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SOIL SALINITY MAPPING AND RISK ASSESSMENT USING REMOTE SENSING AND GIS: THE CASE OF WONJI SUGAR CANE IRRIGATION FARM

By

ENGDAWORK ASFAW

A Thesis Submitted to
The School of Graduate Studies of Addis Ababa University Presented in Partial Fulfillment to the Requirements for the Degree of Masters of Science in Earth Science (Remote Sensing and Geographic Information System)

Addis Ababa University
Addis Ababa, Ethiopia
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This is to certify that the thesis prepared by Engdawork Asfaw, entitled: ***Soil Salinity Mapping and Risk Assessment using Remote sensing and GIS: the case of Wonji Sugarcane Irrigation farm*** and Submitted in partial fulfillment of the requirements for the Degree of Master of Science (Remote Sensing and Geographical Information Systems) compiles with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

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ABSTRACT

Soil salinity is one of the most damaging environmental problems worldwide, especially in arid and semi-arid regions. The aim of this study was to assess the risk of soil salinity in Wonji sugarcane irrigation farm and to develop effective combined remote sensing based statistical regression models to predict and map spatial variation of soil salinity. Different spectral indices were calculated from original bands of landsat images. Statistical correlation between field measurements of Electrical Conductivity (EC), spectral indices and landsat original bands showed that the Salinity Index (SI) had the highest correlation with EC. Combining these remotely sensed variables into one model yielded the best fit with R^2 = 0.78. The result obtained from SI was not only in area wise, but also the level of salinity. Out of the total area, 18.8 and 23 % was identified as moderately and slightly saline respectively. The prediction model that was obtained from the regression analysis was used to derive a salinity map and estimate EC level for the 1985, 1995 and 2012 landsat images. The result of SI shows moderately and slightly saline soils were increased by 10 and 14 ha/yr respectively. The Spatial Overlay model was also developed from ground water table, elevation, geology, soil texture and vegetation density. Three classes have been identified with varying degree of salinity and the result showed about 36% of the study area is non-saline where as 30% and 33.7% is moderately and slightly saline respectively. In spatial overlay salinity model, the class of moderately saline soils was found in the areas underlain by the lacustrine Sediments and shallow ground water level. It is evident that the areas highly vulnerable to salinization greatly related to the ground water level that normally occurred on the lacustrine sediment. The spatial distribution of salt affected area derived from SI and spatial overlay model were similar pattern but of in different extent. The validation of the two models has been carried out by the existing EC values referenced to the same locations by making linear regression to test their predication capability and hence remote sensing soil salinity prediction model has revealed better correlation coefficient of 63 % to the measured ECe. The spatial overlay analysis between salt affected areas and canal and water table was made to assess the spatial distribution as well as the relationship with these features. It was revealed that the spatial distribution was not highly influenced by the features considered except ground water table. The results demonstrate that modeling and mapping spatial variation of soil salinity based on remote sensing data is a promising approach.

Keywords: EC, prediction model, spatial overlay, salinity model, SI

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ABBREVIATIONS

BI	Brightness Index
DEM	Digital Elevation Model
ECe	Electrical conductivity of the saturation extract of soil
ESP	Exchangeable Sodium Percentage
ETM+	Enhanced Thematic Mapper plus
FCC	False Color Composite
GIRDC	Generation Integrated Rural Development Consultant
GIS	Geographic Information System
Ha	Hectare
IRS	Indian Remote Sensing
MSS	Multi-Spectral Scanner
NDSI	Normalized Difference Salinity Index
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
OWWDSE	Oromia Water Works Design and Supervision Enterprise
PCA	Principal Component Analysis
PH	Power of Hydrogen
RGB	Red, Green, Blue
TCC	True Color Composite
TM	Thematic Mapper
USDA	United State Department of Agriculture
VSSI	Vegetation Soil Salinity Index
WSSE	Wonji Shoa Sugarcane Estate

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Soil salinization is the process of enrichment of a soil in soluble salts that results in the information of salt affected soil. Soil salinity in irrigated areas is becoming a serious problem for agriculture. Saline soil conditions have resulted in reduction of the value and productivity of considerable areas of land throughout the world. Salinity commonly occurs in irrigated soil because of the accumulations of soluble salts introduced from the continuous use of irrigation waters containing high or medium quantity of dissolved salts (Jingwei *et al.,* 2008).

