JIMMA UNIVERSITY

COLLEGE OF SOCIAL SCIENCES AND HUMANITIES

DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES

COMPARISON OF GIS-BASED INTERPOLATION METHODS TO PREDICT SPATIAL VARIATION OF MAJOR SOIL CHEMICAL PROPERTIES IN MANA DISTRICT, JIMMA ZONE, SOUTHWEST ETHIOPIA

BY

CHRISTIANE MIGABO NABINTU

A THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES OF JIMMA UNIVERSITY, DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES, IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN GEOGRAPHIC INFORMATION SYSTEMS AND REMOTE SENSING

DECEMBER, 2021

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STATEMENT OF THE AUTHOR

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DECLARATION

This is to certify that this thesis intitled "Comparison of GIS-based interpolation methods to predict spatial variation of major soil chemical properties in Mana District, Jimma Zone, Southwest Ethiopia", accepted in partial fulfillment of the requirements for the award of the Degree of Master of Science in Geographic Information Systems and Remote Sensing by the School of Graduate Studies of Jimma University through the College of Social Sciences and Humanities, done by Christiane Migabo Nabintu, is a genuine work carried out by her under my guidance. The matter embodied in this thesis work has not been submitted earlier for the award of any degree or diploma.

The assistance and help received during the course of this investigation have been duly acknowledged. Therefore, I recommend that it can be accepted as fulfilling the research thesis requirements.

Dr. Kefelegn Getahun ______________________ ______________________ ______________________

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FINAL THESIS APPROVAL FORM

As members of the Board of Examining of the final M.Sc thesis open defense, we certify that we have read and evaluated the thesis prepared by Christiane Migabo Nabintu under the title "Comparison of GIS-based interpolation methods to predict spatial variation of major soil chemical properties in Mana District, Jimma Zone, Southwest Ethiopia" and recommend that the thesis be accepted as fulfilling the thesis requirements for the Degree of Master of Science in Geographic Information Systems and Remote Sensing at Jimma University.

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Final approval and Acceptance

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CERTIFICATION OF THE FINAL THESIS

I hereby certify that all the corrections and recommendations suggested by the board of examiners are incorporated into the final thesis entitled "Comparison of GIS-based interpolation methods to predict spatial variation of major soil chemical properties in Mana District, Jimma Zone, Southwest Ethiopia" by Christiane Migabo Nabintu.

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Dean of SGS	Signature	Date

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LIST OF ABBREVIATIONS

AK	Available potassium
AN	Available nitrogen
AP	Available phosphorus
CEC	Cation exchange capacity
CV	Coefficient of variation
EBK	Empirical Bayesian kriging
GIS	Geographic Positioning System
GPS	Global Information System
IDW	Inverse distance weighting
LPI	Local polynomial interpolation
MRE	Mean relative error
OCK	Ordinary co-kriging
OK	Ordinary kriging
RBF	Radial basis function
RI	Relative improvement
RMSE	Root mean square error
SD	Standard deviation
SIMs	Spatial interpolation methods
SOC	Soil organic carbon
SOM	Soil organic matter
SSA	Sub- Saharan African
TN	Total nitrogen

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Christiane Migabo Nabintu

ABSTRACT

Soil fertility mapping is essential for optimizing agricultural practices and management. This study was conducted in Mana district, southwestern Ethiopia. It aimed at evaluating and comparing three GIS-based spatial interpolation methods (Inverse Distance Weighting: IDW; Ordinary Kriging: OK; and Ordinary Cokriging: OCK) for estimating selected soil chemical properties, and producing a set of accurate maps of selected soil chemical properties. The study included 84 geo-referenced soil samples collected in April 2021 at 0 - 30 cm depth across the entire district, using the systematic sampling technique with 2.5 km × 2.5 km grid. The soil samples were analyzed for selected chemical properties. Descriptive statistics were first applied to the data to evaluate and validate the normal distribution required for geostatistical analysis. The performance of each interpolation method was assessed using cross-validation. The descriptive statistical analyses revealed that besides the topographic aspect which were highly variable, available phosphorus (AP) and available potassium (AK) were the most variable soil properties (CV > 35%); while pH, soil organic carbon (SOC) and total nitrogen (TN) contents were moderately variable (CV varying from 16.28% to 30.53%). Only pH and SOC were normally distributed among all the variables. When comparing the resulting values of the efficiency criteria of cross-validation (RMSE, MRE and RI) for each interpolation method, the OCK technique was best performed for all the five soil chemical properties with lower values of RMSE and MRE, and the best RI. However, for the TN, OK showed the same performance as OCK. Interpolated maps were generated based on OCK for each soil property and indicated their distribution throughout the study area of Mana.

Keywords: Kriging; interpolation method; inverse distance weighting; soil properties.

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the study

Soil fertility mapping is essential when planning land use and developing crop fertilization strategies (Samira et al., 2014). Detailed knowledge of soil properties and their variation in space is a key issue for optimizing agricultural practices and management (Abdel Rahman et al., 2021; Abdennour et al., 2020). Meanwhile, the spatial distribution of soil physico-chemical properties is a fundamental input of precision agriculture and one of the bases for decision and policy makers to make plans and strategies (Abdel Rahman et al., 2021; Calzolari et al., 2021; Shit et al., 2016).

In Ethiopia, agriculture remains the basis of the economy and a major occupation for nearly 85% of the population (Lemenih et al., 2005; Vågen et al., 2013). However, land degradation that involves principally soil erosion and declining soil fertility has become a serious constraint on agricultural productivity in Ethiopia, due to its topography, population growth and land use practices over centuries (Ebabu et al., 2020; Lelago & Buraka, 2019; Lemenih et al., 2005; Vågen et al., 2013). Thus, updated information on soil properties and their variability is necessary for understanding soil constraints in order to optimize and maintain agricultural productivity (Lemenih et al., 2005; Vågen et al., 2013).

The most frequently monitored soil fertility indicators of agricultural land are pH, soil organic carbon (SOC), available nitrogen (AN), available phosphorus (AP), and available potassium (AK). They are the major indicators and determinants of soil quality and fertility as they are strongly linked to plant growth and productivity (Chen et al., 2020; Duan et al., 2020). Therefore, it is very important to predict their spatial distribution for assessing the state of the soil system and planning measures for the rational use of land resources (Myslyva et al., 2019; Shit et al., 2016; Tripathi et al., 2015).

Geostatistics is an effective tool for predicting the spatial variability of soil properties and has been widely applied in several studies (Bhunia et al., 2016; Fischer et al., 2021; Leena et al., 2021; Mirzaei & Sakizadeh, 2016; Tan et al., 2020). Compared to the classic statistics which examine the statistical distribution of a set of sampled data, geostatistics incorporates both the statistical distribution of the sample data and the spatial correlation among the sample data. Because of this difference, many earth science problems are more effectively addressed using geostatistical methods (Hengl, 2007).

Spatial interpolation methods (SIMs) are very potent tools for predicting surface values (Mirzaei & Sakizadeh, 2016). Due to time and financial constraints of field soil sampling and laboratory analyses, SIMs have become essential for predicting the soil properties at unsampled sites, using data from point observations (Fischer et al., 2021; Leena et al., 2021; J. Li & Heap, 2011, 2014). Inverse distance weighting (IDW), ordinary kriging (OK), and ordinary co-kriging (OCK) are the most frequently used SIMs (J. Li & Heap, 2011, 2014; Mirzaei & Sakizadeh, 2016).

1.2. Statement of the problem

Agriculture is a very important sector of Ethiopian economy. However, it is challenged by land degradation and declining soil fertility (Ebabu et al., 2020; Lelago & Buraka, 2019). The characteristics of the soil greatly affect agricultural productivity (Assen & Tegene, 2011). In precision agriculture, it becomes essential to understand the properties of soils and their variability for sustainable use of soil and maximization of agricultural production (Assen & Tegene, 2011; Ayalew et al., 2015). Detail information on soil characteristics is required to make decision with regard to management practices for sustainable agricultural production, rehabilitations of degraded land and solid researches on soil fertility (Lemenih et al., 2005; Vågen et al., 2013). Therefore, it is very important to assess and understand the properties of soil and their spatial variation over an area in order to develop management plans for efficient utilization of soil resources (Ayalew et al., 2015).

SIMs are very useful in assessment of the spatial variability of soil properties and have been widely applied in several studies (Fischer et al., 2021; J. Li & Heap, 2011, 2014; Mirzaei & Sakizadeh, 2016). However, controverses exists regarding the accuracy of one method over another and the selection of an appropriate one (J. Li & Heap, 2014; Mirzaei & Sakizadeh, 2016).

Several studies have been made to characterize the spatial variability of soil characteristics in Ethiopia (Ebabu et al., 2020; Lelago et al., 2016; Lelago & Buraka, 2019; Tesfahunegn et al., 2011; Yimer et al., 2006; Yitbarek et al., 2016). But, on the best of our knowledge, there is not enough information, in the scientific literature, on the comparison of spatial interpolation methods in the field of soil science in Ethiopia, especially in Mana district. Only one study compared the performance of OK, IDW, and RBF for predicting the spatial distribution of soil texture, pH, SOC, and AP in the north-western Amhara region. It showed that OK was best performing for SOC and sand, RBF was most suitable for mapping of AP and clay, while IDW gave better results for pH (Addis et al., 2016). Thus, an effective technique to predict the spatial distribution of soil chemical characteristics in Mana district, Oromia region, would be a necessary component in informed soil fertility management decisions.

1.3. Objectives of the study

1.3.1. General objective

The main aim of this study was to evaluate the effectiveness of various geospatial interpolation methods (IDW, OK, and OCK) to predict the variation and spatial distribution of selected chemical properties of soil (pH, SOC, AP, TN, and AK) in Mana district.

1.3.2. Specific objectives

More specifically, the study addressed the following objectives:

- To compare the performance and accuracy of the IDW, OK and OCK interpolation techniques for predicting selected topsoil chemical properties of the study area.
- To determine the most appropriate spatial interpolation method for mapping the studied soil properties in Mana district.
- To produce maps of soil fertility based on pH, SOC, AP, TN and AK content using the different interpolation methods.

1.4. Research questions

Knowing spatial variability of soil properties is an important task to optimize soil management practices and agricultural productivity. In this regard, the following basic research questions arose:

- Are the performances of IDW, OK and OCK interpolation techniques different in predicting selected chemical properties of Mana district?

- Which of the different interpolation and spatial analysis methods is the best to provide a good ability to predict soil chemical properties in Manna?
- How pH, SOC, TN, AP and AK parameters vary across Mana district area?

1.5. Significance of the study

Soil fertility decline is a major agricultural concern that Ethiopia has been facing. The way soils are managed has its own impact on agricultural productivity and food security. In this regard, the results of the study can contribute a lot by identifying specific sites which need adequate soil management, indicating the fertility variation over Mana district. Soil resources information is essential for understanding soil constraints in order to optimize sustainable management of the agricultural resources and economic growth.

GIS have been applied to assess the spatial variability of soil properties, which is very important in precision agriculture and one of the bases for decision and policy makers to make plans and strategies.

In addition to these, the study can serve as a reference for other researchers and development actors that deal with soil management.

1.6. Scope and limitation of the study

This study was limited geographically to Mana district of the Jimma Zone, Oromia region, Southwest Ethiopia. The study focused on the assessment of GIS-based interpolation methods to predict spatial variation of major soil chemical properties in Mana district. The IDW, OK and OCK methods have been compared using cross-validation to assess the spatial variability of pH, SOC, TN, AP, and AK parameters in the area.

Due to finical constraint, a limited number of soil samples was collected, and only selected soil chemical properties were analyzed. Despite these limitations, the findings of the research provide important basis for relevant interventions for the study area.

1.7. Organization of the paper

The thesis is organized into five chapters. Chapter one presents the introduction, which focuses mainly on the background, problem statement, objectives, hypotheses, significance of the study and scope of the study. Chapter two provides review of related literature which describes some related concepts regarding to soil properties and spatial interpolation methods. It further gives an overview of agriculture and spatial variability of soil properties in Ethiopia. Chapter three deals with description of the study area and methods used in the study. Chapter four presents the results and discussion of the study. Finally, chapter five deals with conclusion and recommendations drawn from the study.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Soil chemical properties

The primary function of soil in relation to chemical properties is to provide nutrients for plant and crop growth (Brady & Weil, 2017). Soil pH, SOC, AN, AP, and AK are the chemical properties to be investigated in this study.

