w_i$	0.8867
$(MWDw)_i = 0.7193*(MWDw)_{i-1} + 0.0273*(Clay)_{i-1} - 0.1742*(Total\ P)_{i-1} + 0.0421*(Fed)_{i-1} - 0.0264*(Fep)_{i-1} + 0.3519*(OCb)_{i-1} - 0.1355*(OCd)_{i-1} - 0.0630*(OCe)_{i-1} + 0.2435*(MC)_{i-1} + w_i$	0.8838
$(MWDw)_i = 0.6266*(MWDw)_{i-1} - 0.0827*(Clay)_{i-1} - 0.1057*(Total\ P)_{i-1} + 0.0824*(Fed)_{i-1} - 0.4530*(OCa)_{i-1} + 0.9729*(OCb)_{i-1} - 0.2248*(OCd)_{i-1} - 0.1404*(OCe)_{i-1} + 0.3112*(MC)_{i-1} + w_i$	0.9725
$(MWDw)_i = 0.6194*(MWDw)_{i-1} - 0.0870*(Clay)_{i-1} - 0.1762*(Total\ P)_{i-1} + 0.0914*(Fep)_{i-1} - 0.2212*(OCa)_{i-1} + 0.6947*(OCb)_{i-1} - 0.2319*(OCd)_{i-1} - 0.1049*(OCe)_{i-1} + 0.4025*(MC)_{i-1} + w_i$	0.7996
$(MWDw)_i = 0.6897*(MWDw)_{i-1} - 0.0588*(Clay)_{i-1} + 0.1084*(Fed)_{i-1} - 0.0502*(Fep)_{i-1} - 0.5533*(OCa)_{i-1} + 0.9500*(OCb)_{i-1} - 0.2128*(OCd)_{i-1} - 0.0983*(OCe)_{i-1} + 0.2115*(MC)_{i-1} + w_i$	0.9848
$(MWDw)_i = 0.8290*(MWDw)_{i-1} - 0.1789*(Total\ P)_{i-1} + 0.0936*(Fed)_{i-1} - 0.0692*(Fep)_{i-1} - 0.5613*(OCa)_{i-1} + 0.9561*(OCb)_{i-1} - 0.2681*(OCd)_{i-1} - 0.0371*(OCe)_{i-1} + 0.2177*(MC)_{i-1} + w_i$	0.9080
$(MWDw)_i = 1.0032*(MWDw)_{i-1} + 0.0553*(Clay)_{i-1} - 0.2726*(Total\ P)_{i-1} - 0.1276*(Fed)_{i-1} + 0.1430*(Fep)_{i-1} - 0.0911*(OCc)_{i-1} - 0.0293*(OCd)_{i-1} - 0.0044*(OCe)_{i-1} + 0.3087*(MC)_{i-1} + w_i$	0.7605
$(MWDw)_i = 0.4747*(MWDw)_{i-1} + 0.0104*(Clay)_{i-1} - 0.1559*(Total\ P)_{i-1} + 0.0249*(Fed)_{i-1} + 0.4109*(OCa)_{i-1} - 0.0046*(OCc)_{i-1} + 0.0031*(OCd)_{i-1} - 0.1612*(OCe)_{i-1} + 0.3815*(MC)_{i-1} + w_i$	0.9907
$(MWDw)_i = 0.4582*(MWDw)_{i-1} - 0.0004*(Clay)_{i-1} - 0.2074*(Total\ P)_{i-1} + 0.0347*(Fep)_{i-1} + 0.4613*(OCa)_{i-1} - 0.0135*(OCc)_{i-1} - 0.0218*(OCd)_{i-1} - 0.1719*(OCe)_{i-1} + 0.4450*(MC)_{i-1} + w_i$	0.9840
$(MWDw)_i = 0.5149*(MWDw)_{i-1} + 0.0031*(Clay)_{i-1} + 0.0254*(Fed)_{i-1} - 0.0054*(Fep)_{i-1} + 0.3509*(OCa)_{i-1} - 0.0085*(OCc)_{i-1} - 0.0320*(OCd)_{i-1} - 0.1249*(OCe)_{i-1} + 0.2619*(MC)_{i-1} + w_i$	0.9838
$(MWDw)_i = 0.8049*(MWDw)_{i-1} - 0.2791*(Total\ P)_{i-1} - 0.0459*(Fed)_{i-1} + 0.1042*(Fep)_{i-1} + 0.2460*(OCa)_{i-1} - 0.0214*(OCc)_{i-1} - 0.0030*(OCd)_{i-1} - 0.1466*(OCe)_{i-1} + 0.3234*(MC)_{i-1} + w_i$	0.8490
$(MWDw)_i = 0.6100*(MWDw)_{i-1} - 0.0013*(Clay)_{i-1} - 0.1588*(Total\ P)_{i-1} + 0.0314*(Fed)_{i-1} + 0.5036*(OCb)_{i-1} - 0.1956*(OCc)_{i-1} - 0.1094*(OCd)_{i-1} - 0.0201*(OCe)_{i-1} + 0.3261*(MC)_{i-1} + w_i$	0.9681
$(MWDw)_i = 0.6216*(MWDw)_{i-1} - 0.0016*(Clay)_{i-1} - 0.2049*(Total\ P)_{i-1} + 0.0297*(Fep)_{i-1} + 0.5273*(OCb)_{i-1} - 0.2083*(OCc)_{i-1} - 0.1108*(OCd)_{i-1} - 0.0341*(OCe)_{i-1} + 0.3661*(MC)_{i-1} + w_i$	0.9645
$(MWDw)_i = 0.5958*(MWDw)_{i-1} - 0.0274*(Clay)_{i-1} + 0.0384*(Fed)_{i-1} + 0.0037*(Fep)_{i-1} + 0.4697*(OCb)_{i-1} - 0.1727*(OCc)_{i-1} - 0.1267*(OCd)_{i-1} - 0.0387*(OCe)_{i-1} + 0.2453*(MC)_{i-1} + w_i$	0.9752
$(MWDw)_i = 0.8265*(MWDw)_{i-1} - 0.2789*(Total\ P)_{i-1} - 0.0305*(Fed)_{i-1} + 0.0874*(Fep)_{i-1} + 0.3493*(OCb)_{i-1} - 0.1108*(OCc)_{i-1} - 0.1181*(OCd)_{i-1} - 0.0542*(OCe)_{i-1} + 0.3133*(MC)_{i-1} + w_i$	0.8452
$(MWDw)_i = 0.6674*(MWDw)_{i-1} - 0.0003*(Clay)_{i-1} - 0.2058*(Total\ P)_{i-1} - 0.2270*(OCa)_{i-1} + 0.8115*(OCb)_{i-1} - 0.2909*(OCc)_{i-1} - 0.0504*(OCd)_{i-1} - 0.0998*(OCe)_{i-1} + 0.3747*(MC)_{i-1} + w_i$	0.9684

$(MWDw)_i = 0.5488*(MWDw)_{i-1}-0.0764*(Clay)_{i-1}+0.0678*(Fed)_{i-1}-0.2868*(OCa)_{i-1}+0.9635*(OCb)_{i-1} - 0.3025*(OCc)_{i-1} - 0.1057*(OCd)_{i-1} - 0.1235*(OCe)_{i-1} + 0.3028*(MC)_{i-1} + w_i$	0.9958
$(MWDw)_i = 0.6412*(MWDw)_{i-1}-0.0506*(Total\ P)_{i-1}+0.0385*(Fed)_{i-1}-0.1041*(OCa)_{i-1}+0.7188*(OCb)_{i-1}-0.1399*(OCc)_{i-1} - 0.6589*(OCd)_{i-1} + 0.2840*(OCe)_{i-1} + 0.2540*(MC)_{i-1} + w_i$	0.9627
$(MWDw)_i = 0.5418*(MWDw)_{i-1}-0.0683*(Clay)_{i-1}+0.0661*(Fep)_{i-1}-0.0569*(OCa)_{i-1}+0.6286*(OCb)_{i-1}-0.2437*(OCc)_{i-1} - 0.1461*(OCd)_{i-1} - 0.0649*(OCe)_{i-1} + 0.3306*(MC)_{i-1} + w_i$	0.9923
$(MWDw)_i = 0.8132*(MWDw)_{i-1}-0.1369*(Total\ P)_{i-1}+0.0495*(Fep)_{i-1}-0.3862*(OCa)_{i-1} +1.0000*(OCb)_{i-1}-0.3372*(OCc)_{i-1} - 0.1938*(OCd)_{i-1} - 0.0511*(OCe)_{i-1} + 0.2267*(MC)_{i-1} + w_i$	0.9439
$(MWDw)_i = 0.7121*(MWDw)_{i-1} + 0.0492*(Fed)_{i-1}- 0.0179*(Fep)_{i-1} - 0.2103*(OCa)_{i-1}+ 0.7496*(OCb)_{i-1}- 0.2728*(OCc)_{i-1} - 0.1112*(OCd)_{i-1} - 0.0552*(OCe)_{i-1} + 0.1430*(MC)_{i-1} + w_i$	0.9634

APPENDIX D: Multiple linear regression equations of wet mean weight diameter for the seven selected soil properties

Equations	**R^2**
$MWDw_i = 0.\ 3489 – 0.0013(Clay) + 0.1712(Total\ P) + 0.5376(Fed) – 9.7184(Fep) + 0.0541(OCa) + 0.0005(OCb) + 0.0144(OCc)$	0.5187
$MWDw_i = 0.3651 – 0.0012(Clay) + 0.1582(Total\ P) + 0.4693(Fed) – 10.2008(Fep) + 0.0534(OCa) + 0.0027(OCb) + 0.0102(OCd)$	0.5184
$MWDw_i = 0.\ 3511 – 0.0012(Clay) + 0.1631(Total\ P) + 0.5431(Fed) – 10.1132(Fep) + 0.0526(OCa) + 0.0098(OCc) + 0.0064(OCd)$	0.5199
$MWDw_i = 0.3899 – 0.0022(Clay) + 0.1930(Total\ P) + 0.6566(Fed) – 11.7054(Fep) + 0.0339(OCb) + 0.0147(OCc) + 0.0155(OCd)$	0.4468
$MWDw_i = 0.2693 – 0.0018(Clay) + 0.2803(Total\ P) + 0.1397(Fed) + 0.0605(OCa) - 0.0016(OCb) + 0.0139(OCc) - 0.0083(OCd)$	0.4527
$MWDw_i = 0.3942 – 0.0014(Clay) + 0.1507(Total\ P) – 9.7102(Fep) + 0.0535(OCa) - 0.0031(OCb) + 0.0069(OCc) + 0.0064(OCd)$	0.5163