The main problems associated with arid and semi-arid regions are salinization and desertification. Soil salinization is a major form of land degradation in agricultural areas, where information on the extent and magnitude of soil salinity is needed for better planning and implementation of effective soil reclamation programs. Salt affected soils and associated problems are most pronounced in arid and semi-arid regions, which offer considerable promise for development as major food producing regions, because of their frequent potential for multiple cropping. Irrigation evaporation of moisture from the surface or shallow depths within the profile and the insufficient annual rainfall to leach down salts from the plant rooting zone favour excessive accumulation of soluble salts in soils of arid and semi-arid regions, rendering such lands to have been used by human beings with only marginal success since the advent of agriculture (Abdelfattah *et al.,* 2009).

Excess salts in the root zone of soils in the arid and semi-arid climates are a worldwide phenomenon. However, the most serious salinity and sodacity problems are being faced in the irrigated arid and semi-arid regions of the world and it is in these regions that irrigation is essential to increase agricultural production to satisfy food requirements. Soil salinity is also a serious problem in areas where groundwater of high salt content is used for irrigation. On the other hand, irrigation is often costly, technically complex and requires skilled management. Failure to apply efficient principles of water management may result in wastage of water through seepage; over watering and inadequate drainage resulting in waterlogging and salinity/sodicity problems, which reduce the soil productivity, eventually leading to loss of cultivable land. Thus, development of technology to control and mitigate salinity and sodicity is particularly an important issue for modern agricultural management, especially for countries such as Ethiopia where arid and semi-arid climatic zones occupy over 60% of the total land area (OWWDSA, 2007).

Soil salinity has resulted in limiting natural resources and agricultural land use. It is a severe environmental hazard that impacts the growth of many crops. Salt affected areas are extended on all the continents. Statistics about the extent of world salt affected soils differ; however, general estimates are close to 1 billion hectares. In addition to these naturally salt affected, around 77 million hectares have been saline as a consequence of human activities (secondary salinization). These areas on average represent 20 % of the world's irrigated lands where as this figure in arid and semiarid countries increase to more than 30 % (Newr *et al.,* 2013).

According to Tamirie Hawando (1994), Salt affected surfaces have increased from 6% to 16% of the total land of Ethiopia in recent years. About 9% of the population lives in the areas affected by salinity. The semi-arid and arid lowlands and valleys in Ethiopia have major problems of salinity and alkalinity, about 44 million ha 36% of the country's total land is potentially susceptible to salinity problems. Out of the 44 million ha, 33 million ha have dominantly salinity problems, 8 million ha have combined salinity and alkalinity problems, and 3 million ha have dominantly alkalinity problems

1.2 Statement of the problem

Nowadays, soil salinity is an increasing environmental problem throughout the world. The global extent of primary salt affected soils due to natural factors is ~955 Million ha, i.e., ~7% of the Earth's continental extent, whereas secondary salinization as a consequence of human activities affects some 77 Million ha Salt excess in soils has detrimental effect on crop yields and agricultural production due to poor land and water management and results in substantial losses of arable soils, especially in the arid and semiarid areas.

Furthermore, salinity also affects other major soil degradation phenomena such as soil dispersion, increased soil erosion, and engineering problems (Metternicht and Zinck, 2003).