2.1.1 Soil reaction or Soil pH

Soil reaction which is indicated by soil pH, is the extent of acidity and alkalinity in a soil (Brady & Weil, 2017; Osman, 2013a). The pH scale of a solution runs from 0 to 14; 7.0 is the neutral point. A pH value less than 7 indicates an acidic solution, while a pH greater than 7 indicates an alkaline solution. For a very heterogeneous media like soil, pH values between 6.5 and 7.5 may be taken as fairly neutral (Osman, 2013a).

Soil pH is the single most important aspect of soil chemistry that affects the process of other nutrient transformations, solubility, availability to plants (Adugna & Abegaz, 2016). It also affects the quantity, activity, and types of microorganisms in soils which in turn influence the decomposition of organic materials (Huang et al., 2021; Myslyva et al., 2019). Therefore, soil pH is one of the several soil quality indicators that give useful information on soil dynamics and nutrient availability and how the soil resource is functioning. Thus, knowing how pH is controlled, how it influences the supply and availability of essential plant nutrients as well as toxic elements, how it affects higher plants and human beings, and how it can be ameliorated, is essential for the conservation and sustainable management of soils throughout the world (Zelleke et al., 2010). Soil acidity and associated low nutrient availability are major constraints to agricultural productivity in acidic soils of Ethiopia, principally Nitisols highlands (Golla, 2019). Currently, it is estimated that about 40% of arable lands of Ethiopia are affected by soil acidity (Lelago & Buraka, 2019) and about 28% of them are dominated by strong acid soils (Golla, 2019).

2.1.2 Soil organic carbon

The SOC is one of the most prominent components of the soil due to its capability to affect plant growth as both a source of energy and a trigger for nutrient availability through mineralization. It plays an important role in the chemical structure of all organic substances (Brady & Weil, 2010). The term soil organic carbon (SOC) is often used to refer to the C component of soil organic matter (SOM). It can be reported as total SOM by multiplying values for SOC by the conventional "Van Bemmelen factor" of 1.724 (Brady & Weil, 2010; Osman, 2013a; Sanchez, 2019a). SOC improves the physical properties of the soil, increases the cation exchange capacity (CEC) and the water holding capacity, plays a major role in soil aggregation and buffers soil from strong changes in pH (Rubio et al., 2021; Zebire et al., 2019). It is also an important factor in the mitigation of climate change effects (Gibson et al., 2021; Yuan et al., 2021).

Several factors can affect the total amount of SOC in a soil and its distribution within the profile such as soil type, climate, topography, mineral composition, management, changes in the natural state of the soil systems (conversion to agriculture, deforestation, and afforestation), and their interactions (Boubehziz et al., 2020; Gibson et al., 2021; Niu et al., 2021).

2.1.3. Total Nitrogen

Nitrogen (N) is one of the most deficient elements in the tropics for crop production. It is a very important and dynamic nutrient element in managed ecosystems (Sanchez, 2019b). Nitrogen is needed by plants usually in the largest amount (1 to >3% of plant on dry weight basis) after C, H, and O. It is a constituent of the chlorophyll molecule, which gives plants the green color and an ability to convert solar energy into chemical energy through the process of photosynthesis. Nitrogen is a constituent of other important biomolecules such as amino acids, proteins, nucleic acids (RNA and DNA), nucleoproteins, and is a necessary component of several vitamins and all enzymes (Priyadarshini et al., 2021). Therefore, nitrogen plays a key role in all metabolic activities of plants.

The total N content of a soil composed of inorganic (NH4+, NO3- and NO2-) and organic forms (SOM) is directly associated with its SOC content (Lelago & Buraka, 2019). The total nitrogen is subject to change due to various factors such as management practices (cropping, fertilization, erosion, and leaching) and climate (temperature and moisture), which determine its level and dynamics (Mohammed Assen, 2003; Yimer et al., 2006). Climatic conditions, especially temperature and rainfall generate dominant influence on the amounts of nitrogen and organic matter found in soils (Osman, 2013b).

2.1.4. Available phosphorus

Phosphorus (P) is the most common plant growth limiting nutrient in the tropical soils next to water and N that has to be corrected in agriculture (Z. Li et al., 2020; Sanchez, 2019b). Following N, P has more widespread influence on both natural and agricultural ecosystems than any other essential elements (Brady & Weil, 2017).

Phosphorus is critical in the early developmental stages of growth (Silva-Leal et al., 2021). It stimulates seed germination, young root formation, seedling growth, flowering, fruiting, and seed development. Phosphorus availability depends on several soil conditions. Some of these are the amount of clay, the type of clay, the pH, the soil temperature, the compaction, the aeration, the moisture content, the kind and amount of fertilizer, the time and method of application, the granule size of fertilizer, and placement (Amarh et al., 2021; Yang et al., 2021).

The availability of phosphorus to plant roots is constrained by both the low total phosphorus level in soils and the small percentage of this level that is present in available forms (Bibiso, 2017). Furthermore, even when soluble sources of phosphorus are added to soils, they are quickly fixed into insoluble forms that in time become quite unavailable to growing plants (Brady & Weil, 2017). Thus effective management of soil phosphorus is crucially important from both an environmental standpoint and for soil fertility (Dunne et al., 2021; Z. Xie et al., 2021).

The main sources of plant available P are the weathering of soil minerals, the decomposition and mineralization of SOM and commercial fertilizers (Adugna & Abegaz, 2016). Most of the soils in Ethiopia and other acid soils are known to have low P contents, not only due to the inherently low available P content, but also due to the high P fixation capacity of the soils (Lelago & Buraka, 2018).

2.1.5 Available potassium

Potassium (K) is the third most important plant growth-limiting nutrient next to N and P (Han et al., 2021). Its behavior in the soil is influenced primarily by soil cation exchange capacity and mineral weathering rather than by microbiological processes (Brady & Weil, 2017). Potassium is especially important in helping plants adapt to environmental stresses. The benefits of good potassium nutrition include improved drought tolerance, improved winter hardiness, better diseases resistance, and greater tolerance to insect pests (T. Li et al., 2021; Wang et al., 2013). Potassium also enhances the quality of flowers, fruits, and vegetables by improving flavor and color and strengthening stems (Wang et al., 2013).

Unlike N and P, potassium does not cause offsite environmental problems or play as direct a role in water quality, but inadequate supplies of this element commonly limit plant productivity and crop quality (Brady & Weil, 2017). Even though most soils have large total supplies of this element, most of that present is tied up as insoluble minerals and is only slowly available for plant use. Plants require potassium in much larger amounts than phosphorus, so careful management practices are necessary to ensure sufficient short- and long-term availability of this nutrient for vigorous plant growth (Brady & Weil, 2010, 2017). Presently, there is growing evidence of increasing potassium deficiency in different parts of Ethiopia (Laekemariam et al., 2018).

The variation in the distribution of potassium depends on the mineral present, particle size distribution, degree of weathering, soil management practices, climatic conditions, degree of soil development, the intensity of cultivation and the parent material from which the soil is formed (Osman, 2013b; Sanchez, 2019b).

The EthioSIS (2014) critical levels of the soil parameters discussed above are presented in table 1.

Table 1: Critical levels for classifying soil properties as reported by EthioSIS

Soil parameter	Status	Critical level
Soil pH(water)	Strongly acidic	<5.5
	Moderately acidic	5.6-6.5
	Neutral	6.6-7.3
	Moderately alkaline	7.3-8.4
	Strongly alkaline	>8.4
Organic matter (%)	Very low	<2.0
	Low	2.0-3.0
	Optimum	3.0-7.0
	High	7.0-8.0
	Very high	>8.0
Total Nitrogen (%)	Very low	<0.1
	Low	0.1-0.15
	Optimum	0.15-0.3
	High	0.3-0.5
	Very high	>0.5
Available P (mg/kg)	Very low	0-15
	Low	15-30
	Optimum	30-80
	High	80-150
	Very high	>150
Exchangeable K (mg/kg)	Very low	<90
	Low	90-190
	Optimum	190-600
	High	600-900
	Very high	>900

Source: (EthioSIS, 2014)

2.2. Overview on agriculture and spatial variability of soil properties in Ethiopia

Agricultural productivity and food security have been particularly challenging in most sub-Saharan African (SSA) countries in general and in Ethiopia in particular, where soil fertility depletion is the major biophysical limiting factor (Lelago & Buraka, 2019; Wolka et al., 2018). Food security and sustainable development are two fundamental and strategic goals in Ethiopia (Tesfahunegn et al., 2011). Agriculture is important for Ethiopian economy as it provides employment for about 85% of its inhabitants (Lemenih et al., 2005). However, among the factors that heavily threaten Ethiopian agriculture are land degradation and associated soil fertility declines (Agegnehu & Amede, 2017; Tesfahunegn et al., 2011). As well, adequate information on soil resources, which is the prerequisite for the design of appropriate land use systems and soil management practices, is not adequately available (Lelago & Buraka, 2018; Yitbarek et al., 2016).

Soil chemical parameters are important indicators of soil fertility and highly variable in space and time, especially in agricultural areas, with implications for crop production (Bogunovic et al., 2017). As soil properties vary spatially and temporally, understanding their spatial distribution, particularly for chemical properties, is very relevant in agricultural planning for optimizing local application of nutrients and fertilizers, thereby improving production system (José & Ana, 2017). Knowledge of soil spatial variability is also necessary to locate homogenous sites that need careful management for sustainable development (Tesfahunegn et al., 2011). Thus, it will contribute to better management decisions to correct problems and at least maintain soil productivity and sustainability, thereby increasing the accuracy of agricultural practices (Bogunovic et al., 2017; Lelago & Buraka, 2018).

There are several causes for spatial variability of soil nutrients such as parent material characteristics, topography, climate, vegetation communities, cultivation history, population growth and land use practices (Ebabu et al., 2020; Lemenih et al., 2005; Vågen et al., 2013; Yimer et al., 2006).

Various studies have focused on spatial interpolation of soil properties, but only a few of them have been undertaken in SSA in general and Ethiopia in particular (José & Ana, 2017; Tesfahunegn et al., 2011). Techniques such as SIMs have been widely employed to assess the spatial distribution of soil properties in agricultural areas and contribute to better land use management (Abidine et al., 2018; Addis et al., 2016; Myslyva et al., 2019). For instance, Tan et al. (2020) indicated that empirical Bayesian kriging (EBK) and OK were more suitable than IDW and spline (S) for assessing the spatial variability of soil chemical properties in Bukit Senorang Estate (Malaysia). In another study conducted in north-west Morocco, OK model was reported to be the best method compared to IDW and Spline for interpolating pH, organic matter and potassium (Samira et al., 2014). As well, a study conducted in West Bengal (India) showed that OK was the most accurate interpolation method for generating spatial distribution of SOC, as compared with IDW, local polynomial interpolation (LPI), radial basis function (RBF), and EBK (Bhunia et al., 2016). On the other hand, Gozdowski et al (2015) evaluated the performance of OCK, OK, IDW, and RBF for the interpolation of soil texture in Poland and showed that OCK was best performed compared to the others. Besides that, Abdel Rahman et al. (2021) has reported that IDW showed higher efficiency than Kriging as a prediction method for mapping the soil properties (AP, AK, AN, SOC, pH, electrical conductivity (EC), etc.) in Egypt. Also, Abidine et al (2018) studied the effectiveness of different interpolation methods (IDW, LPI, RBF and OK) to estimate the spatial distribution of the EC in the Dawling National Park in Mauritania and showed that IDW method was the best estimator, as it had good prediction ability.

However many researchers have used geospatial interpolation techniques and compared their effectiveness in assessing the spatial distribution of the properties of soils and mapping processes, disagreement still exists regarding the accuracy of one interpolation method over another and the selection of an appropriate interpolation method for the data is a controversial issue in the environmental research (Mirzaei & Sakizadeh, 2016; Myslyva et al., 2019). The performance of SIMs depends on many factors including sampling density, sampling design, sample spatial distribution, data quality, correlation between primary and secondary variables, and interaction among factors (J. Li & Heap, 2011, 2014).

2.3. Spatial interpolation methods

Interpolation is the method of predicting the values of attributes at unsampled sites (Y. Xie et al., 2011). Comparing to classic modeling approaches, spatial interpolation methods incorporate information concerning the geographic position of sample points. The explanation behind spatial interpolation is that points closer to each other have more correlations and similarities than those further away (Gozdowski et al., 2015; Y. Xie et al., 2011).

Different interpolation methods are used to generate a continuous surface. Twenty-five of these methods had been compared by Li & Heap (2014) and the similarities amongst each other discussed.