$MWDw_i = 0.3959 – 0.0010(Clay) + 0.3809(Fed) – 11.5880(Fep) + 0.0547(OCa) + 0.0011(OCb) + 0.0072(OCc) + 0.0102(OCd)$	0.5062
$MWDw_i = 0.3043 + 0.1489(Total P) + 0.6394(Fed) – 10.5073(Fep) + 0.0560(OCa) - 0.0011(OCb) + 0.0106(OCc) + 0.0076(OCd)$	0.5144
$MWDw_i = 0.3605 – 0.0013(Clay) + 0.1730(Total P) + 0.4375(Fed) – 9.7276(Fep) + 0.0539(OCa) + 0.0053(OCb) + 0.0074(OCe)$	0.5159
$MWDw_i = 0.3493 – 0.0013(Clay) + 0.1713(Total P) + 0.5357(Fed) – 9.7077(Fep) + 0.0543(OCa) + 0.0148(OCc) - 0.0003(OCe)$	0.5187
$MWDw_i = 0.3731 – 0.0022(Clay) + 0.2169(Total P) + 0.6294(Fed) – 11.2018(Fep) + 0.0343(OCb) + 0.0132(OCc) + 0.0181(OCe)$	0.4459
$MWDw_i = 0.2766 – 0.0018(Clay) + 0.2691(Total P) + 0.1444(Fed) + 0.0617(OCa) - 0.0023(OCb) + 0.0152(OCc) - 0.0109(OCe)$	0.4527
$MWDw_i = 0.3914 – 0.0014(Clay) + 0.1586(Total P) – 9.3258(Fep) + 0.0546(OCa) - 0.0018(OCb) + 0.0112(OCc) + 0.0001(OCe)$	0.5152
$MWDw_i = 0.3961 – 0.0010(Clay) + 0.3685(Fed) – 11.0057(Fep) + 0.0572(OCa) + 0.0034(OCb) + 0.0155(OCc) - 0.0021(OCe)$	0.5033
$MWDw_i = 0.2989 + 0.1581(Total P) + 0.6393(Fed) – 10.0936(Fep) + 0.0572(OCa) + 0.0003(OCb) + 0.0149(OCc) + 0.0013(OCe)$	0.5129
$MWDw_i = 0.3690 – 0.0013(Clay) + 0.1579(Total P) + 0.4468(Fed) – 10.2055(Fep) + 0.0547(OCa) + 0.0113(OCd) - 0.0008(OCe)$	0.5183
$MWDw_i = 0.3901 – 0.0021(Clay) + 0.1997(Total P) + 0.5727(Fed) – 11.7525(Fep) + 0.0356(OCb) + 0.0126(OCd) + 0.0150(OCe)$	0.4469
$MWDw_i = 0.2877 – 0.0019(Clay) + 0.2744(Total P) + 0.0362(Fed) + 0.0614(OCa) + 0.0033(OCb) - 0.0030(OCd) - 0.0004(OCe)$	0.4498
$MWDw_i = 0.4020 – 0.0014(Clay) + 0.1464(Total P) – 9.8172(Fep) + 0.0541(OCa) - 0.0000(OCb) + 0.0101(OCd) - 0.0018(OCe)$	0.5156
$MWDw_i = 0.4111 – 0.0010(Clay) + 0.3295(Fed) – 11.5702(Fep) + 0.0561(OCa) + 0.0045(OCb) + 0.0163(OCd) - 0.0066(OCe)$	0.5061
$MWDw_i = 0.3178 + 0.1434(Total P) + 0.5670(Fed) – 10.6071(Fep) + 0.0566(OCa) + 0.0027(OCb) + 0.0115(OCd) + 0.0000(OCe)$	0.5127
$MWDw_i = 0.4083 – 0.0023(Clay) + 0.2244(Total P) + 0.4770(Fed) – 12.0044(Fep) + 0.0224(OCc) + 0.0151(OCd) + 0.0158(OCe)$	0.4304
$MWDw_i = 0.2735 – 0.0018(Clay) + 0.2741(Total P) + 0.1555(Fed) + 0.0611(OCa) + 0.0161(OCc) - 0.0056(OCd) - 0.0071(OCe)$	0.4533
$MWDw_i = 0.3981 – 0.0014(Clay) + 0.1448(Total P) – 9.6907(Fep) + 0.0533(OCa) + 0.0080(OCc) + 0.0083(OCd) - 0.0055(OCe)$	0.5165
$MWDw_i = 0.4020 – 0.0010(Clay) + 0.3982(Fed) – 11.4860(Fep) + 0.0567(OCa) + 0.0121(OCc) + 0.0146(OCd) - 0.0114(OCe)$	0.5078
$MWDw_i = 0.3066 + 0.1444(Total P) + 0.6512(Fed) – 10.5059(Fep) + 0.0565(OCa) + 0.0i21(OCc) + 0.0094(OCd) - 0.0050(OCe)$	0.5147
$MWDw_i = 0.2892 – 0.0030(Clay) + 0.3456(Total P) + 0.1849(Fed) + 0.0374(OCb) + 0.0151(OCc) - 0.0057(OCd) + 0.0127(OCe)$	0.3567
$MWDw_i = 0.4316 – 0.0023(Clay) + 0.1870(Total P) – 11.2140(Fep) + 0.0303(OCb) + 0.0064(OCc) + 0.0106(OCd) + 0.0118(OCe)$	0.4432
$MWDw_i = 0.4412 – 0.0019(Clay) + 0.4611(Fed) – 13.5456(Fep) + 0.0370(OCb) + 0.0094(OCc) + 0.0182(OCd) + 0.0052(OCe)$	0.4279
$MWDw_i = 0.2972 + 0.1809(Total P) + 0.8260(Fed) – 12.5416(Fep) + 0.0354(OCb) + 0.0104(OCc) + 0.0122(OCd) + 0.0146(OCe)$	0.4313
$MWDw_i = 0.2872 – 0.0019(Clay) + 02698(Total P) + 0.0617(OCa) - 0.0022(OCb) + 0.0156(OCc) - 0.0054(OCd) - 0.0069(OCe)$	0.4530
$MWDw_i = 0.3406 – 0.0015(Clay) - 0.2328(Fed) + 0.0685(OCa) + 0.0018(OCb) + 0.0165(OCc) + 0.0015(OCd) - 0.0174(OCe)$	0.4115
$MWDw_i = 0.1963 + 0.2610(Total P) + 0.2749(Fed) + 0.0666(OCa) - 0.0020(OCb) + 0.0170(OCc) - 0.0054(OCd) - 0.0053(OCe)$	0.4409
$MWDw_i = 0.4309 – 0.0011(Clay) – 11.0988(Fep) + 0.0566(OCa) - 0.0007(OCb) + 0.0092(OCc) + 0.0139(OCd) - 0.0106(OCe)$	0.5058
$MWDw_i = 0.3518 + 0.1279(Total P) – 10.0722(Fep) + 0.0578(OCa) - 0.0038(OCb) + 0.0084(OCc) + 0.0092(OCd) - 0.0040(OCe)$	0.5094
$MWDw_i = 0.3581 + 04957(Fed) – 11.7180(Fep) + 0.0586(OCa) + 0.0008(OCb) + 0.0118(OCc) + 0.0146(OCd) - 0.0100(OCe)$	0.5041
$MWDw_i = 0.1164 – 0.0018(Clay) + 0.0270(Total P) + 0.3886(Fed) – 5.9487(Fep) + 0.0534(OCa) + 0.0105(OCb) + 0.0225(MC)$	0.5719
$MWDw_i = 0.1120 – 0.0018(Clay) + 0.0336(Total P) + 0.4435(Fed) – 6.1544(Fep) + 0.0531(OCa) + 0.0106(OCc) + 0.0219(MC)$	0.5728
$MWDw_i = 0.1240 – 0.0028(Clay) + 0.0601(Total P) + 0.5775(Fed) – 6.9413(Fep) + 0.0423(OCb) + 0.0187(OCc) + 0.0237(MC)$	0.5032
$MWDw_i = 0.0038 – 0.0022(Clay) + 0.0521(Total P) + 0.2249(Fed) + 0.0532(OCa) + 0.0048(OCb) + 0.0033(OCc) + 0.0275(MC)$	0.5497
$MWDw_i = 0.1429 – 0.0019(Clay) + 0.0181(Total P) – 5.8002(Fep) + 0.0515(OCa) + 0.0037(OCb) + 0.0056(OCc) + 0.0222(MC)$	0.5705
$MWDw_i = 0.1060 – 0.0017(Clay) + 0.4412(Fed) – 6.2479(Fep) + 0.0514(OCa) + 0.0063(OCb) + 0.0081(OCc) + 0.0228(MC)$	0.5729
$MWDw_i = 0.0535 + 0.0197(Total P) + 0.6149(Fed) – 6.8457(Fep) + 0.0560(OCa) + 0.0053(OCb) + 0.0105(OCc) + 0.0208(MC)$	0.5621
$MWDw_i = 0.1219 – 0.0017(Clay) + 0.0215(Total P) + 0.3962(Fed) – 6.5840(Fep) + 0.0526(OCa) + 0.0091(OCd) + 0.0221(MC)$	0.5735
$MWDw_i = 0.1379 – 0.0027(Clay) + 0.0354(Total P) + 0.5188(Fed) – 7.8337(Fep) + 0.0408(OCb) + 0.0177(OCd) + 0.0239(MC)$	0.5082

$MWDw_i$ = 0.0097 – 0.0022(Clay) + 0.0508(Total P) + 0.1938(Fed) + 0.0538(OCa) + 0.0071(OCb) - 0.0005(OCd) + 0.0276(MC)	0.5495
$MWDw_i$ = 0.1464 – 0.0019(Clay) + 0.0101(Total P) – 6.1816(Fep) + 0.0505(OCa) + 0.0032(OCb) + 0.0066(OCd) + 0.0222(MC)	0.5715
$MWDw_i$ = 0.1131 – 0.0017(Clay) + 0.4259(Fed) – 6.6297(Fep) + 0.0503(OCa) + 0.0062(OCb) + 0.0079(OCd) + 0.0227(MC)	0.5738
$MWDw_i$ = 0.0632 + 0.0070(Total P) + 0.5766(Fed) – 7.3153(Fep) + 0.0548(OCa) + 0.0057(OCb) + 0.0096(OCd) + 0.0210(MC)	0.5632
$MWDw_i$ = 0.1118 – 0.0018(Clay) + 0.0342(Total P) + 0.3697(Fed) – 6.1944(Fep) + 0.0527(OCa) + 0.0091(OCe) + 0.0224(MC)	0.5724
$MWDw_i$ = 0 1046 – 0.0026(Clay) + 0.0596(Total P) + 0.5176(Fed) – 7.2949(Fep) + 0.0380(OCb) + 0.0233(OCe) + 0.0243(MC)	0.5114
$MWDw_i$ = 0.0059 – 0.0022(Clay) + 0.0512(Total P) + 0.2011(Fed) + 0.0533(OCa) + 0.0062(OCb) + 0.0013(OCe) + 0.0277(MC)	0.5495
$MWDw_i$ = 0.1378 – 0.0019(Clay) + 0.0189(Total P) – 5.8982(Fep) + 0.0504(OCa) + 0.0044(OCb) + 0.0060(OCe) + 0.0225(MC)	0.5708
$MWDw_i$ = 0.1038 – 0.0017(Clay) + 0.3994Fed) – 6.2982(Fep) + 0.0503(OCa) + 0.0077(OCb) + 0.0069(OCe) + 0.0232(MC)	0.5727
$MWDw_i$ = 0.0504 + 0.0196(Total P) + 0.5616(Fed) – 6.9264(Fep) + 0.0543(OCa) + 0.0069(OCb) + 0.0095(OCe) + 0.0213(MC)	0.5621
$MWDw_i$ = 0.1600 – 0.0028(Clay) + 0.0778(Total P) + 0.2429(Fed) – 8.2227(Fep) + 0.0153(OCd) + 0.0291(OCe) + 0.0239(MC)	0.4882
$MWDw_i$ = 0.0120 – 0.0022(Clay) + 0.0563(Total P) + 0.1510(Fed) + 0.0557(OCa) - 0.0012(OCd) + 0.0041(OCe) + 0.0276(MC)	0.5490
$MWDw_i$ = 0.1462 – 0.0019(Clay) + 0.0130(Total P) – 6.2033(Fep) + 0.0514(OCa) + 0.0064(OCd) + 0.0019(OCe) + 0.0222(MC)	0.5714
$MWDw_i$ = 0.1172 – 0.0017(Clay) + 0.3825(Fed) – 6.6585(Fep) + 0.0523(OCa) + 0.0081(OCd) + 0.0022(OCe) + 0.0227(MC)	0.5733
$MWDw_i$ = 0.0642 + 0.0123(Total P) + 0.5433(Fed) – 7.3102(Fep) + 0.0560(OCa) + 0.0085(OCd) + 0.0042(OCe) + 0.0210(MC)	0.5630
$MWDw_i$ = 0.0182 – 0.0034(Clay) + 0.1263(Total P) + 0.0557(Fed) + 0.0165(OCc) + 0.0017(OCd) + 0.0250(OCe) + 0.0303(MC)	0.4529
$MWDw_i$ = 0.1755 – 0.0029(Clay) + 0.0698(Total P) – 7.8319(Fep) + 0.0120(OCc) + 0.0118(OCd) + 0.0222(OCe) + 0.0235(MC)	0.4896
$MWDw_i$ = 0.1492 – 0.0027(Clay) + 0.2968(Fed) – 8.4918(Fep) + 0.0145(OCc) + 0.0147(OCd) + 0.0205(OCe) + 0.0253(MC)	0.4885
$MWDw_i$ = 0.0631 + 0.0680(Total P) + 0.6060(Fed) – 9.6105(Fep) + 0.0167(OCc) + 0.0146(OCd) + 0.0267(OCe) + 0.0215(MC)	0.4626
$MWDw_i$ = 0.0097 – 0.0033(Clay) + 0.0828(Total P) + 0.0381(OCb) + 0.0001(OCc) - 0.0026(OCd) + 0.0194(OCe) + 0.0305(MC)	0.4778
$MWDw_i$ = - 0.0217 – 0.0032(Clay) + 0.1768(Fed) + 0.0413(OCb) + 0.0006(OCc) - 0.0007(OCd) + 0.0175(OCe) + 0.0331(MC)	0.4751
$MWDw_i$ = - 0.1478 + 0.0816(Total P) + 0.5012(Fed) + 0.0439(OCb) + 0.0026(OCc) - 0.0027(OCd) + 0.0249(OCe) + 0.0299(MC)	0.4395
$MWDw_i$ = 0.0159 – 0.0022(Clay) + 0.0540(OCa) + 0.0053(OCb) + 0.0027(OCc) - 0.0016(OCd) + 0.0005(OCe) + 0.0288(MC)	0.5482
$MWDw_i$ = -0.0499 + 0.0337(Total P) + 0.0598(OCa) + 0.0029(OCb) + 0.0028(OCc) - 0.0026(OCd) + 0.0037(OCe) + 0.0265(MC)	0.5307
$MWDw_i$ = 0.0980 – 6.8408(Fep) + 0.0551(OCa) + 0.0011(OCb) + 0.0008(OCc) + 0.0065(OCd) + 0.0026(OCe) + 0.0208(MC)	0.5590

APPENDIX E: State-space equations of wet mean weight diameter for the seven selected soil properties