In Ethiopia, approximately 11 million ha land is salt affected. These areas are mainly concentrated in the Rift Valley, Wabi Shebelle River Basin and various other lowlands and valley bottoms. Similar reports also indicate that a considerable extent of area of land has been abandoned for cultivation due to the prevalence of salt affected soils in the Middle Awash. The Awash river valley specifically in the locations of Melka Sedi plains and Abadir farm the first problems of soil salinity is considered as irrigation induced because of a rising water table due to unbalance of irrigation and natural drainage capability. Another critical regional environmental problem is over irrigation, and their subsequent salinization of fertile soils in the Rift, being more prominent in the irrigation fields in the middle and lower Awash River valleys. The region's high temperature (average annual temperature of 26.7°C), low rainfall (500 mm annually) and high evaporation rate exacerbate the salinization process (Fentaw Abegaz, 2007).

Development of large scale irrigation projects without functional drainage system and appropriate water management practices have led to gradual rise of saline ground water in the Middle Awash region. In effect, development of persistent shallow saline groundwater, capillary rise due to high evaporation and concentration of the soil solution together with the natural some seeps contributed to secondary salinization (Girma and Fentaw, 1996). The ground water level within the sugar estate shows a rising tendency. However, not only within the sugar cane plantation but in the whole region a rise of the water table has been reported .This might be due to irrigation (seepage losses out of reservoirs and channels, over watering) but also due to seepage losses in a great extent from the Lake Koka reservoir. Groundwater level fluctuation at Wonji sugarcane plantation investigations showed that on some fields the groundwater table is less than one meter deep (Dinka and Ndambuki, 2013).

According to Wagari *et al.* (2011), rise in groundwater level has recently become a serious concern at Wonji irrigation field, a concern for possible loss of irrigable land and increase in soil salinity. If grows exceedingly beyond its natural flow, groundwater flooding will be inevitable (Smith, 2008) as cited in (Wagari *et al.*, 2011).

This can cause difficult and unhealthy environment that enhance ecological and environmental damage. Likewise, if the shallow groundwater at Wonji wetland continues growing, land flooding by groundwater will take place that result in loss of the productive lands by increasing soil salinity. This problem can possibly be transformed into economic and social crises. Thus, knowledge of hydrological systems and clear definition of natural recharge and discharge systems including geology of the area as well as ensuring effective use of irrigation water are essential to avoid such possible environmental hazards.

However, soil salinity is quite time and space dynamic since salinization is the consequence of different complex processes of salt redistribution that depend on natural conditions, system features, agricultural practices and drainage management. In addition, observing the returns and benefits of drainage takes such a long time (often more than 25 years) that instantaneous measurements of salinity do not reflect current condition (Jingwei *et al.*, 2008).Observation of many irrigated areas in the world also shows that waterlogging and salinization typically appear only 10 to 50 years after the beginning of the project, depending on the initial depth and recharge rate of the water table and on drainage conditions.

Therefore, large scale and multi temporal studies of salinity, especially in long term changes in salinity in the past, help to understand the nature of salinization and to evaluate the effectiveness of salinity control practices. GIS and remote sensing techniques have become tools for the purpose of identifying and classifying saline soils. Using such technique has given a good indication of its accuracy, cost effectiveness, speed, and labor saving for delineating salt affected soils in most efficient manner. The integration of remote sensing data, in the form of satellite imagery, with GIS has boosted up the ability of delineating and mapping soil salinity. Large numbers of studies have proven that remote sensing is a useful and promising method to identify salt affected soils, especially those with moderate and high salinity (Jabbar and Zhou, 2012). Therefore, the proposed study is taken up to estimate and analyze the salinity level of Wonji sugarcane irrigation farm.

1.3 Objectives

1.3.1 General objective

The general objective of this study was to assess the risk of soil salinity in Wonji sugarcane irrigation farm and to develop effective combined remote sensing based statistical regression models to predict and map spatial variation of soil salinity.