The most widely used interpolation methods to predict soil properties, IDW, OK, and OCK (J. Li & Heap, 2011, 2014; Mirzaei & Sakizadeh, 2016; Shen et al., 2019) will be evaluated in this study.

2.3.1. Inverse distance weighting (IDW)

IDW is one of the oldest spatial prediction technique (Hengl, 2007). It is a deterministic spatial interpolation method based on the premise that values of unsampled points can be predicted as the weighted average of known values within the neighborhood (Shen et al., 2019). Its interpolation function is described by the following equation (Mirzaei & Sakizadeh, 2016; Y. Xie et al., 2011):

$$Z(x) = \frac{\sum_{i=1}^{n} W_i Z_i}{\sum_{i=1}^{n} W_i} \quad \textbf{Equation 1}$$

In which: $W_i = d_i^{-u}$

where $Z(x)$ is the predicted value at an interpolated point, Z_i is the amount at a known point, n is the total number of known points used in interpolation, d_i is the distance between point i and the prediction point and W_i is the weight assigned to point i. Higher weighting values are assigned to points that are closer to the interpolated point (Y. Xie et al., 2011). The weight is inversely proportional to the distance between the prediction locations and the sampled locations, and u is the weighting power that determine how the weight decreases as the distance increases (Mirzaei & Sakizadeh, 2016; Y. Xie et al., 2011).

The approach is one of the most commonly used spatial interpolation methods due to its relative ease of calculation and fast implementation (Hou et al., 2017). However its greatest limitation is that it is not based on any particular model of spatial correlation for the parameters being evaluated, while spatial autocorrelation usually exists and can be applied to provide better interpolation (Hou et al., 2017; Shen et al., 2019).

2.3.2. Kriging

The geostatistical technique of Kriging is the most frequently used interpolation approach (Oliver & Webster, 2015). Unlike IDW and some other interpolation methods that handle soil properties at unsampled locations as a certain mathematical function of a continuous spatial variable, the kriging method is based on a model of stochastic spatial variation (Hou et al., 2017). As with IDW, Kriging is a linear estimator given by a linear combination of the observed values with weights (Y. Xie et al., 2011).

The accuracy of kriging is affected by factors such as the variability and spatial structure of data, the choice of variogram modeling parameters including the variogram shape, range, sill and nugget value, and the number of neighboring measurements used in the calculation (Hou et al., 2017; Oliver & Webster, 2015).

There are several variants of Kriging (Oliver & Webster, 2015; Y. Xie et al., 2011), used depending on the stochastic properties of random fields. The type of kriging defines the linear constraint on weights implied by the unbiased condition (Y. Xie et al., 2011). In this study, only ordinary kriging and co-kriging will be considered.

Ordinary kriging

The OK is a standard version of kriging based on the theory of regionalized variables and assumes that the variables involved are random but spatially correlated on some scale (Hengl, 2007; Shen et al., 2019). It is the most popular method and has proved to be robust for predicting the spatial variability of soil properties (Leena et al., 2021; Oliver & Webster, 2015; Y. Xie et al., 2011). Nevertheless, the accuracy and reliability of predictions are determined by the sampling size and distribution of sampling points (Leena et al., 2021; Shen et al., 2019). Usually, OK is limited by sampling points uniformity and density in complicated areas of study and the auxiliary variable is not considered (Shen et al., 2019).

Its predictions are based on the following standard surface model:

$$Z(s) = \mu(s) + \varepsilon(s) \qquad \textbf{Equation 2}$$

Where the vector **s** is used to represent the surface coordinates (*x*,*y*), μ is the constant stationary function (overall or local mean value of the sampled data) and ε(s) is the spatially correlated stochastic part of variation. (Hengl, 2007; Smith et al., 2018)

The values at unsampled points are computed as a simple linear weighted average of neighboring measured data points, where the weights are determined from the fitted variogram rather than determined by the user. For a specific point, *p*, this can be shown by the following equation (Smith et al., 2018):

$$Z_p = \sum_{i=1}^{n} \lambda_i Z_i \quad \textbf{Equation 3}$$

where λ_i are the weights assigned to the known value of Z_i and Z_p is the estimated value. With the condition that the weights must sum to 1 to ensure that the estimate is unbiased (Oliver & Webster, 2015; Y. Xie et al., 2011):

$$\sum_{i=1}^{n} \lambda_i = 1 \qquad \textbf{Equation 4}$$

Co-Kriging

OCK is an extension of OK from a single spatial random variable to two or more spatially correlated random variables (Abdennour et al., 2020; Bogunovic et al., 2017; Fu et al., 2020). OCK is a versatile statistical approach for spatially unknown point prediction, particularly when both the primary and auxiliary variables are known (Shen et al., 2019).

It has a theoretical benefit of accounting for both autocorrelations and cross correlations among all involved variables although it uses overall parameters. In addition, the spatial information of the auxiliary variables can be used to supplement for inefficiencies associated with the spatial dependency of target variables without significant variation (Hengl, 2007; Shen et al., 2019). Nevertheless, the model presents limitations as only three environmental factors can be used to calculate it (Shen et al., 2019).

Co-Kriging extends the Ordinary Kriging model to the form:

$$Z_1(s) = \mu_1(s) + \varepsilon_1(s) \qquad \textbf{Equation 5}$$

$$Z_2(s) = \mu_2(s) + \varepsilon_2(s) \qquad \textbf{Equation 6}$$

where μ_1 and μ_2 are unknown mean values (constants) and ε_1 and ε_2 are random errors. Each of these sets of random errors may demonstrate autocorrelation and cross-correlation between the datasets, which the procedure attempts to model. Co-Kriging uses this cross-correlation for the improving of $Z_1(\mathbf{s})$ estimation. Co-Kriging can also be used to models other than Ordinary Kriging (Smith et al., 2018).

CHAPTER THREE

3. MATERIALS AND METHODS

3.1. Description of the study area

3.1.1. Location

The study was carried out in Mana district, Jimma zone in the Oromia Region of Ethiopia (Figure 1). Mana district is geographically located between 7°39'0" - 7°52'30" North latitudes and 36°40'30" - 36°54'0" East longitudes, about 368 km from Addis Ababa metropolis and 20 km from Jimma town (Bekele, 2018). It is bordered in the south by Seka Chekorsa district, in the west by Gomma district, in the north by Limmu Kosa district, and in the east by Kersa district (Bekele, 2018; Gabusho, 2019). It has an estimated total area of 480 km² including the rural town of Yebu (Mahmood, 2008).

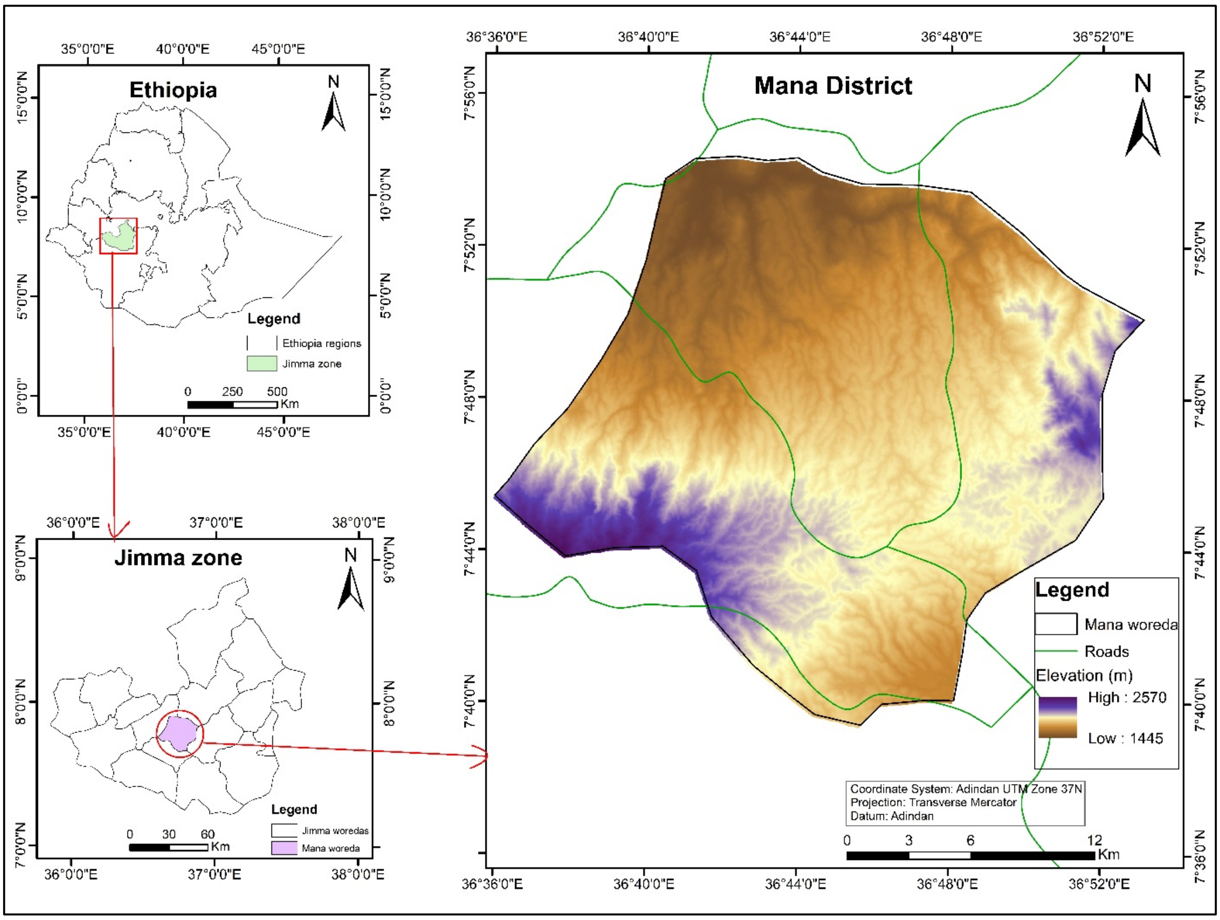

Figure1: Location map of the study area

3.1.2. Relief, Drainage and Climate

Relief: Mana district is found within southwestern highlands of Ethiopia. The elevation range of the district is between 1445 and 2570 m above sea level (see figure 1 above). Its topography is classified into Dega (2.9%), Woinadega (95%) and Kola (2.1%) agro-climatic zones (Gabusho, 2019). The landscape of Mana includes mountains, high forests and plain divided by valleys. Mountains include Weshi and Bebella.

Drainage: The total area of the district's surface drainage pattern is fallen in the Dedesa and Gibe Rivers basins. Wagossa, Wanja, Yebu, Yabo, Jarso (Gulufu), Dawa, kambo, Enkolu, Awatuanso, Laku, Fache, Abari and Sogibo are the major perennial rivers that drain to Gibe and Dedesa Rivers. The first ten are under Dedesa River basin and the remaining three of them are under Gibe River basin. The woreda has no natural and man-made lakes (Bekele, 2018; Gabusho, 2019).

Climate: Mana is within the tropics and so experiences high incoming solar isolation due to high angle of the solar rays with over-head sun twice a year. However, this tropical nature of its climate is rather modified by altitude. Mana part of low altitude (less than 1500 m) experiences high temperature and low precipitation. The central parts of the district do have cool agro-climate with the mean annual temperature ranges between 15°C and 18°C. While the vast part of the district classified to sub-tropical with mean annual temperature ranges between 18°C and 29°C. The medium temperature of the district is 11.27°C and the higher temperature is 28.99°C. The rainfall of the woreda is weakly bimodal with spring a small rainy season during the months of March and April while summer long rainy season during the months of June, July, August, and September. The vast area of the district annual rainfall varies between 1300 mm and 1700 mm (Bekele, 2018).

3.1.3. Geology and soil

Geology: The present surface rock distribution, the land configuration and other natural phenomena in the district are all the results of the past geologic history and tectonic movements in the upper mantle lithosphere portion of the Afro-Arabian landmass. The district is part of the geologic and tectonic history of the Afro-Arabian region, in particular the Horn of Africa (Ibid).

Soil: According to Nigussie et al. (2013) and Alemayehu et al. (2019), the dominant soil types in Jimma zone, particularly Mana district, are Nitisols, and they are much utilized for agricultural production. The land investigation of the district shows that 89.1% is arable (Gabusho, 2019).

3.1.3. Vegetation and farming system

Vegetation: From the total area of Mana district, 86.1% are under annual crops, 2.7% under pasture, 2.8% under forest, and 5.4% are swampy including degraded unusable (Ibid).