Equations	R^2
$(MWDw)_i = 0.9754*(MWDw)_{i-1}+0.0500*(Clay)_{i-1}-0.0346*(Total\ P)_{i-1} + 0.0342*(Fed)_{i-1} - 0.0524*(Fep)_{i-1} -0.3507*(OCa)_{i-1}+0.7006*(OCb)_{i-1} – 0.3375*(OCc)_{i-1} + w_i$	0.8254
$(MWDw)_i = 0.8680*(MWDw)_{i-1}+0.0360*(Clay)_{i-1}–0.0830*(Total\ P)_{i-1}+ 0.1137*(Fed)_{i-1}- 0.1028*(Fep)_{i-1} -0.5525*(OCa)_{i-1} + 1.1571*(OCb)_{i-1} – 0.4524*(OCd)_{i-1} + w_i$	0.8796
$(MWDw)_i = 0.7070*(MWDw)_{i-1}+ 0.1411*(Clay)_{i-1}–0.0712*(Total\ P)_{i-1} + 0.0687*(Fed)_{i-1}- 0.1413*(Fep)_{i-1}+0.4478*(OCa)_{i-1}+ 0.0138*(OCc)_{i-1} – 0.1858*(OCd)_{i-1} + w_i$	0.8750
$(MWDw)_i = 0.8418*(MWDw)_{i-1} + 0.0713*(Clay)_{i-1}- 0.0569*(Total\ P)_{i-1}+ 0.0351*(Fed)_{i-1}- 0.0318*(Fep)_{i-1}+0.6084*(OCb)_{i-1}–0.1559*(OCc)_{i-1} – 0.3290*(OCd)_{i-1} + w_i$	0.8097
$(MWDw)_i = 0.7724*(MWDw)_{i-1}-0.0166*(Clay)_{i-1}+0.0762*(Total\ P)_{i-1} +0.0692*(Fed)_{i-1}- 0.4540*(OCa)_{i-1}+1.2423*(OCb)_{i-1} - 0.4289*(OCc)_{i-1} – 0.2767*(OCd)_{i-1} + w_i$	0.9909
$(MWDw)_i = 1.0081*(MWDw)_{i-1} + 0.0204*(Clay)_{i-1}-0.0435*(Total\ P)_{i-1} +0.0410*(Fep)_{i-1}- 0.6115*(OCa)_{i-1}+1.3097*(OCb)_{i-1}– 0.4405*(OCc)_{i-1} – 0.3010*(OCd)_{i-1} + w_i$	0.9073
$(MWDw)_i = 0.7827*(MWDw)_{i-1}+0.1019*(Clay)_{i-1}+0.0037*(Fed)_{i-1}-0.0413*(Fep)_{i-1}+0.4349*(OCa)_{i-1}-0.1592*(OCb)_{i-1} + 0.1171*(OCc)_{i-1} – 0.2558*(OCd)_{i-1} + w_i$	0.8053
$(MWDw)_i = 0.8944*(MWDw)_{i-1}–0.0233*(Total\ P)_{i-1} + 0.0301*(Fed)_{i-1}+0.0484*(Fep)_{i-1}-0.3144*(OCa)_{i-1}+ 0.9833*(OCb)_{i-1}– 0.2617*(OCc)_{i-1} – 0.3758*(OCd)_{i-1} + w_i$	0.9556
$(MWDw)_i = 0.8326*(MWDw)_{i-1}+ 0.0272*(Clay)_{i-1}-0.1415*(Total\ P)_{i-1} + 0.1788*(Fed)_{i-1} - 0.1635*(Fep)_{i-1}- 0.6311*(OCa)_{i-1}+1.3416*(OCb)_{i-1} – 0.4611*(OCe)_{i-1} + w_i$	0.9177
$(MWDw)_i = 0.7013*(MWDw)_{i-1}+0.1351*(Clay)_{i-1} + 0.0014*(Total\ P)_{i-1} +0.0717*(Fed)_{i-1}-0.1396*(Fep)_{i-1}+0.2873*(OCa)_{i-1}+ 0.0379*(OCc)_{i-1} – 0.1157*(OCe)_{i-1} + w_i$	0.9632
$(MWDw)_i = 0.8585*(MWDw)_{i-1}+ 0.1349*(Clay)_{i-1}- 0.2392*(Total\ P)_{i-1} + .0364*(Fed)_{i-1}- 0.0595*(Fep)_{i-1}+ 0.8288*(OCb)_{i-1}–0.2920*(OCc)_{i-1} – 0.2856*(OCe)_{i-1} + w_i$	0.7989
$(MWDw)_i = 0.7789*(MWDw)_{i-1}- 0.0117*(Clay)_{i-1}- 0.0075*(Total\ P)_{i-1} + 0.0798*(Fed)_{i-1}- 0.5232*(OCa)_{i-1}+1.3836*(OCb)_{i-1}–0.4350*(OCc)_{i-1} – 0.2803*(OCe)_{i-1} + w_i$	0.9922
$(MWDw)_i = 0.9363*(MWDw)_{i-1}+0.0363*(Clay)_{i-1}-0.0953*(Total\ P)_{i-1} +0.0259*(Fep)_{i-1}- 0.5948*(OCa)_{i-1}+1.4439*(OCb)_{i-1} –0.4750*(OCc)_{i-1} – 0.2968*(OCe)_{i-1} + w_i$	0.9488
$(MWDw)_i = 1.0074*(MWDw)_{i-1}+0.0655*(Clay)_{i-1}-0.0741*(Fed)_{i-1}+0.0719*(Fep)_{i-1}-0.0177*(OCa)_{i-1} + 0.2265*(OCb)_{i-1} – 0.1152*(OCc)_{i-1} – 0.1743*(OCe)_{i-1} + w_i$	0.7231
$(MWDw)_i = 0.8239*(MWDw)_{i-1}-0.0476*(Total\ P)_{i-1}+ 0.0816*(Fed)_{i-1}- 0.0216*(Fep)_{i-1} - 0.3363*(OCa)_{i-1} +1.0281*(OCb)_{i-1} –0.3057*(OCc)_{i-1} – 0.2444*(OCe)_{i-1} + w_i$	0.9785
$(MWDw)_i = 0.6271*(MWDw)_{i-1}+0.1152*(Clay)_{i-1} +0.1319*(Total\ P)_{i-1}+0.1596*(Fed)_{i-1}- 0.2907*(Fep)_{i-1} + 0.0770*(OCa)_{i-1}–0.3904*(OCd)_{i-1} + 0.5470*(OCe)_{i-1} + w_i$	0.9676
$(MWDw)_i = 0.8947*(MWDw)_{i-1}+0.1229*(Clay)_{i-1}-0.1754*(Total\ P)_{i-1}+0.0143*(Fed)_{i-1}- 0.0193*(Fep)_{i-1}+ 0.5477*(OCb)_{i-1} – 0.2103*(OCd)_{i-1} –$	

$0.1933*(OCe)_{i-1} + w_i$	0.8755
$(MWDw)_i = 0.7484*(MWDw)_{i-1} - 0.0276*(Clay)_{i-1} + 0.0256*(Total\ P)_{i-1} + 0.0871*(Fed)_{i-1} - 0.5081*(OCa)_{i-1} + 1.2236*(OCb)_{i-1} - 0.3277*(OCd)_{i-1} - 0.2370*(OCe)_{i-1} + w_i$	0.9934
$(MWDw)_i = 0.9201*(MWDw)_{i-1} + 0.0001*(Clay)_{i-1} - 0.0104*(Total\ P)_{i-1} + 0.0231*(Fep)_{i-1} - 0.7329*(OCa)_{i-1} + 1.3217*(OCb)_{i-1} - 0.4225*(OCd)_{i-1} - 0.1210*(OCe)_{i-1} + w_i$	0.9598
$(MWDw)_i = 0.8757*(MWDw)_{i-1} + 0.0154*(Clay)_{i-1} + 0.0796*(Fed)_{i-1} - 0.0500*(Fep)_{i-1} - 0.4922*(OCa)_{i-1} + 0.9702*(OCb)_{i-1} - 0.2768*(OCd)_{i-1} - 0.1364*(OCe)_{i-1} + w_i$	0.9370
$(MWDw)_i = 0.7791*(MWDw)_{i-1} - 0.0101*(Total\ P)_{i-1} + 0.1141*(Fed)_{i-1} - 0.0692*(Fep)_{i-1} - 0.3853*(OCa)_{i-1} + 0.9942*(OCb)_{i-1} - 0.3231*(OCd)_{i-1} - 0.1190*(OCe)_{i-1} + w_i$	0.9706
$(MWDw)_i = 1.1965*(MWDw)_{i-1} + 0.1395*(Clay)_{i-1} - 0.1702*(Total\ P)_{i-1} - 0.1110*(Fed)_{i-1} + 0.0859*(Fep)_{i-1} + 0.0018*(OCc)_{i-1} - 0.1088*(OCd)_{i-1} - 0.0516*(OCe)_{i-1} + w_i$	0.7723
$(MWDw)_i = 0.6144*(MWDw)_{i-1} + 0.0592*(Clay)_{i-1} + 0.1126*(Total\ P)_{i-1} + 0.0236*(Fed)_{i-1} + 0.3747*(OCa)_{i-1} + 0.0602*(OCc)_{i-1} - 0.1078*(OCd)_{i-1} - 0.1558*(OCe)_{i-1} + w_i$	0.9985
$(MWDw)_i = 0.6100*(MWDw)_{i-1} + 0.1255*(Clay)_{i-1} + 0.0309*(Total\ P)_{i-1} - 0.0534*(Fep)_{i-1} + 0.4913*(OCa)_{i-1} + 0.0594*(OCc)_{i-1} - 0.0840*(OCd)_{i-1} - 0.2043*(OCe)_{i-1} + w_i$	0.9941
$(MWDw)_i = 0.8071*(MWDw)_{i-1} + 0.1081*(Clay)_{i-1} + 0.0227*(Fed)_{i-1} - 0.0674*(Fep)_{i-1} + 0.2546*(OCa)_{i-1} + 0.0530*(OCc)_{i-1} - 0.1091*(OCd)_{i-1} - 0.0858*(OCe)_{i-1} + w_i$	0.8726
$(MWDw)_i = 0.9746*(MWDw)_{i-1} + 0.0140*(Total\ P)_{i-1} - 0.0247*(Fed)_{i-1} + 0.0801*(Fep)_{i-1} + 0.0733*(OCa)_{i-1} + 0.0526*(OCc)_{i-1} - 0.1219*(OCd)_{i-1} - 0.0677*(OCe)_{i-1} + w_i$	0.8583
$(MWDw)_i = 0.7101*(MWDw)_{i-1} + 0.0990*(Clay)_{i-1} - 0.1296*(Total\ P)_{i-1} + 0.0345*(Fed)_{i-1} + 1.0083*(OCb)_{i-1} - 0.3582*(OCc)_{i-1} - 0.2239*(OCd)_{i-1} - 0.1571*(OCe)_{i-1} + w_i$	0.9914
$(MWDw)_i = 0.8014*(MWDw)_{i-1} + 0.1411*(Clay)_{i-1} - 0.1478*(Total\ P)_{i-1} - 0.0341*(Fep)_{i-1} + 0.8358*(OCb)_{i-1} - 0.3214*(OCc)_{i-1} - 0.2158*(OCd)_{i-1} - 0.0811*(OCe)_{i-1} + w_i$	0.9618
$(MWDw)_i = 0.7637*(MWDw)_{i-1} + 0.0769*(Clay)_{i-1} + 0.0464*(Fed)_{i-1} - 0.0561*(Fep)_{i-1} + 0.6214*(OCb)_{i-1} - 0.2155*(OCc)_{i-1} - 0.2251*(OCd)_{i-1} - 0.0292*(OCe)_{i-1} + w_i$	0.9311
$(MWDw)_i = 0.8080*(MWDw)_{i-1} - 0.0323*(Total\ P)_{i-1} + 0.0176*(Fed)_{i-1} + 0.0631*(Fep)_{i-1} + 0.6893*(OCb)_{i-1} - 0.2160*(OCc)_{i-1} - 0.3132*(OCd)_{i-1} - 0.0370*(OCe)_{i-1} + w_i$	0.9486
$(MWDw)_i = 0.8239*(MWDw)_{i-1} + 0.0446*(Clay)_{i-1} + 0.0184*(Total\ P)_{i-1} - 0.4383*(OCa)_{i-1} + 1.1786*(OCb)_{i-1} - 0.3492*(OCc)_{i-1} - 0.2134*(OCd)_{i-1} - 0.0868*(OCe)_{i-1} + w_i$	0.9879
$(MWDw)_i = 0.8739*(MWDw)_{i-1} + 0.0507*(Clay)_{i-1} + 0.0255*(Fed)_{i-1} - 0.1778*(OCa)_{i-1} + 0.6864*(OCb)_{i-1} - 0.1737*(OCc)_{i-1} - 0.1999*(OCd)_{i-1} - 0.1017*(OCe)_{i-1} + w_i$	0.9185
$(MWDw)_i = 0.7718*(MWDw)_{i-1} + 0.0789*(Total\ P)_{i-1}\ 0.0568*(Fed)_{i-1} - 0.1955*(OCa)_{i-1} + 0.8157*(OCb)_{i-1} - 0.1432*(OCc)_{i-1} - 0.6897*(OCd)_{i-1} + 0.2851*(OCe)_{i-1} + w_i$	0.9764
$(MWDw)_i = 0.9716*(MWDw)_{i-1} + 0.0464*(Clay)_{i-1} + 0.0275*(Fep)_{i-1} - 0.3442*(OCa)_{i-1} + 0.8773*(OCb)_{i-1} - 0.2900*(OCc)_{i-1} - 0.2990*(OCd)_{i-1} - 0.0034*(OCe)_{i-1} + w_i$	0.8454
$(MWDw)_i = 0.8465*(MWDw)_{i-1} + 0.0445*(Total\ P)_{i-1} + 0.0677*(Fep)_{i-1} - 0.2923*(OCa)_{i-1} + 0.9479*(OCb)_{i-1} - 0.2346*(OCc)_{i-1} - 0.5762*(OCd)_{i-1} + 0.1768*(OCe)_{i-1} + w_i$	0.9738
$(MWDw)_i = 1.0071*(MWDw)_{i-1} - 0.0429*(Fed)_{i-1} + 0.1061*(Fep)_{i-1} - 0.0089*(OCa)_{i-1} + 0.1616*(OCb)_{i-1} + 0.0432*(OCc)_{i-1} - 0.2047*(OCd)_{i-1} - 0.0798*(OCe)_{i-1} + w_i$	0.8145