1.3.2 Specific objectives

- To model salt affected areas in Wonji sugarcane irrigation farm with the application of salt indices and vegetation index.
- To assess the soil salinity change during the period from 1985, 1995 and 2012.
- To assess the spatial distribution of salt affected soils with respect to different parameters (Ground water table, elevation, soil texture, Vegetation density and geology).
- To develop soil salinity risk map of the study area.

1.4 Significance of the study

The result of this research provides fast, timely, relatively cheap as compared to conventional soil salinity detection method. Hence, time series data of remote sensing plays an important role in detecting, mapping and monitoring salt-affected soil using remote sensing and GIS in a promising approach, it allows decision makers to decide what necessary action should be taken in the early stages to prevent soil salinity from becoming prevalent. Spatial data generated by this study used as additional input for development of a decision support on soil salinity mapping and modeling to guide decision makers on how to harmonize and conserve uses for proper irrigation management to protect the area from salinity. Generally the output of the study contribute as a methodological and empirical of the significance of GIS and remote sensing for the assessment and mapping of soil salinity risk in a given area.

1.5 Organization of the study

The research was organized in to six chapters; the first chapter contains background of the study, statement of the problems. In addition, it briefs about the basic questions, objectives. The second chapter deals with review of related literature. This part addresses the relevant literature that is very much associated with the research topic. Hence, it is the background of the Study which is used as a springboard to sketch the direction of the study. It includes; the various arguments on the application of remote sensing and GIS for soil salinity detection and mapping, different theories on the vegetation and soil salinity index modeling and it deals about the factor that contribute the occurrence of soil salinity. The third chapter explains the materials and methods. It clearly indicates the type of methodology used data sources and the different tools and software's. The fourth chapter will be vastly concerned with interpretation, analysis and presentation the output maps. Fifth chapter includes result and discussion. Finally, the last chapter covers conclusion and recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Soil salinity

Soil salinization is one of the most widespread land degradation processes that substantially limit crop productivity, and thus the food security. Soil salinity refers to the surface or near surface accumulation of salts expressed in Electrical Conductivity (EC) of a solution extracted from a water saturated soil paste. According to the US Salinity Staff Laboratory, soils with conductivity of the saturation extract (EC) > 4 dS/m at 25°C, Exchangeable Sodium Percentage (ESP) < 15 and pH (soil reaction) < 8.5 are referred to saline soils (USDA,1954). Salt in the soil mostly derives from the weathering of rocks and primary minerals, which formed transported by water or wind. Other causes of soil salinity are topography, irrigation and dry land salinity, which occur due to forest clearance, overgrazing and cutting bushes that cause water tables to rise and bring saline groundwater close to the land surface. Thus, soil salinity categories are either primary salinity which is naturally occurring or secondary salinity which is human induced. Soil salinity is a prevalent environmental hazard in arid and semiarid regions around the world (Hillel, 2000).

The United Nations Food and Agriculture Organization (FAO) has estimated that saline soil covered 397 million hectares of the total land area of the world. Africa, Asia, Australia, Europe, Latin America, Near East and North America are the most affected areas (Koohafkan, 2012).

Soil salinity adversely affects plant growth, crop production, soil and water quality and it eventually results in soil erosion and land degradation. Soil salinity impacts are not limited only to the environment but also extend to the economy. For instance, the economic losses due to secondary salinization in Batinah region in Oman have been estimated at US$ 1604 ha^{-1} (28%) when the salinity increases from low to medium level and US$ 4352 ha^{-1} (76%) if it jumps from low to high level (Naifer *et al.,* 2011*).*

Basically, soil salinity is a dynamic process with severe consequences for the soil, hydrological, climatic, geochemical, agricultural, social, and economic aspects. Therefore, for greater development and implementation of sufficient soil reclamation programs and preventing any further salinization to sustain agricultural lands and natural ecosystems, information on the spatial extent, nature and distribution of soil salinity is becoming very essential. Thus, timely detection of soil salinity, monitoring and assessment of its severity level and extent become very important in its beginning at local and regional scales.