Farming system: Mana district does have ideal agro-climatic conditions, dominated by tropical, sub-tropical and cool, that are suitable for production of cereals horticultural crops. Crop production is a common practice prevailing in the district next to coffee production. Chat is also widely cultivated in the district. The livelihood of the rural people of the district is dependent on both cereal crops and cash crops such as coffee and chat (Bekele, 2018).

3.2. Soil sampling techniques

3.2.1. Soil sampling design

The systematic sampling technique with a grid of 2.5 km × 2.5 km (as recommended by the ethioSIS) designed in ArcGIS 10.3 software using the sampling design toolset were applied in this study. The systematic method was chosen because it is the most frequently used sampling design and is an appropriate method when no other information is available concerning the soil variability prior to sampling (Addis et al., 2016). Furthermore, geostatistical designs more typically use grid designs model the spatial pattern of soil properties. Systematic sampling design provides more accurate results than simple random sampling, because with this method the samples are distributed more equally over the study area (Tan, 2005). The distribution of sample sites over the study area is shown in Figure 2.

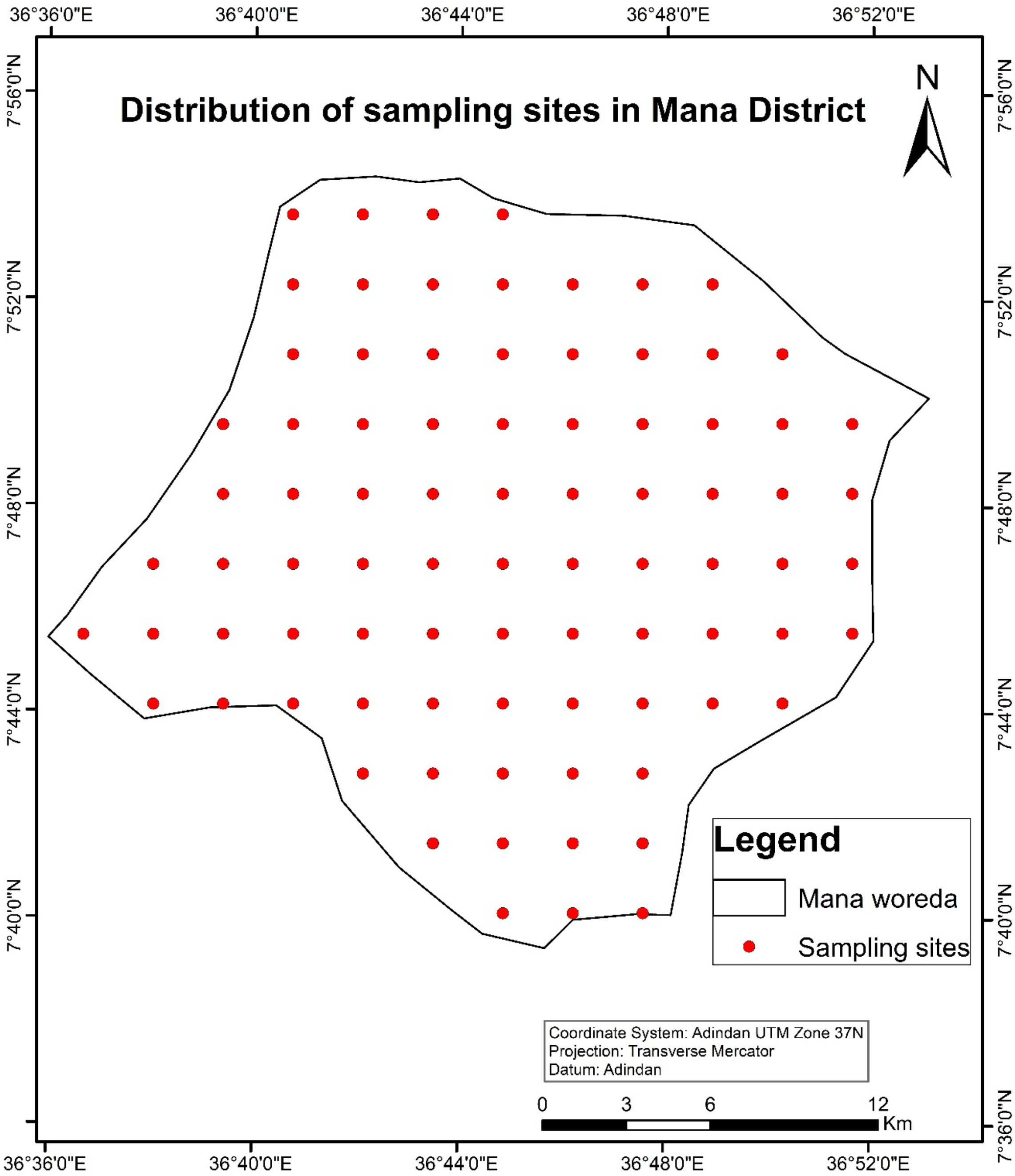

Figure 2: Distribution of sampling sites in Mana district

3.2.2. Soil samples collection and preparation

A total of 84 geo-referenced soil samples have been collected from 9th April to 24th April 2021 at 0 - 30 cm depth across the entire district. The choice of April month was to allow a good and easy sampling as it was at the beginning of the cultural season and before the seedling.

Locations of each sampling site was geotagged using handheld Global Positioning System (GPS) receiver (Garmin GPSMAP 64s). At each location, three topsoil sub-samples were collected using a gouge auger and thoroughly mixed at study site to obtain representative composite soil samples (figure 3). About 1 kg of each composite sample was collected in labelled plastic bag. The purpose to use composite soil sampling technique was to represent the average conditions in the sampled soils. All collected composite soil samples were sent to the soil laboratory of Jimma University College of Agriculture and Veterinary Medicine for analysis.

Figure 3: Uniformly mixing of sub-samples to create composited samples

Before analysis, the composite soil samples were air-dried (figure 4 (a)), grounded using mortar and pestle, and sieved to pass through 2 mm mesh. After sieving, prepared and labeled samples were kept in plastic bags to protect from post sampling changes (figure 4 (b)).

(a) Air-dried samples

(b) labeled samples kept in plastic bags

Figure 4: Preparation of samples before analysis

3.3. Laboratory analysis

The prepared soil samples were analyzed at soil laboratory of Jimma University College of Agriculture and Veterinary Medicine for five selected soil parameters: pH, SOC, total nitrogen, AP, and AK.

The pH was determined on the basis of the potentiometric principle in a 1:2 soil/water solution with an using an electronic pH meter with combination electrodes. (Tan, 2005).

The SOC was determined by the Walkley- Black chromic acid wet combustion method, by titrimetric method, which involves reduction of potassium dichromate ($K_2Cr_2O_7$) by organic carbon compounds and subsequent determination of the unreduced dichromate by oxidation-reduction titration with ferrous ammonium sulfate (Skjemstad & Baldock, 2007; Tan, 2005).

The total nitrogen percentage was determined using the Kjeldahl method which includes digestion, distillation, and titration procedures (Rutherford et al., 2007; Tan, 2005). The soil was digested in concentrated H_2SO_4 with a catalyst mixture to raise the boiling temperature and to promote the conversion from organic-N to ammonium-N. Ammonium-N from the digest was obtained by steam distillation.

The concentrations of AP were estimated after extraction by the sodium bicarbonate method. The procedure is also known as the Olsen method, and is used mostly for extraction of available P method (Tan, 2005).

The AK concentrations was determined after extraction by ammonium acetate method (Chen et al., 2020; Tan, 2005). The AK in the soil was extracted with neutral ammonium acetate of 1molarity and was estimated using the flame photometer.

Figure 5 shows some laboratory analysis procedures.

Figure 5: Some analysis procedures

3.4. Data classification and analysis

The summary of softwares used is presented in table 2 and all undertaken procedures are summarized in the methodological flow chart shown in Figure 6.

3.4.1. Exploratory data analysis

Data obtained from soil test laboratory of pH, soil organic carbon, total nitrogen, available phosphorous, and available potassium were organized and processed in order to evaluate interpolation efficiency of three methods. An exploratory data analysis consisting of basic summary statistics was undertaken aiming to uncover underlying patterns of soil attributes that could influence spatial analysis efficiency. The first step in data treatment previous to the application of any data analysis techniques is summary statistics (Samira et al., 2014).

GraphPad Prism software (Version 8.4.3) was used for descriptive statistical analysis of each soil variable, including mean, standard deviation (SD), minimum, maximum, coefficient of variation (CV), Skewness, and Kurtosis.

A correlation coefficient matrix was carried out among soil variables and aspect topographical parameter, extracted from the digital elevation model (DEM) of Mana with a resolution of 12.5 m. This DEM from Advanced Land Observation Satellite (ALOS) was freely downloaded from the NASA's Earthdata website (https://search.asf.alaska.edu/#/). The aspect was used as the auxiliary variable for the OCK method.

3.4.2. Data transformation

Many statistical procedures, including geostatistical analyses, make the assumption that the variables distribution is normal (Samira et al., 2014). In the case of this study, the QQ-plot, the Kolmogorov-Smirnov test and the D'Agostino & Pearson test were used to verify if the data were normally distributed (Shen et al., 2019) across the area of study and if data fit to geostatistical analyses.

Since non-normality was revealed, the highly skewed distributions needed to be transformed to make them approximately Gaussian or symmetric (Webster & Oliver, 2008). Square transformation (for TN parameter) and Box-Cox transformation (for aspect, AP, and AK parameters) were applied in this study for this purpose. The Box-Cox transformation is one of transformation functions used to achieve the normality of data (Osborne, 2010; Samira et al., 2014). Box-Cox represents a potential best method to normalize data as it offers a series of power transformations that incorporate, extend, and improve on the traditional options (logarithm, square root and inverse) to help researchers easily identify the optimal normalizing transformation for each parameter (Osborne, 2010).

3.4.3. Interpolation and comparison

The interpolations of soil properties data were performed by IDW, OK and OCK interpolation methods using the geostatistical analyst extension of ArcGIS 10.3 software.

The cross validation statistical method was applied to validate the accuracy of those predictions. Cross validation implies consecutively eliminating a data point, estimating its value from the remaining observations and comparing the predicted value with the observed one (Duan et al., 2020; Samira et al., 2014; Yao et al., 2013). To choose the best variogram model for kriging and also the best parameter for IDW, the cross validation technique is generally used (Samira et al., 2014).

The mean relative error (MRE), the root mean square error (RMSE) and the relative improvement (RI), as common validation indices (Shen et al., 2019), were used to compare the different interpolation methods. MRE and RMSE were calculated from the measured and interpolated values at each sample site:

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(Z^{*}(X_i) - Z(X_i))}{Z(X_i)}\right| \quad \textbf{Equation 7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[(Z^{*}(X_i) - Z(X_i))\right]^2} \quad \textbf{Equation 8}$$

where Z*(Xi)* and *Z*(Xi)* are the observed and interpolated values respectively, *i* the location, and *n* is the sample size. Smaller MRE and RMSE values indicate fewer errors (Y. Xie et al., 2011). If the prediction error is unbiased, the MRE should be close to 0. A small RMSE indicates that the prediction value is closer to the measured value, and can be used to compare different models (Shen et al., 2019).

The three interpolation methods were compared two by two to evaluate their accuracy. The RI of a method over another method was calculated using:

$$RI = \frac{(RMSE_2 - RMSE_1)}{RMSE_2} x100 \quad \textbf{Equation 9}$$

where $RMSE_2$ and $RMSE_1$ are respectively the root mean square errors of the methods "2" and "1". The accuracy of the method "2" was considered higher than that of the method "1" if the RI was positive, and vice versa (Shen et al., 2019).

Table 2: Summary of softwares used

Softwares used	Version	Use
EasyGPS	6.17	Quick and simple transfer of geographic coordinates of sampling sites from the computer to the GPS. Control of points and directions, their listing, sorted by name, distance or altitude.
GraphPad Prism	8.4.3	Descriptive statistical analysis. Correlation among soil variables and aspect. Verification of the data distribution. Transformation of non-normal distributed data.
ArcGIS	10.3	Drawing of the sampling design and assignment of geographic coordinates to each sampling site. Geostatistical analysis: Interpolation using the three interpolation methods and the comparison of their performance using cross-validation. Production of soil properties maps.