$(MWDw)_i = 0.6620*(MWDw)_{i-1}+0.0225*(Clay)_{i-1}-0.1865*(Total\ P)_{i-1}+0.0851*(Fed)_{i-1} - 0.1122*(Fep)_{i-1} - 0.1406*(OCa)_{i-1} + 0.3579*(OCb)_{i-1} + 0.2953*(MC)_{i-1} + w_i$	0.9175
$(MWDw)_i = 0.4758*(MWDw)_{i-1}-0.0042*(Clay)_{i-1}-0.1573*(Total\ P)_{i-1} + 0.0252*(Fed)_{i-1}- 0.0274*(Fep)_{i-1} + 0.3429*(OCa)_{i-1} - 0.0943*(OCc)_{i-1} + 0.4246*(MC)_{i-1} + w_i$	0.9369
$(MWDw)_i = 0.7206*(MWDw)_{i-1}-0.0158*(Clay)_{i-1}-0.2122*(Total\ P)_{i-1} - 0.0313*(Fed)_{i-1}+ 0.0648*(Fep)_{i-1}+0.4289*(OCb)_{i-1} - 0.3184*(OCc)_{i-1} + 0.3497*(MC)_{i-1} + w_i$	0.7362
$(MWDw)_i = 0.5729*(MWDw)_{i-1}-0.0648*(Clay)_{i-1}-0.1704*(Total\ P)_{i-1} +0.0488*(Fed)_{i-1}-0.1762*(OCa)_{i-1} + 0.6588*(OCb)_{i-1} - 0.3242*(OCc)_{i-1} + 0.4424*(MC)_{i-1} + w_i$	0.9639
$(MWDw)_i = 0.3678*(MWDw)_{i-1}-0.0307*(Clay)_{i-1}-0.2020*(Total\ P)_{i-1} + 0.0389*(Fep)_{i-1}+0.5330*(OCa)_{i-1} - 0.0211*(OCb)_{i-1} - 0.2253*(OCc)_{i-1} + 0.5278*(MC)_{i-1} + w_i$	0.9804
$(MWDw)_i = 0.5884*(MWDw)_{i-1} - 0.0626*(Clay)_{i-1} + 0.0521*(Fed)_{i-1} - 0.0005*(Fep)_{i-1} - 0.3386*(OCa)_{i-1} + 1.0143*(OCb)_{i-1} - 0.5940*(OCc)_{i-1} + 0.3283*(MC)_{i-1} + w_i$	0.9962
$(MWDw)_i = 0.6836*(MWDw)_{i-1} - 0.1842*(Total\ P)_{i-1} - 0.0216*(Fed)_{i-1} + 0.0530*(Fep)_{i-1} + 0.1900*(OCa)_{i-1} + 0.1983*(OCb)_{i-1} - 0.2733*(OCc)_{i-1} + 0.3373*(MC)_{i-1} + w_i$	0.9120
$(MWDw)_i = 0.5307*(MWDw)_{i-1} + 0.0565*(Clay)_{i-1} - 0.1747*(Total\ P)_{i-1} + 0.0766*(Fed)_{i-1} - 0.1127*(Fep)_{i-1}+ 0.4001*(OCa)_{i-1} - 0.0814*(OCd)_{i-1} + 0.2889*(MC)_{i-1} + w_i$	0.8783
$(MWDw)_i = 0.6968*(MWDw)_{i-1} + 0.0293*(Clay)_{i-1} - 0.1376*(Total\ P)_{i-1} + 0.0720*(Fed)_{i-1} - 0.0686*(Fep)_{i-1} + 0.4127*(OCb)_{i-1} - 0.2143*(OCd)_{i-1} + 0.1959*(MC)_{i-1} + w_i$	0.8294
$(MWDw)_i = 0.5959*(MWDw)_{i-1} - 0.0766*(Clay)_{i-1} - 0.1061*(Total\ P)_{i-1} + 0.0715*(Fed)_{i-1} - 0.3747*(OCa)_{i-1} + 0.8780*(OCb)_{i-1} - 0.3383*(OCd)_{i-1} + 0.3365*(MC)_{i-1} + w_i$	0.9811
$(MWDw)_i = 0.7288*(MWDw)_{i-1} - 0.0638*(Clay)_{i-1} - 0.1438*(Total\ P)_{i-1}\ 0.0546*(Fep)_{i-1} - 0.5282*(OCa)_{i-1}+ 0.9951*(OCb)_{i-1} - 0.3822*(OCd)_{i-1} + 0.3228*(MC)_{i-1} + w_i$	0.9387
$(MWDw)_i = 0.6860*(MWDw)_{i-1} - 0.0416*(Clay)_{i-1} + 0.1394*(Fed)_{i-1} - 0.1100*(Fep)_{i-1} - 0.5987*(OCa)_{i-1} + 1.0080*(OCb)_{i-1} - 0.2874*(OCd)_{i-1} + 0.1879*(MC)_{i-1} + w_i$	0.9885
$(MWDw)_i = 0.7844*(MWDw)_{i-1} - 0.2219*(Total\ P)_{i-1} + 0.0176*(Fed)_{i-1} + 0.0452*(Fep)_{i-1} - 0.3108*(OCa)_{i-1} + 0.6844*(OCb)_{i-1} - 0.3341*(OCd)_{i-1} + 0.3180*(MC)_{i-1} + w_i$	0.9690
$(MWDw)_i = 0.4904*(MWDw)_{i-1} - 0.0086*(Clay)_{i-1} - 0.2203*(Total\ P)_{i-1} + 0.0221*(Fed)_{i-1} - 0.0137*(Fep)_{i-1} + 0.2683*(OCa)_{i-1} - 0.0545*(OCe)_{i-1} + 0.5012*(MC)_{i-1} + w_i$	0.9542
$(MWDw)_i = 0.6473*(MWDw)_{i-1} + 0.0328*(Clay)_{i-1} – 0.2087*(Total\ P)_{i-1} + 0.0724*(Fed)_{i-1} - 0.0811*(Fep)_{i-1} + 0.2782*(OCb)_{i-1} - 0.0635*(OCe)_{i-1} + 0.3069*(MC)_{i-1} + w_i$	0.9326
$(MWDw)_i = 0.6161*(MWDw)_{i-1} - 0.1075*(Clay)_{i-1} - 0.1761*(Total\ P)_{i-1} + 0.0938*(Fed)_{i-1} - 0.5016*(OCa)_{i-1} + 1.0310*(OCb)_{i-1} - 0.3425*(OCe)_{i-1} + 0.3745*(MC)_{i-1} + w_i$	0.9701
$(MWDw)_i = 0.6194*(MWDw)_{i-1} - 0.1082*(Clay)_{i-1} - 0.2498*(Total\ P)_{i-1} + 0.1005*(Fep)_{i-1} - 0.2871*(OCa)_{i-1} + 0.7383*(OCb)_{i-1} - 0.3009*(OCe)_{i-1} + 0.4762*(MC)_{i-1} + w_i$	0.8846
$(MWDw)_i = 0.4973*(MWDw)_{i-1} + 0.0351*(Clay)_{i-1} + 0.0616*(Fed)_{i-1} - 0.0666*(Fep)_{i-1} + 0.3600*(OCa)_{i-1} - 0.0052*(OCb)_{i-1} - 0.1296*(OCe)_{i-1} + 0.2320*(MC)_{i-1} + w_i$	0.9948
$(MWDw)_i = 0.6491*(MWDw)_{i-1} - 0.2639*(Total\ P)_{i-1} + 0.0537*(Fed)_{i-1} - 0.0322*(Fep)_{i-1} + 0.0065*(OCa)_{i-1} + 0.2618*(OCb)_{i-1} - 0.0845*(OCe)_{i-1} + 0.3909*(MC)_{i-1} + w_i$	0.9517
$(MWDw)_i = 0.9976*(MWDw)_{i-1} + 0.0654*(Clay)_{i-1} - 0.2045*(Total\ P)_{i-1} - 0.1010*(Fed)_{i-1} + 0.1111*(Fep)_{i-1} - 0.0994*(OCd)_{i-1}- 0.0094*(OCe)_{i-1} + 0.2246*(MC)_{i-1} + w_i$	0.7900

$(MWDw)_i = 0.4098*(MWDw)_{i-1} - 0.0602*(Clay)_{i-1} - 0.1456*(Total\ P)_{i-1} + 0.0341*(Fed)_{i-1} + 0.2768*(OCa)_{i-1} - 0.1690*(OCd)_{i-1} + 0.1191*(OCe)_{i-1} + 0.5209*(MC)_{i-1} + w_i$	0.9837
$(MWDw)_i = 0.4437*(MWDw)_{i-1} - 0.0506*(Clay)_{i-1} - 0.2245*(Total\ P)_{i-1} + 0.0553*(Fep)_{i-1} + 0.3832*(OCa)_{i-1} - 0.1097*(OCd)_{i-1} - 0.0544*(OCe)_{i-1} + 0.5440*(MC)_{i-1} + w_i$	0.9356
$(MWDw)_i = 0.4559*(MWDw)_{i-1} - 0.0013*(Clay)_{i-1} + 0.0743*(Fed)_{i-1} - 0.0603*(Fep)_{i-1} + 0.4181*(OCa)_{i-1} - 0.0904*(OCd)_{i-1} - 0.0818*(OCe)_{i-1} + 0.2720*(MC)_{i-1} + w_i$	0.9733
$(MWDw)_i = 0.6601*(MWDw)_{i-1} - 0.2413*(Total\ P)_{i-1} + 0.0270*(Fed)_{i-1} - 0.0050*(Fep)_{i-1} + 0.2382*(OCa)_{i-1} - 0.0350*(OCd)_{i-1} - 0.0347*(OCe)_{i-1} + 0.3709*(MC)_{i-1} + w_i$	0.8955
$(MWDw)_i = 0.8918*(MWDw)_{i-1} + 0.0763*(Clay)_{i-1} - 0.2533*(Total\ P)_{i-1} - 0.0380*(Fed)_{i-1} - 0.0791*(OCc)_{i-1} + 0.0410*(OCd)_{i-1} + 0.0500*(OCe)_{i-1} + 0.2942*(MC)_{i-1} + w_i$	0.8171
$(MWDw)_i = 0.8798*(MWDw)_{i-1} + 0.0485*(Clay)_{i-1} - 0.2911*(Total\ P)_{i-1} + 0.0112*(Fep)_{i-1} + 0.0134*(OCc)_{i-1} + 0.0377*(OCd)_{i-1} - 0.0303*(OCe)_{i-1} + 0.3169*(MC)_{i-1} + w_i$	0.8307
$(MWDw)_i = 0.8791*(MWDw)_{i-1} - 0.0043*(Clay)_{i-1} - 0.0999*(Fed)_{i-1} + 0.1270*(Fep)_{i-1} - 0.1162*(OCc)_{i-1} - 0.1233*(OCd)_{i-1} + 0.0857*(OCe)_{i-1} + 0.2406*(MC)_{i-1} + w_i$	0.7785
$(MWDw)_i = 0.9985*(MWDw)_{i-1} - 0.3307*(Total\ P)_{i-1} - 0.1407*(Fed)_{i-1} + 0.2055*(Fep)_{i-1} - 0.0600*(OCc)_{i-1} - 0.0938*(OCd)_{i-1} + 0.0156*(OCe)_{i-1} + 0.3884*(MC)_{i-1} + w_i$	0.7928
$(MWDw)_i = 0.6282*(MWDw)_{i-1} + 0.0132*(Clay)_{i-1} - 0.1613*(Total\ P)_{i-1} + 0.4777*(OCb)_{i-1} - 0.2412*(OCc)_{i-1} - 0.1631*(OCd)_{i-1} + 0931*(OCe)_{i-1} + 0.3363*(MC)_{i-1} + w_i$	0.9668
$(MWDw)_i = 0.5142*(MWDw)_{i-1} - 0.0489*(Clay)_{i-1} + 0.0464*(Fed)_{i-1} + 0.5398*(OCb)_{i-1} - 0.2434*(OCc)_{i-1} - 0.1870*(OCd)_{i-1} + 0.0544*(OCe)_{i-1} + 0.3123*(MC)_{i-1} + w_i$	0.9925
$(MWDw)_i = 0.7485*(MWDw)_{i-1} - 0.1951*(Total\ P)_{i-1} + 0.0306*(Fed)_{i-1} + 0.4414*(OCb)_{i-1} - 0.1599*(OCc)_{i-1} - 0.1603*(OCd)_{i-1} - 0.0043*(OCe)_{i-1} + 0.2814*(MC)_{i-1} + w_i$	0.9002
$(MWDw)_i = 0.5462*(MWDw)_{i-1} - 0.0309*(Clay)_{i-1} - 0.1147*(OCa)_{i-1} + 0.7077*(OCb)_{i-1} - 0.2770*(OCc)_{i-1} - 0.1334*(OCd)_{i-1} - 0.0292*(OCe)_{i-1} + 0.3138*(MC)_{i-1} + w_i$	0.9918
$(MWDw)_i = 0.6084*(MWDw)_{i-1} - 0.0520*(Total\ P)_{i-1} - 0.0225*(OCa)_{i-1} + 0.6823*(OCb)_{i-1} - 0.1095*(OCc)_{i-1} - 0.7071*(OCd)_{i-1} + 0.2771*(OCe)_{i-1} + 0.2995*(MC)_{i-1} + w_i$	0.9555
$(MWDw)_i = 0.7470*(MWDw)_{i-1} + 0.0435*(Fep)_{i-1} - 0.1992*(OCa)_{i-1} + 0.7675*(OCb)_{i-1} - 0.2888*(OCc)_{i-1} - 0.3234*(OCd)_{i-1} + 0.0752*(OCe)_{i-1} + 0.1650*(MC)_{i-1} + w_i$	0.9441

APPENDIX F: Multiple linear regression equations of wet mean weight diameter for the six selected soil properties