Conventionally, soil salinity has been measured by collecting in situ soil samples and analyzing those samples in the laboratory to determine their solute concentrations or electrical conductivity. However, these methods are time consuming and costly since dense sampling is required to adequately characterize the spatial variability of an area (Brunner *et al.*, 2007).

Remote sensing data and techniques have been progressively applied to monitor and map soil salinity since 1960s when black and white and color aerial photographs are used to delineate salt affected soils. Multispectral data such as Landsat, SPOT, IKONOS, Quick Bird and the Indian Remote Sensing (IRS) series of satellites, as well as hyper spectral data such as EO-1 Hyperion have been found to be useful in detecting, mapping and monitoring soil salinity (Farifteh, 2007; Dehni and Lounis, 2012).

Generally, remote sensing uses the electromagnetic energy reflected from targets to obtain information about the Earth's surface with different levels of detail. So based on this concept, the spectral reflectance of salt features at the soil surface has been widely studied using remote sensing and used as a direct indicator for soil salinity detection and mapping. However, when the soil moisture is high or the crust salt is invisible on the soil surface or mixed with other soil constituents, this direct approach becomes complicated and may yield unreliable results since these factors influence the soil spectral reflectance. But, the present scattered vegetation on the soil surfaces can serve as a sign of the salinity problem, making it possible to indirectly detect and map areas that are affected by soil salinity using the reflectance from vegetation. Normally, unhealthy vegetation has a lower photosynthetic activity, causing increased visible reflectance and the reduced near infrared reflectance (NIR) from the vegetation (Weiss *et al.,* 2001). This pattern has been found in various plants subjected to salinity stress. Therefore, based on this finding, several vegetation indices (VIs) such as Normalized Differential Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) have been used as indirect indicators to assess and map soil salinity. Similarly, a number of researchers have developed different salinity indices to detect and map soil salinity such as Normalized Difference Salinity Index (NDSI) and Salinity Index (SI).

2.2 Application of remote sensing for soil salinity detection

Ground based electromagnetic measurements of soil EC are generally accepted as the most effective method for quantification of soil salinity. Unfortunately, these methods are expensive, time consuming and need considerable human resources for land surveying. Moreover, the dynamic nature of soil salinity and sodicity in space and time makes it more difficult to use conventional methods for comparisons over large areas (IDNP, 2002). However, advances in computer and information technology have introduced new group of tools, methods, instruments and systems. Rapid developments in new technologies such as Remote Sensing and Geographic Information System provide new approaches to meet the demand of resource related modeling of soil salinity (Aksoy *et al.,* 2009).

Remote sensing is one of the key tools in monitoring local, regional and global environmental issues. More recently, much attention has been paid to spatial analysis due to the merging of geographic information system and satellite images for environmental research applications. Remote sensing can also significantly contribute to detecting salt related surface features and has been used for soil salinity mapping in recent times(Jabbar *et al.,* 2012).

However, quantitative results of soil salinity from remote sensing applications are difficultly achieved without plenty of auxiliary data such as groundwater depth and groundwater mineralization rate, which are insufficient and difficult to obtain, especially in remote arid area (Metternicht and Zinck, 2003).The integration of remote sensing data in the form of satellite imagery with the GIS has boosted up the ability of delineating and mapping soil salinity. It made many researchers of this field in recent years to follow such approach with different methods and applications, but salinity is a dynamic process. Therefore, two important aspects are needed to be accomplished in order to monitor it, delineating the salt affected soils and detecting the temporal and spatial changes in this occurrence (Nwer *et al.*, 2013).