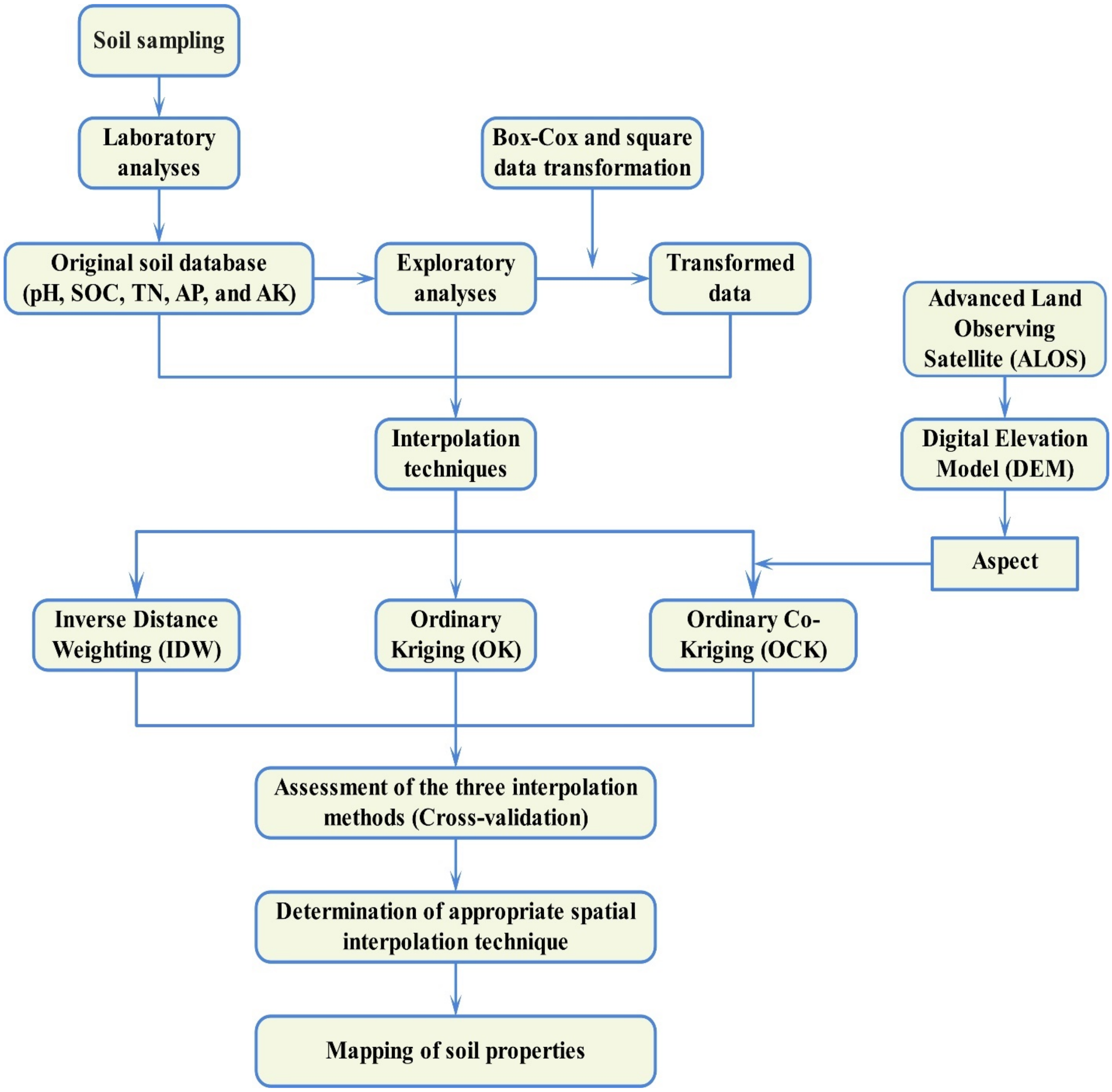

Figure 6: Methodological flow chart

CHAPTER FOUR

4. RESULTS AND DISCUSSION

4.1. Summary statistics

The descriptive statistics of the surveyed soil properties and aspect measured at each sampling point are summarized in table 3.

Table 3: Descriptive statistical summary

Variable	Mean	Std.Dev.	Min	Max	CV	Skewness	Kurtosis
Aspect	168.12	111.48	1.00	358.26	66.31	0.08	1.68
pH	5.16	0.84	3.49	7.3	16.28	0.28	2.77
OC (%)	2.26	0.69	1.05	3.9	30.53	0.16	2.14
AP (ppm)	15.73	6.49	8.37	38.08	41.26	1.31	4.54
TN (%)	0.20	0.06	0.09	0.34	30.00	0.14	2.09
AK (cmol/kg)	12.58	5.19	6.7	30.47	41.26	1.31	4.54

ppm: particles per million, cmol/kg: centimole per kilogram.

The most selective factor which indicates the overall variation from one data series to another is the coefficient of variation (CV) (Addis et al., 2016; Bhunia et al., 2018). Based on Warrick guidelines, the property shows low variability when CV is < 15%, moderate variability when the CV is between 15% and 35%, and a high variability when the CV is >35% (Warrick, 1998). According to these guidelines, the topographic aspect had a high variability (66.31%). Among the soil chemical properties, AP and AK showed the highest variability (41.26%), while pH showed the least (16.28%). Similar studies by Samira et al. (2014) in the Northwest of Morocco, Addis et al. (2016) in the northwestern Amhara region of Ethiopia, Ebabu et al. (2020) in the Upper Blue Nile basin of Ethiopia, Tan et al. (2020) in in Bukit Senorang Estate in Malaysia, and Abdel Rahman et al. (2021) in the Behera Governorate of Egypt documented that the lowest CV was obtained for pH, whereas the highest CV was obtained for AP and AK. The large variation of soil properties is due to the landscape position, elevation, soil texture, precipitation, soil parent material and soil genesis, agronomic practices, vegetation characteristics and historical fertilization application (Bhunia et al., 2018; Brady & Weil, 2017; Ebabu et al., 2020; Tan et al., 2020).

In this study, variables with high coefficient of variation were highly skewed and did not fit the normality standards. Non-normality of data can have negative implications for geostatistical analysis (Bogunovic et al., 2017). In addition to descriptive statistics, other statistical tests (QQ plot, Kolmogorov-Smirnov, and D'Agustino & Pearson test) were applied to check for normality. Only pH and SOC variables were normally distributed (figure 4). The other variables (Aspect, TN, AP, and AK) showed a non-normal distribution. So, the Box-Cox transformation (Equation: $Y = \frac{Y^k - 1}{k}$) was applied to the data for Aspect, AP, and AK (with k=0.84, -0.01 and 0.01, respectively) and the square transformation (Equation: $Y = Y^k$) for TN variable (with k = 2). Those transformations resulted in the best fit of a normal distribution (figure 7).

All the remaining data processing, from the variogram computation and the cross-validation tests to the spatial prediction, were carried out with the transformed data.

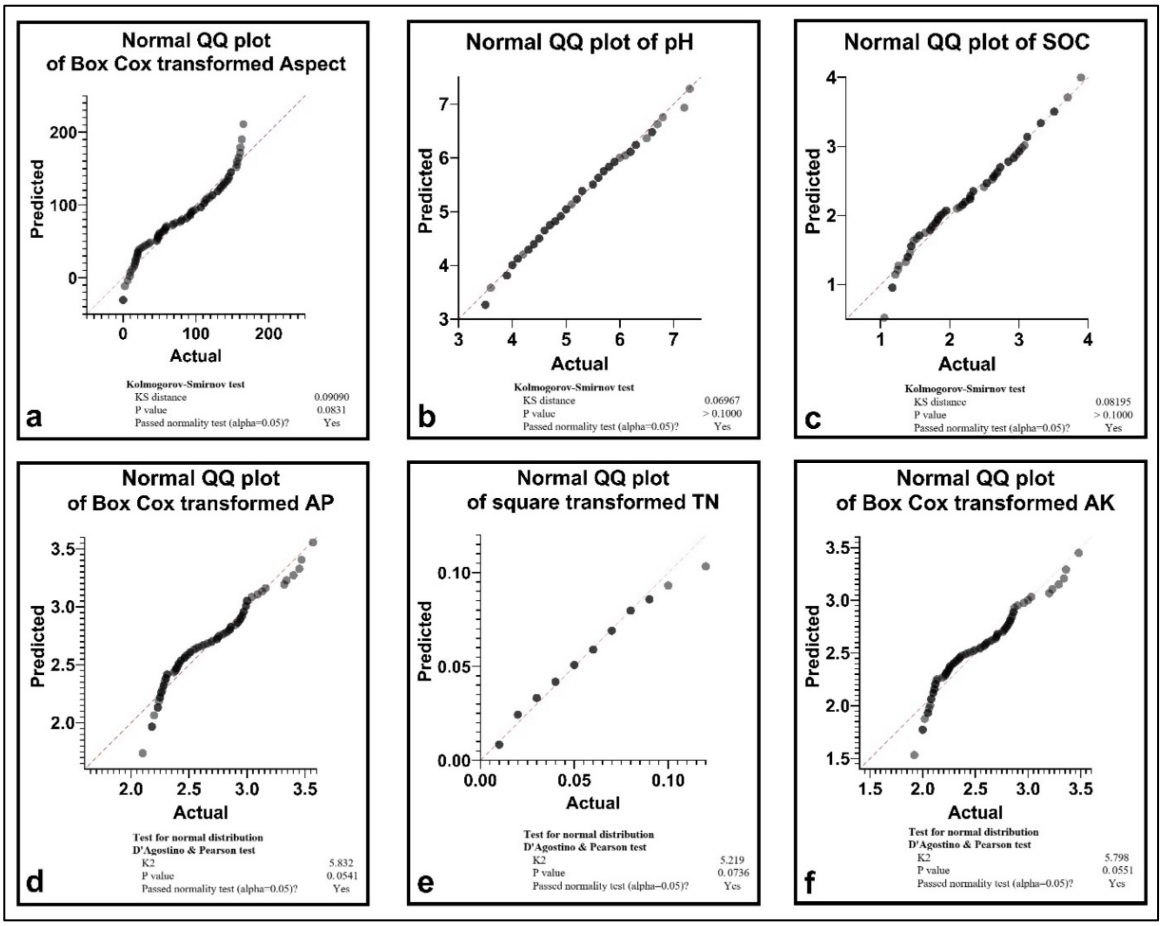

Figure 7: Normal QQ plot of Aspect (a), pH (b), SOC (c), AP (d), TN (e), and AK (f).

4.2. Comparing models using cross-validation

For every soil property the exponential model was used to fit the semi variograms for both OK and OCK. The aspect was used as auxiliary variable for OCK. Concerning IDW, the best weighting parameters were found using the optimizer parameter tools of the Geostatistical Analyst extension of the Arc GIS software. The optimal power value was found to be one for all soil parameters. However, all the three interpolation methods (IDW, OK and OCK) were implemented using the same neighborhood structure divided into four sectors with 45 degree offset including a maximum of five and a minimum of two neighbors per sector as their precision is strongly influenced by the number of the closest neighbors used for estimation (Addis et al., 2016; J. Li & Heap, 2011; Samira et al., 2014).

The cross-validation indicators of all the spatial interpolation techniques tested are shown in table 4. Cross-validation is a commonly used and useful technique for evaluating interpolation methods. The RMSE and MRE provide a measure of interpolation precision, with lower values indicating more precise methods, while the ME measures the bias (Mirzaei & Sakizadeh, 2016). As well, table 5 shows the RI of each method compared to others for each soil property.

Table 4: Cross-validation results of IDW, OK and OCK

Soil property	Interpolation method	Cross-validation results		
		ME	RMSE	MRE
pH	IDW	0.0015	0.7961	0.1543
	OK	0.0011	0.8090	0.1568
	OCK	0.0005	0.7829	0.1517
SOC	IDW	0.0182	0.6910	0.3058
	OK	0.0090	0.6859	0.3035
	OCK	0.0133	0.6845	0.3029
TN	IDW	0.0005	0.0246	0.0016
	OK	0.0004	0.0243	0.0015
	OCK	0.0005	0.0243	0.0015
AP	IDW	-0.0057	0.3615	1.8075
	OK	-0.0002	0.3606	1.8028
	OCK	-0.0017	0.3581	1.7905
AK	IDW	-0.0060	0.3815	0.0303
	OK	-0.0002	0.3805	0.0302
	OCK	-0.0018	0.3779	0.0300

Table 5: Relative improvement of each method

Soil property	Interpolation method 1	Interpolation method 2		
		IDW	OK	OCK
pH	IDW	0.0000	-1.6113	1.6589
	OK	1.5857	0.0000	3.2183
	OCK	-1.6869	-3.3254	0.0000
SOC	IDW	0.0000	0.7441	0.9501
	OK	-0.7496	0.0000	0.2076
	OCK	-0.9592	-0.2080	0.0000
TN	IDW	0.0000	1.1945	1.2075
	OK	-1.2090	0.0000	0.0132
	OCK	-1.2223	-0.0132	0.0000
AP	IDW	0.0000	0.2569	0.9400
	OK	-0.2576	0.0000	0.6848
	OCK	-0.9489	-0.6896	0.0000
AK	IDW	0.0000	0.2654	0.9440
	OK	-0.2661	0.0000	0.6804
	OCK	-0.9530	-0.6851	0.0000

The predictions of the five soil attributes were relatively unbiased as the ME was very close to 0 for all methods and soil properties. The interpolation of soil properties data resulted in a RMSE between 0.7829 and 0.7961 for pH, 0.6845 and 0.6910 for SOC, 0.0243 and 0.0246 for TN, 0.3581 and 0.3615 for AP, 0.3779 and 0.3815 for AK. The best performance was obtained by OCK comparing to other methos for pH, SOC, AP, and AK. For TN, the performance of OCK and OK were similar.