Equations	R^2
$MWDw_i = 0.3723 - 0.0014(Clay) + 0.1702(Total\ P) + 0.3993(Fed) - 9.4455(Fep) + 0.0564(OCa) + 0.0087(OCb)$	0.5154
$MWDw_i = 0.3491 - 0.0013(Clay) + 0.1714(Total\ P) + 0.5355(Fed) - 9.7149(Fep) + 0.0542(OCa) + 0.0146(OCc)$	0.5187
$MWDw_i = 0.3856 - 0.0024(Clay) + 0.2142(Total\ P) + 0.6583(Fed) - 10.8177(Fep) + 0.0389(OCb) + 0.0259(OCc)$	0.4400
$MWDw_i = 0.2685 - 0.0018(Clay) + 0.2758(Total\ P) + 0.1205(Fed) + 0.0593(OCa) - 0.0035(OCb) + 0.0079(OCc)$	0.4506
$MWDw_i = 0.3915 - 0.0014(Clay) + 0.1585(Total\ P) - 9.3225(Fep) + 0.0546(OCa) - 0.0018(OCb) + 0.0113(OCc)$	0.5152
$MWDw_i = 0.3952 - 0.0010(Clay) + 0.3655(Fed) - 11.0656(Fep) + 0.0567(OCa) + 0.0032(OCb) + 0.0141(OCc)$	0.5033
$MWDw_i = 0.2993 + 0.1576(Total\ P) + 0.6413(Fed) - 10.0617(Fep) + 0.0575(OCa) + 0.0004(OCb) + 0.0158(OCc)$	0.5128
$MWDw_i = 0.3680 - 0.0012(Clay) + 0.1586(Total\ P) + 0.4488(Fed) - 10.2041(Fep) + 0.0545(OCa) + 0.0109(OCd)$	0.5182
$MWDw_i = 0.4105 - 0.0022(Clay) + 0.1860(Total\ P) + 0.5547(Fed) - 11.8593(Fep) + 0.0396(OCb) + 0.0212(OCd)$	0.4435
$MWDw_i = 0.2873 - 0.0019(Clay) + 0.2748(Total\ P) + 0.0369(Fed) + 0.0614(OCa) + 0.0033(OCb) - 0.0032(OCd)$	0.4498
$MWDw_i = 0.4000 - 0.0014(Clay) + 0.1482(Total\ P) - 9.8119(Fep) + 0.0538(OCa) - 0.0003(OCb) + 0.0091(OCd)$	0.5155
$MWDw_i = 0.4048 - 0.0010(Clay) + 0.3336(Fed) - 11.6191(Fep) + 0.0550(OCa) + 0.0036(OCb) + 0.0129(OCd)$	0.5054
$MWDw_i = 0.3179 + 0.1433(Total\ P) + 0.5669(Fed) - 10.6072(Fep) + 0.0566(OCa) + 0.0026(OCb) + 0.0116(OCd)$	0.5127
$MWDw_i = 0.4229 - 0.0024(Clay) + 0.2141(Total\ P) + 0.4925(Fed) - 12.0719(Fep) + 0.0295(OCc) + 0.0221(OCd)$	0.4271
$MWDw_i = 0.2687 - 0.0018(Clay) + 0.2710(Total\ P) + 0.1469(Fed) + 0.0600(OCa) + 0.0134(OCc) - 0.0085(OCd)$	0.4527
$MWDw_i = 0.3938 - 0.0014(Clay) + 0.1494(Total\ P) - 9.7049(Fep) + 0.0524(OCa) + 0.0059(OCc) + 0.0061(OCd)$	0.5161
$MWDw_i = 0.3966 - 0.0010(Clay) + 0.3758(Fed) - 11.5890(Fep) + 0.0550(OCa) + 0.0075(OCc) + 0.0103(OCd)$	0.5062
$MWDw_i = 0.3037 + 0.1486(Total\ P) + 0.6443(Fed) - 10.5093(Fep) + 0.0556(OCa) + 0.0102(OCc) + 0.0075(OCd)$	0.5144
$MWDw_i = 0.2992 - 0.0031(Clay) + 0.3369(Total\ P) + 0.2030(Fed) + 0.0389(OCb) + 0.0201(OCc) - 0.0004(OCd)$	0.3547
$MWDw_i = 0.4426 - 0.0024(Clay) + 0.1780(Total\ P) - 11.2362(Fep) + 0.0316(OCb) + 0.0110(OCc) + 0.0156(OCd)$	0.4414
$MWDw_i = 0.4443 - 0.0019(Clay) + 0.4727(Fed) - 13.5256(Fep) + 0.0375(OCb) + 0.0115(OCc) + 0.0203(OCd)$	0.4275
$MWDw_i = 0.3056 + 0.1693(Total\ P) + 0.8568(Fed) - 12.6226(Fep) + 0.0353(OCb) + 0.0162(OCc) + 0.0186(OCd)$	0.4285
$MWDw_i = 0.2816 - 0.0019(Clay) + 0.2758(Total\ P) + 0.0606(OCa) - 0.0022(OCb) + 0.0131(OCc) - 0.0082(OCd)$	0.4525
$MWDw_i = 0.3315 - 0.0015(Clay) - 0.2764(Fed) + 0.0661(OCa) + 0.0017(OCb) + 0.0096(OCc) - 0.0053(OCd)$	0.4077
$MWDw_i = 0.1932 + 0.2656(Total\ P) + 0.2669(Fed) + 0.0657(OCa) - 0.0021(OCb) + 0.0150(OCc) - 0.0075(OCd)$	0.4405
$MWDw_i = 0.4243 - 0.0011(Clay) - 11.2153(Fep) + 0.0550(OCa) - 0.0007(OCb) + 0.0051(OCc) + 0.0099(OCd)$	0.5044
$MWDw_i = 0.3491 + 0.1315(Total\ P) - 10.0788(Fep) + 0.0571(OCa) - 0.0038(OCb) + 0.0069(OCc) + 0.0076(OCd)$	0.5092
$MWDw_i = 0.3553 + 0.4714(Fed) - 11.7988(Fep) + 0.0570(OCa) + 0.0007(OCb) + 0.0078(OCc) + 0.0108(OCd)$	0.5028
$MWDw_i = 0.3646 - 0.0013(Clay) + 0.1759(Total\ P) + 0.3964(Fed) - 9.6967(Fep) + 0.0559(OCa) + 0.0089(OCe)$	0.5154
$MWDw_i = 0.3833 - 0.0022(Clay) + 0.2185(Total\ P) + 0.5386(Fed) - 11.2120(Fep) + 0.0385(OCb) + 0.0250(OCe)$	0.4435
$MWDw_i = 0.2884 - 0.0019(Clay) + 0.2713(Total\ P) + 0.0391(Fed) + 0.0614(OCa) + 0.0027(OCb) - 0.0029(OCe)$	0.4496
$MWDw_i = 0.3943 - 0.0014(Clay) + 0.1620(Total\ P) - 9.3971(Fep) + 0.0543(OCa) + 0.0024(OCb) + 0.0062(OCe)$	0.5134
$MWDw_i = 0.4088 - 0.0010(Clay) + 0.2599(Fed) - 11.0393(Fep) + 0.0570(OCa) + 0.0085(OCb) + 0.0060(OCe)$	0.5001
$MWDw_i = 0.3101 + 0.1599(Total\ P) + 0.5379(Fed) - 10.1143(Fep) + 0.0570(OCa) + 0.0052(OCb) + 0.0092(OCe)$	0.5099

$MWDw_i = 0.4357 – 0.0024(Clay) + 0.2264(Total\ P) + 0.2810(Fed) – 12.2665(Fep) + 0.0110(OCd) + 0.0267(OCe)$	0.4232
$MWDw_i = 0.2905 – 0.0019(Clay) + 0.27541(Total\ P) + 0.0124(Fed) + 0.0626(OCa) - 0.0025(OCd) + 0.0001(OCe)$	0.4496
$MWDw_i = 0.4020 – 0.0014(Clay) + 0.1464(Total\ P) – 9.8171(Fep) + 0.0541(OCa) + 0.0101(OCd) - 0.0018(OCe)$	0.5156
$MWDw_i = 0.4154 – 0.0010(Clay) + 0.2960(Fed) – 11.5864(Fep) + 0.0578(OCa) + 0.0171(OCd) - 0.0060(OCe)$	0.5058
$MWDw_i = 0.3201 + 0.1442(Total\ P) + 0.5480(Fed) – 10.6088(Fep) + 0.0575(OCa) + 0.0119(OCd) + 0.0004(OCe)$	0.5126
$MWDw_i = 0.3174 – 0.0032(Clay) + 0.3774(Total\ P) - 0.0172(Fed) + 0.0290(OCc) - 0.0015(OCd) + 0.0185(OCe)$	0.3332
$MWDw_i = 0.4451 – 0.0024(Clay) + 0.2126(Total\ P) – 11.6378(Fep) + 0.0187(OCc) + 0.0146(OCd) + 0.0163(OCe)$	0.4275
$MWDw_i = 0.4805 – 0.0021(Clay) + 0.2497(Fed) – 14.1790(Fep) + 0.0231(OCc) + 0.0240(OCd) + 0.0101(OCe)$	0.4045
$MWDw_i = 0.3188 + 0.2046(Total\ P) + 0.6662(Fed) – 12.9877(Fep) + 0.0234(OCc) + 0.0169(OCd) + 0.0204(OCe)$	0.4101
$MWDw_i = 0.3053 – 0.0030(Clay) + 0.3398(Total\ P) + 0.0366(OCb) + 0.0138(OCc) - 0.0056(OCd) + 0.0129(OCe)$	0.3563
$MWDw_i = 0.3774 – 0.0028(Clay) - 0.3044(Fed) + 0.0473(OCb) + 0.0147(OCc) + 0.0033(OCd) + 0.0021(OCe)$	0.2885
$MWDw_i = 0.1583 + 0.3323(Total\ P) + 0.4049(Fed) + 0.0419(OCb) + 0.0155(OCc) - 0.0056(OCd) + 0.0183(OCe)$	0.3223
$MWDw_i = 0.3214 – 0.0015(Clay) + 0.0687(OCa) + 0.0029(OCb) + 0.0181(OCc) + 0.0016(OCd) -+ 0.0180(OCe)$	0.4108
$MWDw_i = 0.2177 + 0.2516(Total\ P) + 0.0668(OCa) - 0.0032(OCb) + 0.0151(OCc) - 0.0053(OCd) - 0.0049(OCe)$	0.4399
$MWDw_i = 0.1326 – 0.0019(Clay) + 0.0331(Total\ P) + 0.2775(Fed) – 5.7699(Fep) + 0.0580(OCa) + 0.0223(MC)$	0.5699
$MWDw_i = 0.1454 – 0.0030(Clay) + 0.545(Total\ P) + 0.3984(Fed) – 6.4728(Fep) + 0.0555(OCb) + 0.0247(MC)$	0.4960
$MWDw_i = 0.0089 – 0.0022(Clay) + 0.0505(Total\ P) + 0.1958(Fed) + 0.0537(OCa) + 0.0068(OCb) + 0.0276(MC)$	0.5495
$MWDw_i = 0.1449 – 0.0019(Clay) + 0.0173(Total\ P) – 5.6876(Fep) + 0.0524(OCa) + 0.0074(OCb) + 0.0225(MC)$	0.5699
$MWDw_i = 0.1148 – 0.0018(Clay) + 0.3658(Fed) – 6.0236(Fep) + 0.0526(OCa) + 0.0109(OCb) + 0.0231(MC)$	0.5715
$MWDw_i = 0.0626 + 0.0152(Total\ P) + 0.5189(Fed) – 6.5912(Fep) + 0.0578(OCa) + 0.0114(OCb) + 0.0213(MC)$	0.5598
$MWDw_i = 0.1758 – 0.0032(Clay) + 0.1062(Total\ P) + 0.3643(Fed) – 7.0825(Fep) + 0.0449(OCc) + 0.0227(MC)$	0.4707
$MWDw_i = 0.0079 – 0.0022(Clay) + 0.0550(Total\ P) + 0.2037(Fed) + 0.0550(OCa) + 0.0052(OCc) + 0.0274(MC)$	0.5494
$MWDw_i = 0.1446 – 0.0019(Clay) + 0.0208(Total\ P) – 5.8026(Fep) + 0.0529(OCa) + 0.0072(OCc) + 0.0221(MC)$	0.5703
$MWDw_i = 0.1108 – 0.0017(Clay) + 0.4092(Fed) – 6.2389(Fep) + 0.0537(OCa) + 0.0105(OCc) + 0.0227(MC)$	0.5723
$MWDw_i = 0.0579 + 0.0229(Total\ P) + 0.5907(Fed) – 6.8284(Fep) + 0.0579(OCa) + 0.0126(OCc) + 0.0206(MC)$	0.5617
$MWDw_i = 0.0076 – 0.0033(Clay) + 0.0863(Total\ P) + 0.3066(Fed) + 0.0431(OCb) + 0.0134(OCc) + 0.0300(MC)$	0.4733
$MWDw_i = 0.1678 – 0.0030(Clay) + 0.0456(Total\ P) – 6.4921(Fep) + 0.0403(OCb) + 0.0154(OCc) + 0.0239(MC)$	0.4991
$MWDw_i = 0.1212 – 0.0028(Clay) + 0.5230(Fed) – 7.1039(Fep) + 0.0439(OCb) + 0.0183(OCc) + 0.0252(MC)$	0.5016
$MWDw_i = 0.0352 + 0.0472(Total\ P) + 0.8423(Fed) – 8.2090(Fep) + 0.0475(OCb) + 0.0240(OCc) + 0.0218(MC)$	0.4729
$MWDw_i = 0.0244 – 0.0022(Clay) + 0.0455(Total\ P) + 0.0534(OCa) + 0.0039(OCb) + 0.0021(OCc) + 0.0274(MC)$	0.5491
$MWDw_i = -0.0010 – 0.0021(Clay) + 0.1712(Fed) + 0.0538(OCa) + 0.0059(OCb) + 0.0028(OCc) + 0.0290(MC)$	0.5485
$MWDw_i = -0.0786 + 0.0419(Total\ P) + 0.3753(Fed) + 0.0597(OCa) + 0.0042(OCb) + 0.0054(OCc) + 0.0267(MC)$	0.5324
$MWDw_i = 0.1407 – 0.0019(Clay) - 5.8609(Fep) + 0.0517(OCa) + 0.0042(OCb) + 0.0055(OCc) + 0.0227(MC)$	0.5704
$MWDw_i = 0.0956 + 0.0024(Total\ P) - 6.4160(Fep) + 0.0571(OCa) + 0.0027(OCb) + 0.0070(OCc) + 0.0209(MC)$	0.5573
$MWDw_i = 0.0.0530 + 0.5955(Fed) - 6.8904(Fep) + 0.0561(OCa) + 0.0057(OCb) + 0.0103(OCc) + 0.02130(MC)$	0.5619
$MWDw_i = 0.2194 – 0.0031(Clay) + 0.0577(Total\ P) + 0.1344(Fed) – 8.6463(Fep) + 0.0356(OCd) + 0.0235(MC)$	0.4740
$MWDw_i = 0.0183 – 0.0022(Clay) + 0.0529(Total\ P) + 0.1396(Fed) + 0.0567(OCa) + 0.0012(OCd) + 0.0275(MC)$	0.5487
$MWDw_i = 0.1488 – 0.0019(Clay) + 0.0105(Total\ P) – 6.2174(Fep) + 0.0518(OCa) + 0.0074(OCd) + 0.0222(MC)$	0.5713
$MWDw_i = 0.1208 – 0.0017(Clay) + 0.3785(Fed) – 6.6632(Fep) + 0.0528(OCa) + 0.0094(OCd) + 0.0226(MC)$	0.5733