The results of MRE and RI were similar to that of RMSE. Once again, OCK was more accurate than IDW and OK methods, with smaller MRE and best RI for all the soil parameters. However, for TN, OCK was as accurate as OK, and both outperformed IDW method.

Taking all the above-mentioned indicators into account, the OCK showed the best performance for predicting the spatial variation of the five soil properties (pH, SOC, TN, AP, and AK). But for the TN, OK showed the same performance as OCK. In fact, the cross-validation indicators values do not present sharp fluctuations, but the differences obtained between the three methods are sufficient to demonstrate the efficiency of OCK.

These results were consistent with the findings of other researchers. A study in the Northeast Jiaodong Peninsula in eastern China reported that comparing to OK, OCK method were practical and efficient for spatial prediction of soil pH (Fu et al., 2020). Other studies in the Damavand rangelands in northeast of Tehran (Dadgar et al., 2014) and in the Black Sea backward region of Turkey (Göl et al., 2017) showed that the OCK method was the most appropriate model in estimating SOC.

Li and Heap (2011) showed that although the performance of all frequently used interpolation methods is affected by CV, OCK is less sensitive to CV than OK and IDW in terms of RMSE This can be explained by the use of ancillary variable for OCK method. Terrain attributes are the most commonly used auxiliary variables in soil properties mapping (Abdennour et al., 2020). In this study, the topographic aspect was used. As confirmed by many other studies, the contribution of the auxiliary information improves the accuracy of predictions of soil properties (Fu et al., 2020; Gozdowski et al., 2015). According to Gozdowski et al. (2015), interpolation of soil parameters without ancillary variables leads to higher errors of prediction.

4.3. Interpolation

Figures 8 to 12 show the interpolation of the five soil properties using ordinary cokriging method which was the best performer. All these maps were produced at the scale of 1:170,000.

The observed soil pH data had a value from 3.49 to 7.3. Figure 8 reveals that 78 % of the Mana soil has a pH lower than 5.5. According to EthioSIS critical levels for soil reaction in table 1, soils of Mana range from strongly acidic to neutral (EthioSIS, 2014). However, the majority of soils of Mana district are strongly acids. This is expected as it is estimated that about 40% of the Ethiopian cultivated land is affected by soil acidity and aluminum toxicity, and about 28% of these soils are strongly acidic (Golla, 2019; Lelago & Buraka, 2018). This acidity could be due to high tillage frequency, intensive farming over a number of years with use of inorganic fertilizers (especially ammonium based fertilizers), and low amount of organic matter because of erosion or aluminum toxicity (Adugna & Abegaz, 2016; Jemal & Tesfaye, 2020; Nigussie et al., 2013). Soil acidity in humid tropics, is also due to the leaching of basic cations in soils caused by high rainfall conditions, which results in rapid erosion (Adugna & Abegaz, 2016; Golla, 2019). The availability of major nutrients for plants is optimal in the soil pH range between 5.5 and 7.5 (José & Ana, 2017; Samira et al., 2014). This soil acidity and associated low nutrient availability are major constraints to agricultural productivity in acidic soils of Ethiopia, principally Nitisols of highlands (Golla, 2019). The acidic nature of Ethiopian

Nitisols was also reported by (Nigussie et al., 2013). Thus, it is pertinent to consider this soil pH map while advising crop management and fertilization strategies in the study area.

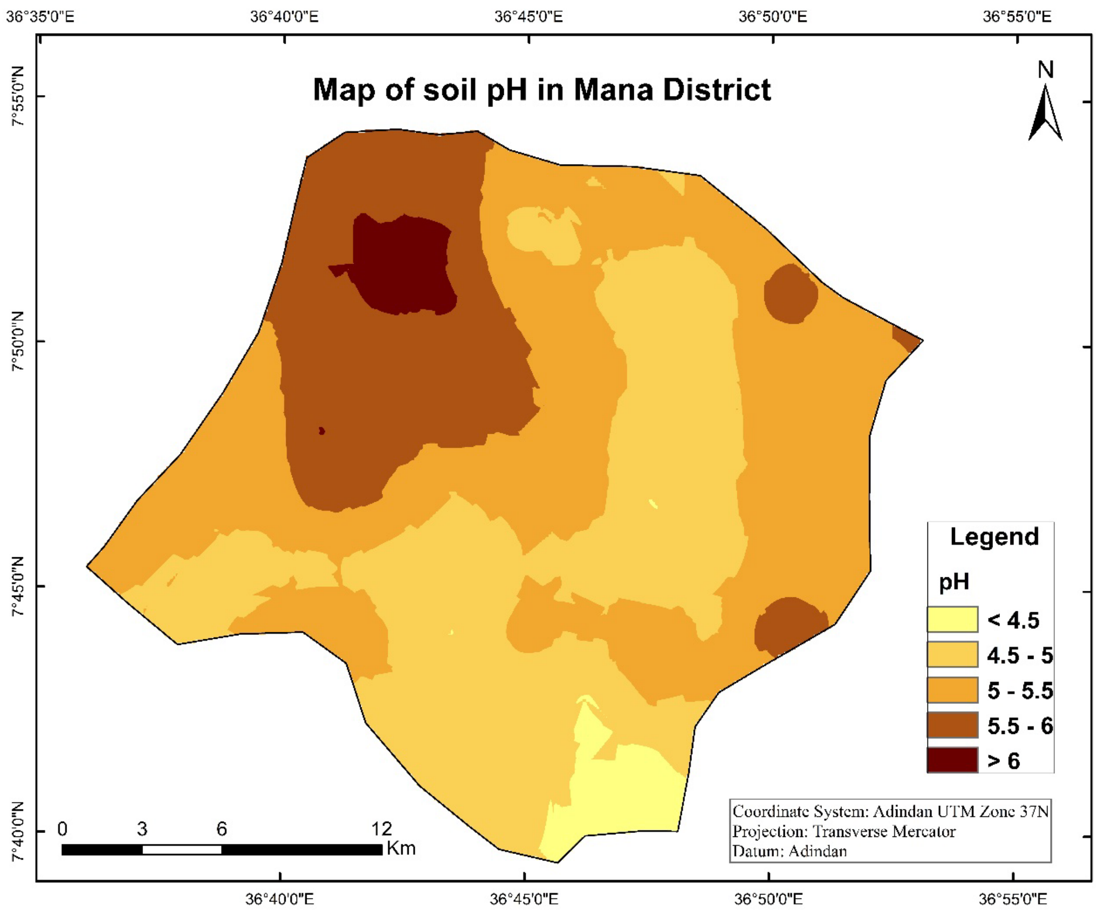

Figure 8: Map of pH in Mana district

Based on the interpolation map of SOC (Figure 9), the entire area of Mana presents a clear deficiency of soil organic carbon with values under 3.5 % (Landon, 1991). The values range from very low to medium levels (EthioSIS, 2014). This could be as a result of inappropriate agricultural practices used by farmers (such as removal of vegetation cover and repetitive harvesting of crops), and losses of soil nutrients caused by soil erosion and slow onsite biological decomposition (Bhunia et al., 2018; Samira et al., 2014). According to Shit et al. (2016), the spatial variability of SOC is mainly influenced by structural factors, such as climate, parent material, topography, soil properties and other natural factors (Shit et al., 2016). Generally, most of cultivated Ethiopian soils have low organic carbon content which is attributed to land use history (Chekol & Mnalku, 2012). The results are in agreement with the findings of (Bibiso, 2017) who reported that intensive cultivation significantly depleted SOC and resulted in reduction of total nitrogen. This depletion in SOC content is likely to affect the productivity of soil.

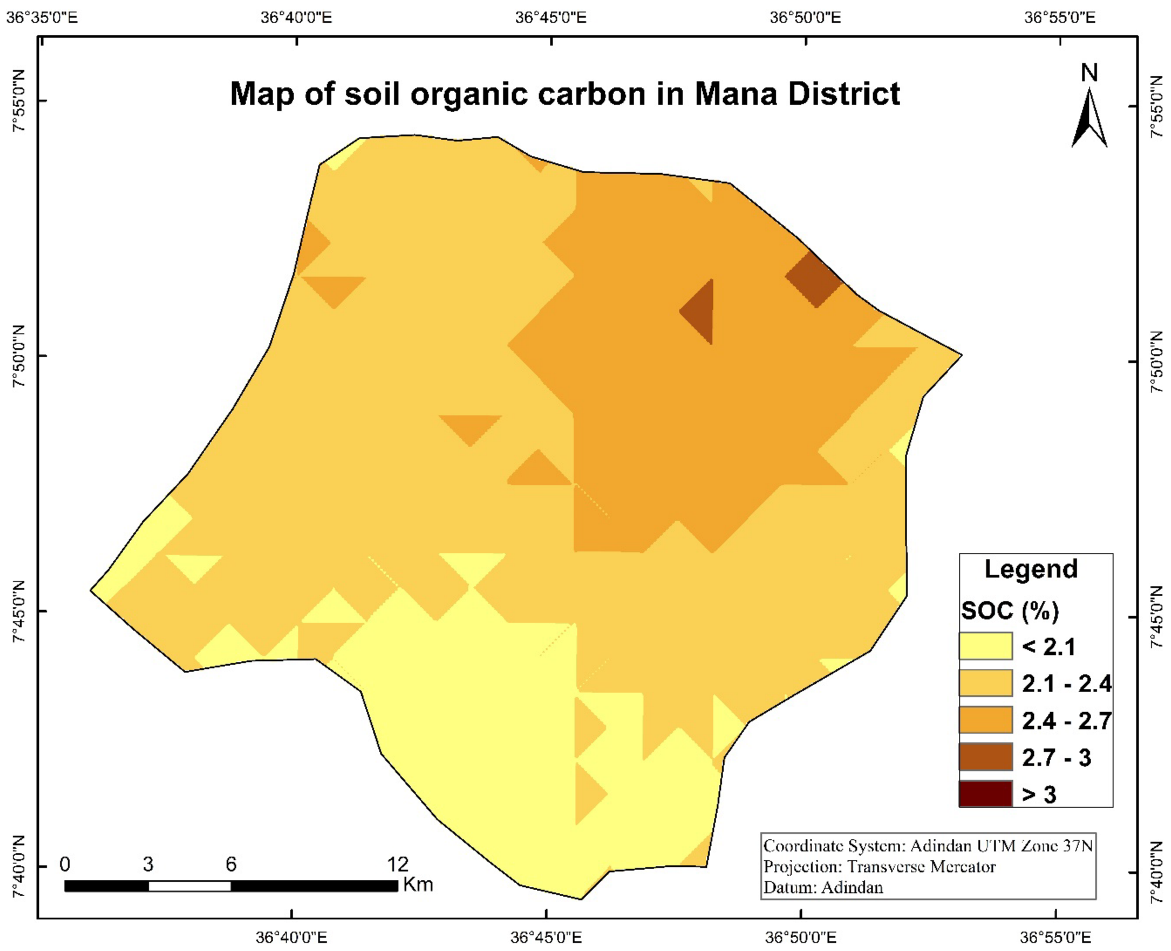

Figure 9: Map of SOC in Mana district

The TN varied widely across Mana district (Figure 10) from the low to medium category (Benton, 2003; EthioSIS, 2014; Landon, 1991) and showed a similar spatial pattern as SOC. This is in accordance with the findings of Lelago & Buraka (2018) and Duan et al. (2020) who reported that the variation of TN is associated with the variation in the amount of available organic matter in the soil. According to Negasa et al. (2017), the significant reduction in TN in the continuously cultivated fields, as it is the case for 86.1% of Mana district (Gabusho, 2019), could be attributed to the mineralization of the organic substrates derived from crop residue whenever added following intensive cultivation; whereas the soil layers with higher organic matter contents had the highest TN content (Negasa et al., 2017). The nitrogen leaching problem can also be another reason for the decline of TN as the area of Mana receives high rainfall. In addition, the study by Mohammed (2003) indicated that the Ethiopian highland soils have low total N content and there is a high crop response to N fertilizers in these soils. Nigussie et al. (2013) also reported the deficiency of nitrogen in the cultivated Nitisol of southwestern Ethiopia.