$MWDw_i$ = 0.0706 + 0.0086(Total P) + 0.5337(Fed) – 7.3387(Fep) + 0.0570(OCa) + 0.0109(OCd) + 0.0209(MC)	0.5627
$MWDw_i$ = 0.0458 – 0.0036(Clay) + 0.1159(Total P) + 0.0745(Fed) + 0.0280(OCc) + 0.0126(OCd) + 0.0297(MC)	0.4446
$MWDw_i$ = 0.2048 – 0.0030(Clay) + 0.0588(Total P) – 8.0131(Fep) + 0.0218(OCc) + 0.0216(OCd) + 0.0229(MC)	0.4832
$MWDw_i$ = 0.1748 – 0.0029(Clay) + 0.3289(Fed) – 8.6387(Fep) + 0.0236(OCc) + 0.0236(OCd) + 0.0244(MC)	0.4830
$MWDw_i$ = 0.0915 + 0.0547(Total P) + 0.6499(Fed) – 9.9457(Fep) + 0.0291(OCc) + 0.0268(OCd) + 0.0206(MC)	0.4532
$MWDw_i$ = 0.0313 – 0.0034(Clay) + 0.0719(Total P) + 0.0403(OCb) + 0.0055(OCc) + 0.0055(OCd) + 0.0301(MC)	0.4730
$MWDw_i$ = - 0.0036 – 0.0033(Clay) + 0.2101(Fed) + 0.0432(OCb) + 0.0079(OCc) + 0.0064(OCd) + 0.0325(MC)	0.4712
$MWDw_i$ = -0.1294 + 0.0682(Total P) + 0.5471(Fed) + 0.471(OCb) + 0.0128(OCc) + 0.0078(OCd) + 0.0294(MC)	0.4314
$MWDw_i$ = 0.0165 – 0.0022(Clay) + 0.0541(OCa) + 0.0053(OCb) + 0.0029(OCc) - 0.0015(OCd) + 0.0287(MC)	0.5482
$MWDw_i$ = -0.0463 + 0.0313(Total P) + 0.0604(OCa) + 0.0029(OCb) + 0.0042(OCc) - 0.0012(OCd) + 0.0264(MC)	0.5306
$MWDw_i$ = 0.1010 – 6.8427(Fep) + 0.0555(OCa) + 0.0011(OCb) + 0.0019(OCc) + 0.0075(OCd) + 0.0207(MC)	0.5589
$MWDw_i$ = 0.1495 – 0.0029(Clay) + 0.1010(Total P) + 0.1679(Fed) – 7.4923(Fep) + 0.0431(OCe) + 0.0245(MC)	0.4830
$MWDw_i$ = 0.0119 – 0.0022(Clay) + 0.0549(Total P) + 0.1542(Fed) + 0.0556(OCa) + 0.0031(OCe) + 0.0276(MC)	0.5490
$MWDw_i$ = 0.1392 – 0.0019(Clay) + 0.0226(Total P) – 5.9068(Fep) + 0.0521(OCa) + 0.0074(OCe) + 0.0224(MC)	0,5705
$MWDw_i$ = 0.1107 – 0.0017(Clay) + 0.3346(Fed) – 6.2784(Fep) + 0.0533(OCa) + 0.0091(OCe) + 0.0232(MC)	0.5718
$MWDw_i$ = 0.0568 + 0.0238(Total P) + 0.5076(Fed) – 6.8965(Fep) + 0.0569(OCa) + 0.0115(OCe) + 0.0212(MC)	0.5614
$MWDw_i$ = 0.0180 – 0.0034(Clay) + 0.1285(Total P) + 0.0556(Fed) + 0.0171(OCc) + 0.0263(OCe) + 0.0303(MC)	0.4528
$MWDw_i$ = 0.1636 – 0.0029(Clay) + 0.0876(Total P) – 7.3074(Fep) + 0.0158(OCc) + 0.0305(OCe) + 0.0238(MC)	0.4867
$MWDw_i$ = 0.1359 – 0.0028(Clay) + 0.2467(Fed) – 7.8804(Fep) + 0.0191(OCc) + 0.0310(OCe) + 0.0261(MC)	0.4839
$MWDw_i$ = 0.0481 + 0.0891(Total P) + 0.5848(Fed) – 8.9737(Fep) + 0.0213(OCc) + 0.0372(OCe) + 0.0218(MC)	0.4582
$MWDw_i$ = 0.0103 – 0.0032(Clay) + 0.0799(Total P) + 0.0378(OCb) - 0.0006(OCc) + 0.0176(OCe) + 0.0305(MC)	0.4777
$MWDw_i$ = -0.0215 – 0.0032(Clay) + 0.1771(Fed) + 0.0412(OCb) + 0.0005(OCc) + 0.0170(OCe) + 0.0331(MC)	0.4751
$MWDw_i$ = -0.1471 + 0.0786(Total P) + 0.4993(Fed) + 0.0435(OCb) + 0.0019(OCc) + 0.0231(OCe) + 0.0300(MC)	0.4394
$MWDw_i$ = 0.0166 – 0.0022(Clay) + 0.0540(OCa) + 0.0051(OCb) + 0.0023(OCc) - 0.0007(OCe) + 0.0287(MC)	0.5481
$MWDw_i$ = -0.0493 + 0.0308(Total P) + 0.0598(OCa) + 0.0025(OCb) + 0.0022(OCc) + 0.0018(OCe) + 0.0266(MC)	0.5306
$MWDw_i$ = 0.0896 - 6.5660(Fep) + 0.0554(OCa) + 0.0022(OCb) + 0.0025(OCc) + 0.0069(OCe) + 0.0212(MC)	0.5581
$MWDw_i$ = 0. 0295 – 0.0035(Clay) + 0.1241(Total P) - 0.0936(Fed) + 0.0051(OCd) + 0.0332(OCe) + 0.0310(MC)	0.4490
$MWDw_i$ = 0.1771 – 0.0029(Clay) + 0.0709(Total P) – 7.9912(Fep) + 0.0146(OCd) + 0.0283(OCe) + 0.0240(MC)	0.4874
$MWDw_i$ = 0.1602 – 0.0028(Clay) + 0.1709(Fed) – 8.5530(Fep) + 0.0177(OCd) + 0.0277(OCe) + 0.0258(MC)	0.4855
$MWDw_i$ = 0.0745 + 0.0652(Total P) + 0.4615(Fed) – 9.7147(Fep) + 0.0181(OCd) + 0.0350(OCe) + 0.0222(MC)	0.4586
$MWDw_i$ = 0.0097 – 0.0033(Clay) + 0.0827(Total P) + 0.0381(OCb) - 0.0026(OCd) + 0.0194(OCe) + 0.0305(MC)	0.4778
$MWDw_i$ = - 0.0215 – 0.0032(Clay) + 0.1728(Fed) + 0.0415(OCb) + 0.0006(OCd) + 0.0177(OCe) + 0.0331(MC)	0.4751
$MWDw_i$ = - 0.1469 + 0.0807(Total P) + 0.4846(Fed) + 0.0447(OCb) - 0.0023(OCd) + 0.0259(OCe) + 0.0301(MC)	0.4394
$MWDw_i$ = 0.0154 – 0.0022(Clay) + 0.0539(OCa) + 0.0063(OCb) - 0.0012(OCd) + 0.0016(OCe) + 0.0289(MC)	0.5481
$MWDw_i$ = - 0.0505 + 0.0332(Total P) + 0.0597(OCa) + 0.0038(OCb) - 0.0022(OCd) + 0.0048(OCe) + 0.0267(MC)	0.5306
$MWDw_i$ = 0.0980 – 6.8456(Fep) + 0.0551(OCa) + 0.0014(OCb) + 0.0067(OCd) + 0.0030(OCe) + 0.0209(MC)	0.5589
$MWDw_i$ = 0.0231 – 0.0035(Clay) + 0.1245(Total P) + 0.0161(OCc) + 0.0017(OCd) + 0.0251(OCe) + 0.0303(MC)	0.4528
$MWDw_i$ = 0.0102 – 0.0034(Clay) - 0.0912(Fed) + 0.0160(OCc) + 0.0050(OCd) + 0.0232(OCe) + 0.0339(MC)	0.4457
$MWDw_i$ = - 0. 1230 + 0.1212(Total P) + 0.2817(Fed) + 0.0193(OCc) + 0.0023(OCd) + 0.0322(OCe) + 0.0296(MC)	0.4067

$MWDw_i$ = - 0.0050 – 0.0032(Clay) + 0.0405(OCb) - 0.0005(OCc) - 0.0007(OCd) + 0.0178(OCe) + 0.0329(MC)	0.4747
$MWDw_i$ = - 0.1073 + 0.0663(Total P) + 0.0420(OCb) - 0.0008(Occ) - 0.0025(OCd) + 0.0258(OCe) + 0.0298(MC)	0.4363
$MWDw_i$ = 0.0798 – 8.5446(Fep) + 0.0366(OCb) - 0.0030(OCc) + 0.0095(OCd) + 0.0219(OCe) + 0.0230(MC)	0.4801
$MWDw_i$ = - 0. 0549 + 0.0601(OCa) + 0.0036(OCb) + 0.0026(OCc) - 0.0019(OCd) + 0.0028(OCe) + 0.0275(MC)	0.5302

APPENDIX G: State-space equations of wet mean weight diameter for the six selected soil properties