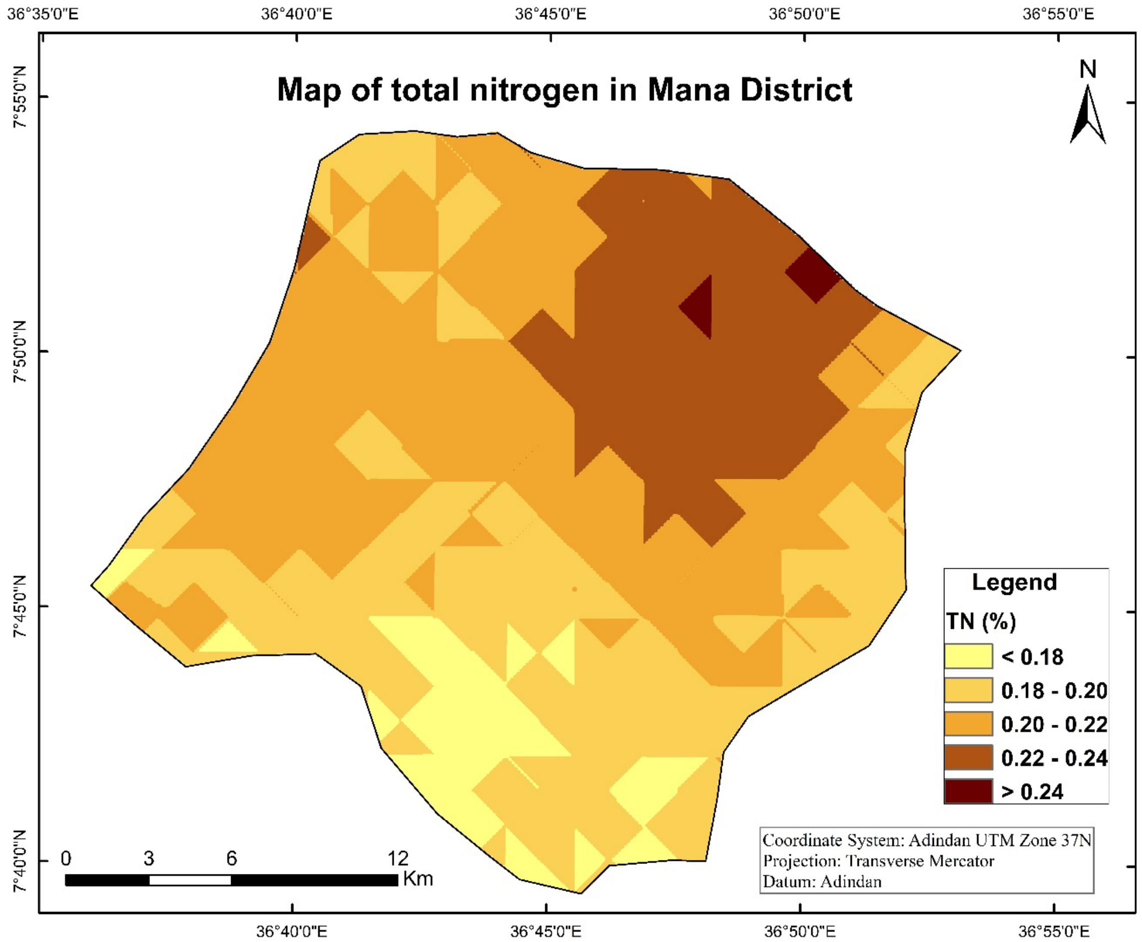

Figure 10: Map of TN in Mana district

The AP content in Mana district, as presented in the interpolated map (Figure 11), ranged from very low to medium (8.37 to 38.08 ppm) according to the ratings of critical levels in Ethiopia (EthioSIS, 2014). Phosphorus is known as the master key to agriculture, since lack of available P in the soils limits the growth of both cultivated and uncultivated plants (Osman, 2013b). In tropical agriculture, P is the most limiting nutrient next to N and this holds true for Ethiopian soils (Negasa et al., 2017). Studies show that the existence of low level of available phosphorus is a common characteristic of most Ethiopian highland soils (Golla, 2019; Lelago et al., 2016). The low availability of phosphorous in Mana area might be due to its fixation by cation such as aluminum (Al) and iron (Fe), as their presence is expected at the favorable acidic soil reaction of the study area (Bibiso, 2017). These findings agree with those of Nigussie et al. (2013) who reported the high phosphorous sorption capacity of Ethiopian Nitisol and the fact that phosphorus availability is related to soil pH. Phosphorus is unique among the anions, as it has low mobility and availability, which is determined by soil pH and exchangeable acidity. In addition, it is difficult to manage because it reacts strongly with both solution and solid phases of the soil (Negasa et al., 2017). For the production of healthy plants and profitable yields, the management need of phosphorus comes second, after the need for the management of N (Brady & Weil, 2017).

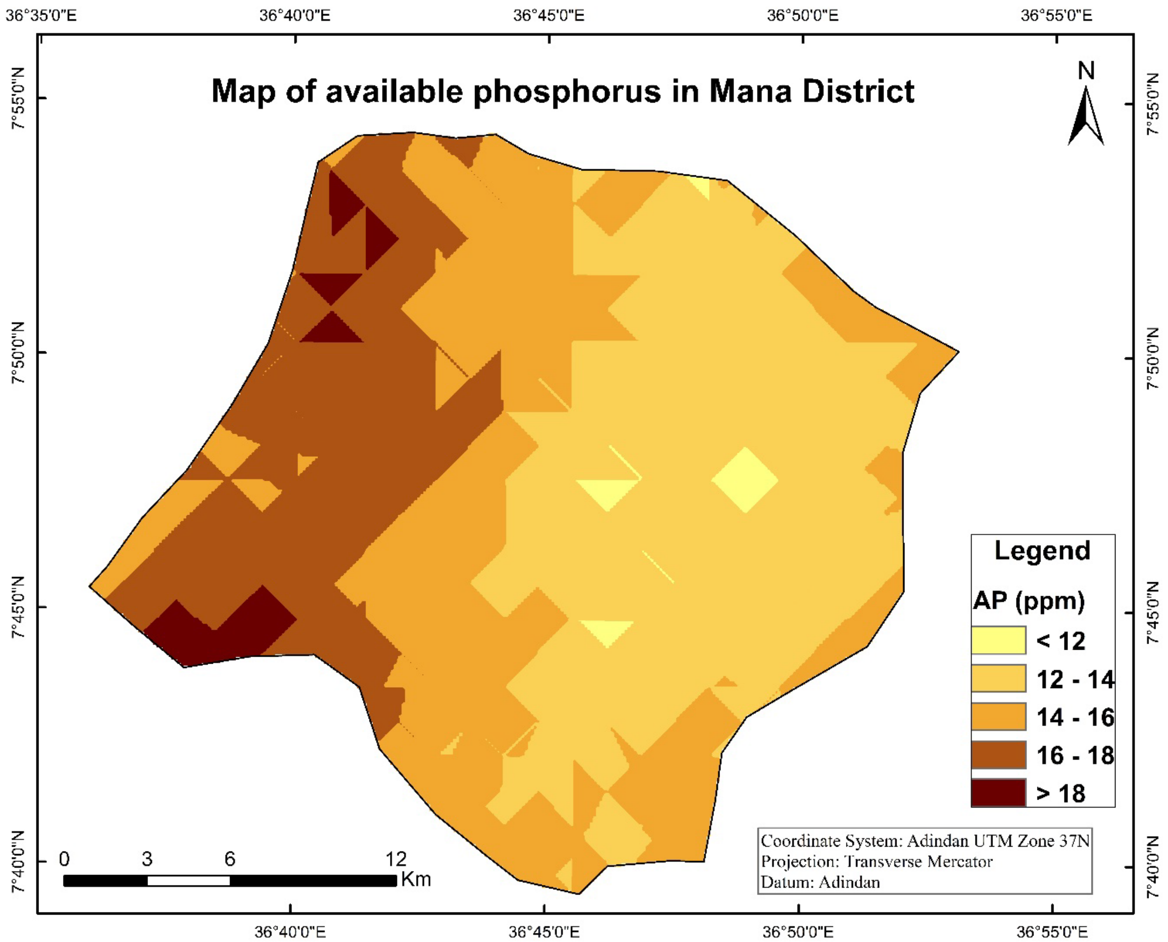

Figure 11: Map of AP in Mana district

The interpolated map of AK (Figure 12) shows that all the soils in Mana district have high level of potassium according to (EthioSIS, 2014), since all values are above 2 cmol/kg (1 cmol/kg = 390 mg/kg). The results were in accordance with the common belief that Ethiopian soils are rich in K (Bibiso, 2017).This means that K availability would not be a limiting factor for crop production in Mana district. These results are supported by the findings of previous studies in Ethiopian highlands (Hailu et al., 2015; Nigussie et al., 2013). However, they contrast with the findings of Laekemariam et al. (2018) in Southern Ethiopia. The potential potassium availability in a soil is great if the proportion of clay minerals, high in potassium, is too (Lelago et al., 2016).

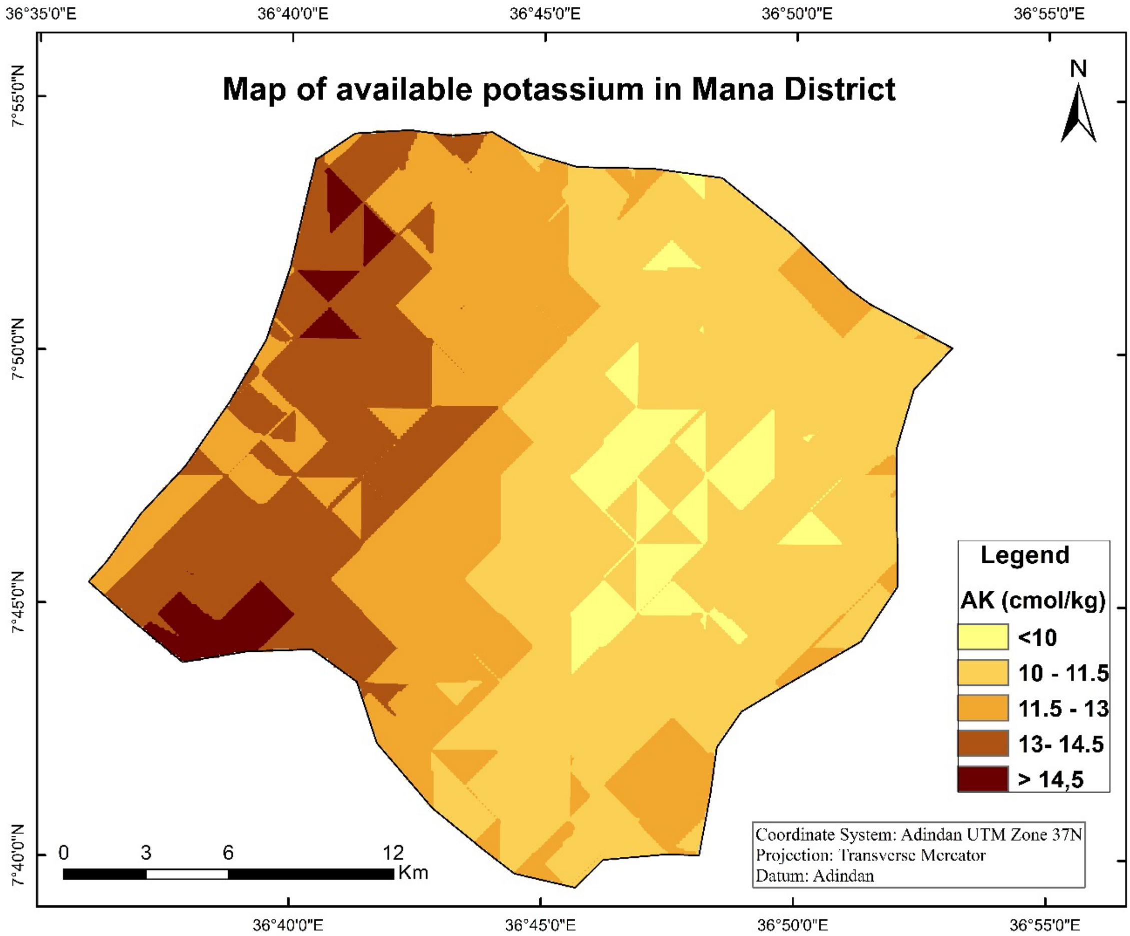

Figure 12: Map of AK in Mana district

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This study analyzed the accuracy of commonly used spatial interpolation techniques (IDW, OK, and OCK) and determined the best performed spatial interpolation method for mapping of five soil chemical properties (pH, SOC, TN, AP and AK) measured from 84 soil samples collected in Mana district in Ethiopia.