Equations
$(MWDw)_i = 0.7699*(MWDw)_{i-1}+0.0331*(Clay)_{i-1}–0.0834*(Total\ P)_{i-1}+0.1972*(Fed)_{i-1}- 0.2580*(Fep)_{i-1} -0.5679*(OCa)_{i-1}+ 0.892$
$(MWDw)_i = 0.5088*(MWDw)_{i-1}+ 0.1232*(Clay)_{i-1}+ 0.0769*(Total\ P)_{i-1} +0.1304*(Fed)_{i-1}- 0.2244*(Fep)_{i-1}+0.4525*(OCa)_{i-1}-0.08$
$(MWDw)_i = 0.9043*(MWDw)_{i-1}+0.1192*(Clay)_{i-1}–0.1806*(Total\ P)_{i-1} +0.0231*(Fed)_{i-1}-0.0686*(Fep)_{i-1}+0.5782*(OCb)_{i-1} - 0.39$
$(MWDw)_i = 0.8229*(MWDw)_{i-1} +0.0163*(Clay)_{i-1}+0.0240*(Total\ P)_{i-1} +0.0387*(Fed)_{i-1}-0.3161*(OCa)_{i-1}+0.8641*(OCb)_{i-1}- 0.46$
$(MWDw)_i = 1.0765*(MWDw)_{i-1}+0.0677*(Clay)_{i-1}-0.1120*(Total\ P)_{i-1} - 0.0082*(Fep)_{i-1}-0.4237*(OCa)_{i-1} +0.7749*(OCb)_{i-1} -0.38$
$(MWDw)_i = 0.8744*(MWDw)_{i-1}+0.0959*(Clay)_{i-1}-0.0110*(Fed)_{i-1}-0.0408*(Fep)_{i-1}+0.1285*(OCa)_{i-1} +0.0920*(OCb)_{i-1} - 0.1522*$
$(MWDw)_i = 0.8732*(MWDw)_{i-1}+0.0031*(Total\ P)_{i-1}+0.0477*(Fed)_{i-1}-0.0130*(Fep)_{i-1}-0.2017*(OCa)_{i-1}+ 0.6412*(OCb)_{i-1} - 0.370$
$(MWDw)_i = 0.6910*(MWDw)_{i-1}+0.1469*(Clay)_{i-1}-0.0993*(Total\ P)_{i-1}+ 0.0669*(Fed)_{i-1}- 0.1369*(Fep)_{i-1} +0.5093*(OCa)_{i-1} - 0.195$
$(MWDw)_i = 0.7839*(MWDw)_{i-1}+0.0917*(Clay)_{i-1}-0.1201*(Total\ P)_{i-1} +0.0844*(Fed)_{i-1}-0.1057*(Fep)_{i-1}+ 0.5944*(OCb)_{i-1} - 0.346$
$(MWDw)_i = 0.7825*(MWDw)_{i-1}-0.0341*(Clay)_{i-1}+0.0584*(Total\ P)_{i-1}+0.0768*(Fed)_{i-1}-0.5300*(OCa)_{i-1}+1.1777*(OCb)_{i-1} - 0.54$
$(MWDw)_i = 1.0021*(MWDw)_{i-1}-0.0075*(Clay)_{i-1}-0.0443*(Total\ P)_{i-1}+0.0605*(Fep)_{i-1}-0.6987*(OCa)_{i-1}+1.2450*(OCb)_{i-1} - 0.573$
$(MWDw)_i = 0.8861*(MWDw)_{i-1}+0.0513*(Clay)_{i-1}+0.0467*(Fed)_{i-1}-0.0617*(Fep)_{i-1}-0.2148*(OCa)_{i-1}+0.5666*(OCb)_{i-1} - 0.2892*$
$(MWDw)_i = 0.7829*(MWDw)_{i-1}-0.0109*(Total\ P)_{i-1}+0.0994*(Fed)_{i-1}-0.0377*(Fep)_{i-1}-0.3672*(OCa)_{i-1} + 1.0411*(OCb)_{i-1} - 0.526$
$(MWDw)_i = 1.1262*(MWDw)_{i-1}+0.1143*(Clay)_{i-1}–0.1033*(Total\ P)_{i-1}-0.0738*(Fed)_{i-1}+0.0442*(Fep)_{i-1}- 0.0178*(OCc)_{i-1} - 0.106$
$(MWDw)_i = 0.5410*(MWDw)_{i-1}+0.0835*(Clay)_{i-1}+0.0740*(Total\ P)_{i-1}+0.0105*(Fed)_{i-1}+0.6125*(OCa)_{i-1}-0.0558*(OCc)_{i-1} - 0.282$
$(MWDw)_i = 0.9040*(MWDw)_{i-1} + 0.1718*(Clay)_{i-1}-0.1966*(Total\ P)_{i-1}-0.0376*(Fep)_{i-1}+0.4307*(OCa)_{i-1}-0.0736*(OCc)_{i-1} - 0.21$
$(MWDw)_i = 0.7046*(MWDw)_{i-1}+0.1175*(Clay)_{i-1}+0.0232*(Fed)_{i-1}-0.0722*(Fep)_{i-1} + 0.4862*(OCa)_{i-1} - 0.0478*(OCc)_{i-1} - 0.228$
$(MWDw)_i = 0.9678*(MWDw)_{i-1}+0.0225*(Total\ P)_{i-1}-0.0200*(Fed)_{i-1}+0.0722*(Fep)_{i-1}+0.0989*(OCa)_{i-1}+0.0099*(OCc)_{i-1} - 0.170$
$(MWDw)_i = 0.6802*(MWDw)_{i-1}+0.0469*(Clay)_{i-1}+0.0099*(Total\ P)_{i-1}+0.0408*(Fed)_{i-1}+0.9048*(OCb)_{i-1}-0.3045*(OCc)_{i-1} - 0.39$
$(MWDw)_i = 0.9913*(MWDw)_{i-1}+0.1174*(Clay)_{i-1}-0.1556*(Total\ P)_{i-1}-0.0060*(Fep)_{i-1}+0.4304*(OCb)_{i-1}-0.1320*(OCc)_{i-1} - 0.260$
$(MWDw)_i = 0.7810*(MWDw)_{i-1}+0.0597*(Clay)_{i-1}+0.0511*(Fed)_{i-1}-0.0507*(Fep)_{i-1}+0.6404*(OCb)_{i-1}- 0.1849*(OCc)_{i-1} - 0.312$
$(MWDw)_i = 0.9980*(MWDw)_{i-1}-0.0678*(Total\ P)_{i-1}-0.0412*(Fed)_{i-1}+0.1395*(Fep)_{i-1} + 0.5101*(OCb)_{i-1}- 0.0625*(OCc)_{i-1} - 0.493$
$(MWDw)_i = 0.9133*(MWDw)_{i-1}+0.1577*(Clay)_{i-1}-0.1911*(Total\ P)_{i-1}+0.5026*(OCa)_{i-1}-0.1352*(OCb)_{i-1}-0.0308*(OCc)_{i-1} - 0.227$
$(MWDw)_i = 0.6356*(MWDw)_{i-1}+0.1475*(Clay)_{i-1}-0.0374*(Fed)_{i-1}+0.8923*(OCa)_{i-1}- 0.4165*(OCb)_{i-1} + 0.0099*(OCc)_{i-1} - 0.247$
$(MWDw)_i = 0.7621*(MWDw)_{i-1}+0.0363*(Total\ P)_{i-1}+0.0728*(Fed)_{i-1}-0.2971*(OCa)_{i-1} +1.0845*(OCb)_{i-1}-0.1971*(OCc)_{i-1}- 0.481$
$(MWDw)_i = 1.0040*(MWDw)_{i-1}+0.0425*(Clay)_{i-1}+0.0407*(Fep)_{i-1}-0.3415*(OCa)_{i-1} + 0.8900*(OCb)_{i-1} - 0.3521*(OCc)_{i-1} - 0.294$
$(MWDw)_i = 0.8534*(MWDw)_{i-1}+0.0185*(Total\ P)_{i-1}+ 0.0909*(Fep)_{i-1}-0.2507*(OCa)_{i-1}+0.9320*(OCb)_{i-1}-0.1811*(OCc)_{i-1} - 0.480$
$(MWDw)_i = 0.9940*(MWDw)_{i-1}-0.0624*(Fed)_{i-1}+0.1883*(Fep)_{i-1} - 0.1597*(OCa)_{i-1} + 0.6451*(OCb)_{i-1} - 0.0063*(OCc)_{i-1} - 0.616$
$(MWDw)_i = 0.7930*(MWDw)_{i-1}+0.1138*(Clay)_{i-1}+0.0135*(Total\ P)_{i-1}+0.0642*(Fed)_{i-1}-0.1366*(Fep)_{i-1} +0.1360*(OCa)_{i-1} - 0.002$
$(MWDw)_i = 0.7993*(MWDw)_{i-1}+0.1079*(Clay)_{i-1}-0.1869*(Total\ P)_{i-1}+0.0883*(Fed)_{i-1}-0.0891*(Fep)_{i-1} + 0.6787*(OCb)_{i-1} - 0.416$
$(MWDw)_i = 0.7515*(MWDw)_{i-1}-0.0650*(Clay)_{i-1}-0.0477*(Total\ P)_{i-1}+0.1238*(Fed)_{i-1}-0.6497*(OCa)_{i-1}+1.5009*(OCb)_{i-1} - 0.626$
$(MWDw)_i = 0.9659*(MWDw)_{i-1}-0.0006*(Clay)_{i-1}-0.1228*(Total\ P)_{i-1}+0.0319*(Fep)_{i-1}-0.7634*(OCa)_{i-1}+1.4101*(OCb)_{i-1} - 0.541$
$(MWDw)_i = 0.9857*(MWDw)_{i-1}+0.0662*(Clay)_{i-1}-0.0471*(Fed)_{i-1}+0.0350*(Fep)_{i-1}-0.0031*(OCa)_{i-1}+0.1397*(OCb)_{i-1} - 0.1868*$
$(MWDw)_i = 0.7527*(MWDw)_{i-1}-0.0956*(Total\ P)_{i-1}+0.1708*(Fed)_{i-1}-0.1204*(Fep)_{i-1}-0.4544*(OCa)_{i-1}+ 1.2153*(OCb)_{i-1} - 0.488$
$(MWDw)_i = 0.9930*(MWDw)_{i-1}+0.1111*(Clay)_{i-1}-0.0393*(Total\ P)_{i-1}-0.0193*(Fed)_{i-1}-0.0378*(Fep)_{i-1}- 0.2603*(OCd)_{i-1} + 0.233$
$(MWDw)_i = 0.7773*(MWDw)_{i-1}+0.0031*(Clay)_{i-1}+0.2447*(Total\ P)_{i-1}-0.0017*(Fed)_{i-1}-0.0680*(OCa)_{i-1}- 0.5394*(OCd)_{i-1} + 0.566$
$(MWDw)_i = 0.8863*(MWDw)_{i-1}+0.0753*(Clay)_{i-1}+0.1625*(Total\ P)_{i-1}-0.1109*(Fep)_{i-1}-0.1947*(OCa)_{i-1}-0.6240*(OCd)_{i-1} + 0.782$
$(MWDw)_i = 0.7926*(MWDw)_{i-1}+0.1064*(Clay)_{i-1}+0.0233*(Fed)_{i-1}-0.0650*(Fep)_{i-1}+0.3155*(OCa)_{i-1}-0.1172*(OCd)_{i-1} - 0.071$
$(MWDw)_i = 0.9872*(MWDw)_{i-1}+0.0348*(Total\ P)_{i-1}-0.0149*(Fed)_{i-1}+0.0565*(Fep)_{i-1}+0.0368*(OCa)_{i-1}-0.0923*(OCd)_{i-1} - 0.027$
$(MWDw)_i = 0.9178*(MWDw)_{i-1}+0.0890*(Clay)_{i-1}+0.0145*(Total\ P)_{i-1}-0.0145*(Fed)_{i-1}+0.0266*(OCc)_{i-1}-0.0649*(OCd)_{i-1} + 0.011$
$(MWDw)_i = 1.0249*(MWDw)_{i-1}+0.1294*(Clay)_{i-1}-0.1069*(Total\ P)_{i-1}-0.0432*(Fep)_{i-1}+0.0470*(OCc)_{i-1}- 0.0376*(OCd)_{i-1} - 0.032$
$(MWDw)_i = 1.0583*(MWDw)_{i-1}+0.0957*(Clay)_{i-1}-0.0783*(Fed)_{i-1}+0.0460*(Fep)_{i-1}-0.0473*(OCc)_{i-1}-0.1864*(OCd)_{i-1} + 0.096$
$(MWDw)_i = 1.0690*(MWDw)_{i-1}-0.0117*(Total\ P)_{i-1}-0.0684*(Fed)_{i-1}+0.1372*(Fep)_{i-1}+0.0570*(OCc)_{i-1} - 0.1518*(OCd)_{i-1} - 0.051$
$(MWDw)_i = 0.7487*(MWDw)_{i-1}+0.1124*(Clay)_{i-1}-0.0954*(Total\ P)_{i-1}+0.8532*(OCb)_{i-1}-0.3310*(OCc)_{i-1}-0.2423*(OCd)_{i-1} - 0.065$
$(MWDw)_i = 0.7205*(MWDw)_{i-1}+0.0633*(Clay)_{i-1}+0.0291*(Fed)_{i-1}+0.7929*(OCb)_{i-1}-0.2868*(OCc)_{i-1}-0.2667*(OCd)_{i-1} - 0.068$
$(MWDw)_i = 0.6532*(MWDw)_{i-1}+0.0793*(Total\ P)_{i-1}+0.0623*(Fed)_{i-1}+0.8178*(OCb)_{i-1}-0.2387*(OCc)_{i-1}-0.5948*(OCd)_{i-1}+ 0.201$
$(MWDw)_i = 0.9830*(MWDw)_{i-1}+0.0676*(Clay)_{i-1}-0.2765*(OCa)_{i-1}+0.7304*(OCb)_{i-1}-0.2364*(OCc)_{i-1} - 0.3278*(OCd)_{i-1} + 0.045$
$(MWDw)_i = 0.8765*(MWDw)_{i-1}+0.0688*(Total\ P)_{i-1}- 0.2162*(OCa)_{i-1}+0.7660*(OCb)_{i-1}-0.1169*(OCc)_{i-1}-0.7809*(OCd)_{i-1}+ 0.37$
$(MWDw)_i = 0.5046*(MWDw)_{i-1}-0.0026*(Clay)_{i-1}-0.1785*(Total\ P)_{i-1}+0.0238*(Fed)_{i-1}-0.0315*(Fep)_{i-1} + 0.2677*(OCa)_{i-1} + 0.403$

$$(MWDw)_i = 0.7148*(MWDw)_{i-1}+0.0135*(Clay)_{i-1}-0.1569*(Total\ P)_{i-1}+0.0419*(Fed)_{i-1}-0.0541*(Fep)_{i-1} + 0.1860*(OCb)_{i-1} + 0.24$$

$$(MWDw)_i = 0.5255*(MWDw)_{i-1}-0.1086*(Clay)_{i-1}-0.1717*(Total\ P)_{i-1}+0.0545*(Fed)_{i-1}- 0.3414*(OCa)_{i-1}+ 0.5823*(OCb)_{i-1} + 0.44$$

$$(MWDw)_i = 0.3434*(MWDw)_{i-1}+0.0429*(Clay)_{i-1}-0.2029*(Total\ P)_{i-1}-0.0306*(Fep)_{i-1}+0.7403*(OCa)_{i-1} - 0.3385*(OCb)_{i-1} + 0.43$$

$$(MWDw)_i = 0.3967*(MWDw)_{i-1}+0.1002*(Clay)_{i-1}+0.0855*(Fed)_{i-1}-0.1616*(Fep)_{i-1}+0.6565*(OCa)_{i-1} - 0.2648*(OCb)_{i-1} + 0.17$$

$$(MWDw)_i = 0.6887*(MWDw)_{i-1}-0.1951*(Total\ P)_{i-1}+0.1183*(Fed)_{i-1}-0.1401*(Fep)_{i-1}-0.3629*(OCa)_{i-1} + 0.5971*(OCb)_{i-1} + 0.275$$

$$(MWDw)_i = 0.8971*(MWDw)_{i-1}-0.0015*(Clay)_{i-1}-0.2081*(Total\ P)_{i-1} - 0.1115*(Fed)_{i-1}+0.1427*(Fep)_{i-1} - 0.0859*(OCc)_{i-1} + 0.35$$

$$(MWDw)_i = 0.4006*(MWDw)_{i-1}-0.0171*(Clay)_{i-1}-0.1534*(Total\ P)_{i-1} +0.0216*(Fed)_{i-1}+0.4009*(OCa)_{i-1}- 0.1352*(OCc)_{i-1} + 0.47$$

$$(MWDw)_i = 0.3678*(MWDw)_{i-1}-0.0354*(Clay)_{i-1}-0.2150*(Total\ P)_{i-1}+0.0267*(Fep)_{i-1}+0.4557*(OCa)_{i-1}-0.1722*(OCc)_{i-1} + 0.56$$

$$(MWDw)_i = 0.4018*(MWDw)_{i-1}+0.0191*(Clay)_{i-1}+0.0835*(Fed)_{i-1}-0.1147*(Fep)_{i-1}+0.3882*(OCa)_{i-1} - 0.0977*(OCc)_{i-1} + 0.30$$

$$(MWDw)_i = 0.5202*(MWDw)_{i-1}-0.2163*(Total\ P)_{i-1}+0.0168*(Fed)_{i-1}-0.0032*(Fep)_{i-1}+0.3193*(OCa)_{i-1} - 0.0832*(OCc)_{i-1} + 0.42$$

$$(MWDw)_i = 0.7571*(MWDw)_{i-1}+0.0257*(Clay)_{i-1}-0.2331*(Total\ P)_{i-1}+ 0.0056*(Fed)_{i-1}+0.3925*(OCb)_{i-1}-0.2590*(OCc)_{i-1} + 0.29$$

$$(MWDw)_i = 0.7395*(MWDw)_{i-1}-0.0034*(Clay)_{i-1}-0.2545*(Total\ P)_{i-1}+0.0423*(Fep)_{i-1}+0.4016*(OCb)_{i-1} - 0.2729*(OCc)_{i-1} + 0.33$$

$$(MWDw)_i = 0.6019*(MWDw)_{i-1}+0.0048*(Clay)_{i-1}+0.0487*(Fed)_{i-1}-0.0346*(Fep)_{i-1}+0.6027*(OCb)_{i-1} - 0.4482*(OCc)_{i-1} + 0.21$$

$$(MWDw)_i = 0.8006*(MWDw)_{i-1}-0.2489*(Total\ P)_{i-1}-0.0381*(Fed)_{i-1}+0.0936*(Fep)_{i-1}+0.4217*(OCb)_{i-1} - 0.3845*(OCc)_{i-1} + 0.33$$

$$(MWDw)_i = 0.2978*(MWDw)_{i-1}+0.0203*(Clay)_{i-1}-0.1335*(Total\ P)_{i-1}+0.8254*(OCa)_{i-1}-0.2901*(OCb)_{i-1}-0.1478*(OCc)_{i-1} + 0.41$$

$$(MWDw)_i = 0.4746*(MWDw)_{i-1}-0.0914*(Clay)_{i-1}+0.0525*(Fed)_{i-1}-0.1511*(OCa)_{i-1}+0.7506*(OCb)_{i-1} - 0.4455*(OCc)_{i-1} + 0.39$$

$$(MWDw)_i = 0.6422*(MWDw)_{i-1}-0.1811*(Total\ P)_{i-1}+0.0190*(Fed)_{i-1}+0.1470*(OCa)_{i-1}+0.2537*(OCb)_{i-1}- 0.2669*(OCc)_{i-1} + 0.36$$

$$(MWDw)_i = 0.4391*(MWDw)_{i-1}-0.0980*(Clay)_{i-1}+0.0611*(Fep)_{i-1}+0.0247*(OCa)_{i-1}+0.5536*(OCb)_{i-1}- 0.4518*(OCc)_{i-1} + 0.46$$

$$(MWDw)_i = 0.4521*(MWDw)_{i-1}-0.1659*(Total\ P)_{i-1}+0.0232*(Fep)_{i-1}+0.4177*(OCa)_{i-1}+0.1424*(OCb)_{i-1}-0.3248*(OCc)_{i-1} + 0.44$$

$$(MWDw)_i = 0.5984*(MWDw)_{i-1}+0.0676*(Fed)_{i-1}-0.0500*(Fep)_{i-1}-0.1452*(OCa)_{i-1}+0.7484*(OCb)_{i-1} - 0.4567*(OCc)_{i-1} + 0.222$$

$$(MWDw)_i = 1.0312*(MWDw)_{i-1}+0.0827*(Clay)_{i-1}-0.1600*(Total\ P)_{i-1}-0.0716*(Fed)_{i-1}+0.0590*(Fep)_{i-1} - 0.0853*(OCd)_{i-1} + 0.13$$

$$(MWDw)_i = 0.3664*(MWDw)_{i-1}-0.0166*(Clay)_{i-1}-0.1747*(Total\ P)_{i-1}+0.0395*(Fed)_{i-1}+0.5120*(OCa)_{i-1} - 0.1783*(OCd)_{i-1} + 0.44$$

$$(MWDw)_i = 0.3761*(MWDw)_{i-1}-0.0026*(Clay)_{i-1}-0.1977*(Total\ P)_{i-1}+0.0075*(Fep)_{i-1}+0.5275*(OCa)_{i-1} - 0.1930*(OCd)_{i-1} + 0.46$$

$$(MWDw)_i = 0.4477*(MWDw)_{i-1}+0.0489*(Clay)_{i-1}+0.1044*(Fed)_{i-1}-0.1420*(Fep)_{i-1}+0.4512*(OCa)_{i-1} - 0.1272*(OCd)_{i-1} + 0.202$$

$$(MWDw)_i = 0.5552*(MWDw)_{i-1}-0.2183*(Total\ P)_{i-1}+0.0420*(Fed)_{i-1}-0.0231*(Fep)_{i-1}+0.2987*(OCa)_{i-1} - 0.0660*(OCd)_{i-1} + 0.393$$

$$(MWDw)_i = 0.9572*(MWDw)_{i-1}+0.0871*(Clay)_{i-1}-0.2238*(Total\ P)_{i-1}-0.0268*(Fed)_{i-1}+0.1073*(OCc)_{i-1} - 0.1050*(OCd)_{i-1} + 0.18$$

$$(MWDw)_i = 0.9929*(MWDw)_{i-1}+0.0862*(Clay)_{i-1}-0.2189*(Total\ P)_{i-1}-0.0042*(Fed)_{i-1}+0.0695*(OCc)_{i-1}- 0.0860*(OCd)_{i-1} + 0.14$$

$$(MWDw)_i = 1.0521*(MWDw)_{i-1}+0.0603*(Clay)_{i-1}-0.0946*(Fed)_{i-1}+0.0906*(Fep)_{i-1} - 0.0970*(OCc)_{i-1} - 0.0883*(OCd)_{i-1} + 0.06$$

$$(MWDw)_i = 0.9543*(MWDw)_{i-1}-0.2945*(Total\ P)_{i-1}-0.1066*(Fed)_{i-1}+0.1664*(Fep)_{i-1} - 0.0381*(OCc)_{i-1} - 0.0647*(OCd)_{i-1} + 0.36$$

$$(MWDw)_i = 0.7689*(MWDw)_{i-1}+0.0532*(Clay)_{i-1}-0.1938*(Total\ P)_{i-1}+0.4289*(OCb)_{i-1}-0.1777*(OCc)_{i-1} -0.1250*(OCd)_{i-1} + 0.2$$

$$(MWDw)_i = 0.4904*(MWDw)_{i-1}-0.0543*(Clay)_{i-1}+0.0639*(Fed)_{i-1}+0.6567*(OCb)_{i-1}- 0.1631*(OCc)_{i-1} -0.3113*(OCd)_{i-1} + 0.30$$

$$(MWDw)_i = 0.7108*(MWDw)_{i-1}-0.1404*(Total\ P)_{i-1}+0.0392*(Fed)_{i-1}+0.4730*(OCb)_{i-1}- 0.1497*(OCc)_{i-1} -0.1908*(OCd)_{i-1} + 0.24$$

$$(MWDw)_i = 0.4847*(MWDw)_{i-1}-0.0344*(Clay)_{i-1}+0.0185*(OCa)_{i-1}+0.5543*(OCb)_{i-1}-0.2614*(OCc)_{i-1} -0.1391*(OCd)_{i-1} + 0.36$$

$$(MWDw)_i = 0.6363*(MWDw)_{i-1}-0.2364*(Total\ P)_{i-1}+0.4836*(OCa)_{i-1}-0.0115*(OCb)_{i-1}-0.1074*(OCc)_{i-1} -0.1504*(OCd)_{i-1} + 0.36$$

$$(MWDw)_i = 0.7226*(MWDw)_{i-1}+0.0921*(Fep)_{i-1}-0.2820*(OCa)_{i-1}+1.0498*(OCb)_{i-1}-0.2057*(OCc)_{i-1} -0.5432*(OCd)_{i-1} + 0.153$$

$$(MWDw)_i = 0.8905*(MWDw)_{i-1}+0.0289*(Clay)_{i-1}-0.2282*(Total\ P)_{i-1}-0.0704*(Fed)_{i-1}+0.0851*(Fep)_{i-1} - 0.0310*(OCe)_{i-1} + 0.31$$

$$(MWDw)_i = 0.3922*(MWDw)_{i-1}-0.0369*(Clay)_{i-1}-0.2119*(Total\ P)_{i-1}+0.0338*(Fed)_{i-1}+0.3381*(OCa)_{i-1} - 0.0836*(OCe)_{i-1} + 0.55$$

$$(MWDw)_i = 0.3840*(MWDw)_{i-1}-0.0650*(Clay)_{i-1}-0.2776*(Total\ P)_{i-1}+0.0609*(Fep)_{i-1}+ 0.3808*(OCa)_{i-1}-0.1374*(OCe)_{i-1} + 0.64$$

$$(MWDw)_i = 0.4606*(MWDw)_{i-1}+0.0308*(Clay)_{i-1}+0.0691*(Fed)_{i-1}-0.0796*(Fep)_{i-1}+0.3942*(OCa)_{i-1} - 0.1454*(OCe)_{i-1} + 0.255$$

$$(MWDw)_i = 0.4973*(MWDw)_{i-1}-0.2166*(Total\ P)_{i-1}+0.0832*(Fed)_{i-1}-0.1209*(Fep)_{i-1}+0.1215*(OCa)_{i-1}+0.1599*(OCe)_{i-1} + 0.456$$

$$(MWDw)_i = 0.7622*(MWDw)_{i-1}+0.0214*(Clay)_{i-1}-0.2641*(Total\ P)_{i-1}-0.0223*(Fed)_{i-1}-0.0706*(OCc)_{i-1} +0.1002*(OCe)_{i-1} + 0.450$$

$$(MWDw)_i = 0.8125*(MWDw)_{i-1}+0.0035*(Clay)_{i-1}-0.2907*(Total\ P)_{i-1}+0.0369*(Fep)_{i-1}-0.0326*(OCc)_{i-1}+0.0386*(OCe)_{i-1} + 0.42$$

$$(MWDw)_i = 0.8311*(MWDw)_{i-1}+0.0201*(Clay)_{i-1}-0.0530*(Fed)_{i-1}+0.0292*(Fep)_{i-1}-0.2252*(OCc)_{i-1} + 0.1756*(OCe)_{i-1} + 0.21$$

$$(MWDw)_i = 0.9301*(MWDw)_{i-1}-0.2790*(Total\ P)_{i-1}-0.1249*(Fed)_{i-1}+0.1808*(Fep)_{i-1}-0.0762*(OCc)_{i-1} - 0.0292*(OCe)_{i-1} + 0.384$$

$$(MWDw)_i = 0.5720*(MWDw)_{i-1}+0.0078*(Clay)_{i-1}-0.1718*(Total\ P)_{i-1}+0.6114*(OCb)_{i-1}-0.2708*(OCc)_{i-1}- 0.1145*(OCe)_{i-1} + 0.34$$

$$(MWDw)_i = 0.5140*(MWDw)_{i-1}-0.0494*(Clay)_{i-1}+0.0501*(Fed)_{i-1}+0.5427*(OCb)_{i-1}- 0.2428*(OCc)_{i-1} - 0.1212*(OCe)_{i-1} + 0.293$$

$$(MWDw)_i = 0.5837*(MWDw)_{i-1}-0.1741*(Total\ P)_{i-1}+0.0357*(Fed)_{i-1}+0.5163*(OCb)_{i-1}-0.1943*(OCc)_{i-1}- 0.1219*(OCe)_{i-1} + 0.339$$

$$(MWDw)_i = 0.5444*(MWDw)_{i-1}-0.0432*(Clay)_{i-1}-0.1980*(OCa)_{i-1}+0.8336*(OCb)_{i-1}-.3625*(OCc)_{i-1} - 0.1171*(OCe)_{i-1} + 0.325$$

$$(MWDw)_i = 0.6775*(MWDw)_{i-1}-0.1111*(Total\ P)_{i-1}-0.2291*(OCa)_{i-1}+0.8109*(OCb)_{i-1}-0.2874*(OCc)_{i-1} - 0.1539*(OCe)_{i-1} + 0.27$$

$$(MWDw)_i = 0.6820*(MWDw)_{i-1}+0.0322*(Fep)_{i-1}-0.1274*(OCa)_{i-1}+0.6876*(OCb)_{i-1}-0.2817*(OCc)_{i-1}-0.1833*(OCe)_{i-1} + 0.176$$

$$(MWDw)_i = 0.7936*(MWDw)_{i-1}+0.0313*(Clay)_{i-1}-0.1537*(Total\ P)_{i-1}-0.0273*(Fed)_{i-1}-0.2840*(OCd)_{i-1} +0.3170*(OCe)_{i-1} + 0.30$$

$$(MWDw)_i = 0.8499*(MWDw)_{i-1}+0.0532*(Clay)_{i-1}-0.1870*(Total\ P)_{i-1} -0.0204*(Fep)_{i-1} - 0.2579*(OCd)_{i-1} +0.2898*(OCe)_{i-1} + 0.25$$

$$(MWDw)_i = 0.9384*(MWDw)_{i-1}+0.0348*(Clay)_{i-1}-0.0680*(Fed)_{i-1}+0.0794*(Fep)_{i-1}-0.1249*(OCd)_{i-1} - 0.0024*(OCe)_{i-1} + 0.130$$

$$(MWDw)_i = 0.9869*(MWDw)_{i-1}-0.2753*(Total\ P)_{i-1}-0.1085*(Fed)_{i-1}+0.1682*(Fep)_{i-1} - 0.0781*(OCd)_{i-1} - 0.0320*(OCe)_{i-1} + 0.32$$

$(MWDw)_i = 0.6492*(MWDw)_{i-1}+0.0013*(Clay)_{i-1}-0.1048*(Total\ P)_{i-1}+0.2585*(OCb)_{i-1}-0.3079*(OCd)_{i-1}+0.1769*(OCe)_{i-1} + 0.30$
$(MWDw)_i = 0.5525*(MWDw)_{i-1} -0.0506*(Clay)_{i-1}+0.0565*(Fed)_{i-1}+0.3834*(OCb)_{i-1}-0.2221*(OCd)_{i-1}-0.0124*(OCe)_{i-1} + 0.28$
$(MWDw)_i = 0.6402*(MWDw)_{i-1}-0.0311*(Total\ P)_{i-1}+0.0191*(Fed)_{i-1}+0.3434*(OCb)_{i-1}-0.4802*(OCd)_{i-1}+0.2430*(OCe)_{i-1} + 0.24$
$(MWDw)_i = 0.6746*(MWDw)_{i-1} - 0.0613*(Clay)_{i-1} -0.6130*(OCa)_{i-1}+1.0257*(OCb)_{i-1}-0.2653*(OCd)_{i-1}-0.0736*(OCe)_{i-1} + 0.29$
$(MWDw)_i = 0.7079*(MWDw)_{i-1}-0.0384*(Total\ P)_{i-1}-0.3677*(OCa)_{i-1}+0.9386*(OCb)_{i-1}-0.9279*(OCd)_{i-1}+0.4000*(OCe)_{i-1} + 0.26$
$(MWDw)_i = 0.7964*(MWDw)_{i-1} + 0.0618*(Fep)_{i-1} - 0.1489*(OCa)_{i-1}+0.5720*(OCb)_{i-1}-0.4593*(OCd)_{i-1}+0.0301*(OCe)_{i-1}+ 0.135$
$(MWDw)_i = 0.8486*(MWDw)_{i-1}+0.0448*(Clay)_{i-1}-0.2934*(Total\ P)_{i-1}-0.0500*(OCc)_{i-1}+0.0408*(OCd)_{i-1}+0.0364*(OCe)_{i-1}+ 0.358$
$(MWDw)_i = 0.6474*(MWDw)_{i-1}-0.0290*(Clay)_{i-1}+0.0106*(Fed)_{i-1}-0.0319*(OCc)_{i-1}-0.0733*(OCd)_{i-1}+0.1131*(OCe)_{i-1} + 0.347$
$(MWDw)_i = 0.7683*(MWDw)_{i-1}-0.2899*(Total\ P)_{i-1}-0.0037*(Fed)_{i-1}-0.0126*(OCc)_{i-1}-0.0556*(OCd)_{i-1} + 0.0912*(OCe)_{i-1} + 0.47$
$(MWDw)_i = 0.5400*(MWDw)_{i-1}-0.0260*(Clay)_{i-1}+0.4837*(OCb)_{i-1}-0.2849*(OCc)_{i-1}-0.2490*(OCd)_{i-1} + 0.1950*(OCe)_{i-1} + 0.3252$
$(MWDw)_i = 0.7424*(MWDw)_{i-1}-0.2148*(Total\ P)_{i-1}+0.4868*(OCb)_{i-1}-0.1764*(OCc)_{i-1}-0.2110*(OCd)_{i-1} +0.0289*(OCe)_{i-1} + 0.32$
$(MWDw)_i = 0.6376*(MWDw)_{i-1}+0.0234*(Fep)_{i-1}+0.4883*(OCb)_{i-1}-0.2632*(OCc)_{i-1} - 0.2840*(OCd)_{i-1} + 0.1533*(OCe)_{i-1} + 0.230$
$(MWDw)_i = 0.6330*(MWDw)_{i-1}+0.0393*(OCa)_{i-1}+0.3755*(OCb)_{i-1}-0.0787*(OCc)_{i-1} - 0.8298*(OCd)_{i-1} +0.5153*(OCe)_{i-1} + 0.32$