Basic summary statistics was undertaken for the exploratory data analysis to uncover underlying patterns of soil attributes that could influence spatial analysis efficiency. On the other hand, the interpolations were assessed in methods using the geostatistical analyst extension of ArcGIS 10.3 software using the geostatistical analyst extension. Cross-validation was used to compare the performance of selected spatial interpolation methods. The exponential semi-variogram was used for OK and OCK, while the optimum weighting parameter of one was used for IDW.

Based on the results obtained, these conclusions follow:

The descriptive statistical analyses revealed that besides the topographic aspect which were highly variable, AP and AK were the most variable soil properties, with CV > 35%; while pH, SOC and TN contents were moderately variable, with CV varying from 16.28% to 30.53%.

The predictions of the selected soil properties were relatively unbiased as the mean errors were very close to 0. When comparing the resulting values of the efficiency criteria (RMSE, MRE and RI) for each interpolation method, the OCK technique was best performed for all the five soil chemical properties. However, for the TN, OK showed the same performance as OCK. This OCK method included the topographic aspect as auxiliary variable to improve the accuracy of the spatial predictions.

Overall, the results of the cross-validation statistics for each spatial interpolation technique showed that however OCK was the most accurate method compared to IDW and OK, there was not sharp fluctuations in values between them.

5.2. Recommendations

Based on the conclusions, the following recommendations were formulated:

- For farmers:

To consider the correction of soil acidity by the different existing methods (by liming the soil, or adding basic materials to neutralize the acid present) as most plants grow well in the pH range between 5.5 and 7.5.

To fertilize their soils on basis of their cultures exigences because it was shown in this study that soils of Mana have deficiencies in SOC, TN and AP.

To use the soil properties maps produced in this study for site management of soil.

- For decision and policy makers who use soil maps as an input in soil management, to consider the influence of the soil maps produced in this study to improve agricultural potential of soils and maximize agricultural production in Mana district.
- Also, future studies in Mana district should consider the different approaches which include diverse spatial interpolation methods, land management practices, land use, and other topographic conditions to improve the efficiency of each spatial interpolation method.

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APPENDIX

Raw results of laboratory analysis of soil samples

SAMPLE CODE	SHAPE	POINT LONGITUDE	POINT LATITUDE	ALTITUDE	ASPECT	pH	%SOC	AP (ppm)	%TN	AK (meq/100 g)
1	Point	36.747923	7.668126	1891	232.13	4.42	1.716	9.98	0.15	7.98
2	Point	36.770574	7.668244	1785	30.07	4.56	2.535	21.13	0.22	16.90
3	Point	36.793224	7.66836	1747	95.19	4.3	3.003	20.08	0.26	16.06
4	Point	36.725153	7.690605	2066	24.44	4.85	1.170	18.14	0.10	14.51
5	Point	36.747804	7.690724	1959	230.71	4.92	1.794	18.95	0.15	15.16
6	Point	36.770456	7.690843	1789	105.95	4.09	1.443	9.26	0.12	7.41
7	Point	36.793108	7.69096	1734	18.43	3.99	3.120	9.74	0.27	7.80
8	Point	36.70238	7.713082	2237	189.46	4.56	2.925	23.15	0.25	18.52
9	Point	36.725032	7.713203	2050	154.44	5	2.613	10.23	0.23	8.18
10	Point	36.747685	7.713323	1996	182.12	4.95	1.392	16.93	0.12	13.54
11	Point	36.770338	7.713442	1913	196.39	3.49	1.443	12.09	0.12	9.67
12	Point	36.792991	7.713559	1906	213.69	5.48	1.260	12.73	0.11	10.19
13	Point	36.634301	7.735308	2476	83.99	4.42	1.248	19.35	0.11	15.48
14	Point	36.656953	7.735433	2454	153.43	5.24	1.833	12.73	0.16	10.19
15	Point	36.679605	7.735557	2349	149.04	6.25	1.478	21.85	0.13	17.48

SAMPLE CODE	SHAPE	POINT LONGITUDE	POINT LATITUDE	ALTITUDE	ASPECT	pH	%SOC	AP (ppm)	%TN	AK (meq/100 g)
16	Point	36.702258	7.73568	2171	108.43	5.25	2.145	19.92	0.18	15.93
17	Point	36.724912	7.735801	2124	29.48	3.9	1.911	9.08	0.16	7.27
18	Point	36.747565	7.735921	1999	127.87	6.03	2.730	11.68	0.24	9.35
19	Point	36.770219	7.73604	2019	30.96	5.85	1.716	9.99	0.15	7.99
20	Point	36.792873	7.736158	1968	315.00	5.78	2.683	29.28	0.23	23.43
21	Point	36.815528	7.736275	1940	185.19	4.3	2.293	9.74	0.20	7.80
22	Point	36.838183	7.73639	2047	278.13	7.2	1.755	31.70	0.15	25.36
23	Point	36.611522	7.757778	2332	25.82	5.88	2.340	16.12	0.20	12.90
24	Point	36.634175	7.757905	2138	308.66	4.29	2.730	19.67	0.24	15.74
25	Point	36.656828	7.75803	2027	13.39	4.5	2.730	20.89	0.24	16.71
26	Point	36.679482	7.758155	2061	62.53	4.54	1.950	16.04	0.17	12.83
27	Point	36.702136	7.758278	2048	23.20	4.76	2.223	16.45	0.19	13.16
28	Point	36.72479	7.758399	2033	102.53	4.03	1.424	17.33	0.12	13.87
29	Point	36.747445	7.75852	1988	347.74	4.45	1.560	10.23	0.13	8.18
30	Point	36.7701	7.758639	1965	358.26	4.49	3.120	14.83	0.27	11.86
31	Point	36.792756	7.758758	1967	26.57	4.1	2.340	10.23	0.20	8.18
32	Point	36.815412	7.758875	2023	83.66	4.69	2.925	10.07	0.25	8.05
33	Point	36.838068	7.75899	2023	135.00	5.27	1.560	12.01	0.13	9.60

SAMPLE CODE	SHAPE	POINT LONGITUDE	POINT LATITUDE	ALTITUDE	ASPECT	pH	%SOC	AP (ppm)	%TN	AK (meq/100 g)
34	Point	36.860724	7.759105	2047	127.15	4.8	1.170	14.42	0.10	11.54
35	Point	36.634048	7.780502	1983	336.80	5.32	1.825	20.48	0.16	16.39
36	Point	36.656703	7.780627	1857	87.44	4.63	1.950	18.14	0.17	14.51
37	Point	36.679358	7.780752	1945	290.56	6.15	1.825	19.27	0.16	15.42
38	Point	36.702013	7.780875	1863	14.04	6.28	2.535	20.32	0.22	16.26
39	Point	36.724668	7.780998	1890	80.54	4.56	1.443	16.28	0.12	13.03
40	Point	36.747325	7.781119	1923	251.57	4.87	2.730	9.50	0.24	7.60
41	Point	36.769981	7.781238	1932	180.00	5.65	2.184	11.68	0.19	9.35
42	Point	36.792638	7.781357	1922	105.26	3.92	3.042	10.39	0.26	8.31
43	Point	36.815295	7.781474	1977	8.97	5.18	3.120	12.25	0.27	9.80
44	Point	36.837952	7.78159	2008	333.43	5.12	1.053	15.31	0.09	12.25
45	Point	36.86061	7.781705	2360	87.88	5.63	1.872	8.37	0.16	6.70
46	Point	36.656577	7.803225	1774	0.00	4.98	3.120	17.74	0.27	14.19
47	Point	36.679233	7.80335	1745	352.87	6.57	3.900	11.52	0.34	9.22
48	Point	36.70189	7.803473	1722	38.66	5.9	1.365	12.65	0.12	10.12
49	Point	36.724546	7.803596	1812	281.31	5.57	2.340	10.15	0.20	8.12
50	Point	36.747204	7.803717	1840	251.57	5.6	1.646	21.05	0.14	16.84
51	Point	36.769861	7.803837	1861	347.01	5.3	3.081	13.38	0.27	10.70

SAMPLE CODE	SHAPE	POINT LONGITUDE	POINT LATITUDE	ALTITUDE	ASPECT	pH	%SOC	AP (ppm)	%TN	AK (meq/100 g)
52	Point	36.792519	7.803956	1892	30.96	4.2	3.315	9.50	0.29	7.60
53	Point	36.815178	7.804074	1874	45.00	5.16	2.535	9.58	0.22	7.67
54	Point	36.837836	7.80419	1914	225.00	5.22	2.293	24.84	0.20	19.87
55	Point	36.860495	7.804306	2181	242.35	5.68	2.106	11.36	0.18	9.09
56	Point	36.656451	7.825822	1597	59.04	4.8	1.213	9.02	0.10	7.21
57	Point	36.679108	7.825947	1657	296.57	5.67	3.510	23.95	0.30	19.16
58	Point	36.701766	7.826071	1664	51.34	5.21	2.496	19.80	0.22	15.84
59	Point	36.724424	7.826194	1703	-1.00	6.83	2.340	33.40	0.20	26.72
60	Point	36.747082	7.826316	1745	180.00	5.56	2.184	13.05	0.19	10.44
61	Point	36.769741	7.826436	1798	81.25	5.75	2.652	15.48	0.23	12.38
62	Point	36.7924	7.826555	1828	84.29	5.29	2.847	9.66	0.25	7.73
63	Point	36.81506	7.826673	1832	100.01	5.15	2.964	10.96	0.26	8.76
64	Point	36.83772	7.82679	1963	213.69	4.71	2.301	10.31	0.20	8.25
65	Point	36.86038	7.826906	1958	307.23	4.6	2.847	11.17	0.25	8.94
66	Point	36.678983	7.848544	1568	225.00	5.5	1.521	9.02	0.13	7.21
67	Point	36.701642	7.848669	1578	270.00	6.45	1.794	20.80	0.15	16.64
68	Point	36.724301	7.848792	1607	251.57	6.6	2.223	34.05	0.19	27.24
69	Point	36.746961	7.848914	1676	270.00	5.01	3.315	10.07	0.29	8.05

SAMPLE CODE	SHAPE	POINT LONGITUDE	POINT LATITUDE	ALTITUDE	ASPECT	pH	%SOC	AP (ppm)	%TN	AK (meq/100 g)
70	Point	36.769621	7.849035	1765	315.00	4.96	1.872	11.52	0.16	9.22
71	Point	36.792281	7.849154	1787	3.81	3.86	3.705	14.10	0.32	11.28
72	Point	36.814942	7.849273	1762	225.00	3.6	2.633	11.44	0.23	9.15
73	Point	36.837603	7.84939	1921	288.43	7.3	3.510	38.08	0.30	30.47
74	Point	36.678857	7.871142	1493	213.69	6.06	2.297	20.32	0.20	16.26
75	Point	36.701518	7.871267	1511	303.69	6.3	2.535	13.62	0.22	10.90
76	Point	36.724178	7.87139	1596	270.00	6.67	3.120	30.01	0.27	24.01
77	Point	36.746839	7.871513	1514	33.69	3.5	1.170	11.28	0.10	9.02
78	Point	36.7695	7.871634	1624	168.69	5.2	2.691	9.83	0.23	7.86
79	Point	36.792162	7.871754	1712	225.00	5.49	2.340	12.41	0.20	9.93
80	Point	36.814824	7.871872	1675	335.85	4.88	1.739	18.02	0.15	14.42
81	Point	36.678731	7.893739	1517	170.54	6.2	3.003	20.89	0.26	16.71
82	Point	36.701393	7.893864	1449	180.00	5.48	1.443	17.99	0.12	14.39
83	Point	36.724055	7.893988	1485	341.57	5.03	1.392	11.28	0.12	9.02
84	Point	36.746717	7.894111	1473	315.00	5.6	2.633	9.83	0.23	7.86