2.2.1 Vegetation index for soil salinity detection

Vegetation index is a common spectral index that identifies the presence of chlorophyll. Various crop indices have been derived using the fact that chlorophyll strongly absorbs the light energy in the red part and highly reflects in the near infrared part. Accordingly, numerous researchers have conducted studies on the mapping and delineation of soil salinity using different Spectral Vegetation Indices (SVI). Among the vegetation indices, NDVI, SAVI, Ratio Vegetation Index (RVI) and Tasseled Cap Transformation that consisted of the Soil Brightness Index (SBI), Green Vegetation Index (GVI), and the Wetness Index (WI) have been used in soil salinity studies (Matinfar *et al.*,2013; Jabbar and Chen, 2008; Dehni and Lounis, 2012). Due to absorption in the visible range and high reflectance in the NIR range of the electromagnetic spectrum, the NDVI has been widely used to map soil salinity by monitoring halophytic plants (Elnaggar and Noller, 2009; Jabbar and Chen, 2008). The difference in reflectance between the visible and NIR bands is divided by the sum of the two band reflectance. This normalizes differences in the amount of incoming light and produces a number from −1 to 1; the range of actual values is approximately 0.1 for bare soils to 0.9 for healthy vegetation (Deering and Rouse, 1975) as cited in (Allbed and Kumar, 2013).

In Mexico, Fernandez- Buces *et al.* (2006) found a significant correlation between NDVI, EC and SAR. Moreover, Perez Gonzalez *et al.* (2006), have correlated the NDVI of halophytic vegetation with the spatial variability of the chemical and physical properties of transect to identify saline hydromorphic soils. Their results showed the NDVI to be very proper in detecting halophytic plant and relating it to saline soils. Additionally, Bannari *et al.* (2008) have stated that because of plant growth declines due to soil salinity, salt stress could be predicted using the NDVI.

However, researchers such as Metternicht and Zinck (1997); Koshal (2010) argue that detecting soil salinity using the NDVI is challenging because the presence of vegetation could cause spectral confusion with the reflectance properties of salt and also because the NDVI is considered an unreliable indicator, as it is also correlated to other yield variables such as chlorophyll content, biomass and leaf area.

According to Liu and Huete (1995) as cited in Allbed and Kumar (2013) have developed a modification of the NDVI to reduce the atmospheric and canopy background noise, the enhanced soil and atmosphere resistant vegetation index (EVI). A comparison study of the efficiency of the EVI and NDVI calculated from Multiyear Moderate Resolution Imaging Spectro radiometer (MODIS) imagery for assessing soil salinity in the Red River Valley, United States has been conducted by Lobell *et al.* (2010). They found that the EVI is a more reliable indicator of salinity than the NDVI. The use of the RVI to measure the spectral reflectance of soybean canopy and elephant grass under different salinity and irrigation treatments was investigated by Wang *et al*. (2002). The results showed that the canopy spectral reflectance in the NIR region was reduced as salinity level increase.

The effectiveness of this index for soil salinity detection and mapping has been studied by several researchers. For example, in the United Arab Emirates (UAE) Alhammadi and Glenn (2008) used the SAVI index for detecting date palm health under soil salinity. They found that the SAVI values decreased with increasing soil salinity; for instance, the SAVI value was 0.155 at the lowest salinity level of 6900 parts per whereas the value decreased to 0.104 at the very high salinity of 41,000 ppm. These results showed the potential of using the date palm, which is a halophytic plant, as an indirect indicator of soil salinity as well as the effectiveness of the SAVI in detecting plant stress related to severe salinity and thus permitting the identification and mapping of saline areas indirectly.

2.2.2 Soil salinity index

Similarly, various spectral salinity indices have been developed for salt mineral detection and mapping. Douaoui *et al.* (2006) have proposed three salinity indices produced from SPOT XS imagery to detect and map soil salinity hazards in a semi-arid environment in Algeria. They found that those indices were strongly correlated with measured values, but considerably underestimated the salinity of areas with high levels of surface salt. Besides, Khan *et al.* (2005) have proposed three spectral salinity indices, the Brightness index (BI), Normalized Difference Salinity Index (NDSI) and

Salinity Index (SI) from the LISS-II sensor of the IRS-1B satellite to assess hydro saline land degradation in Pakistan. Among these indices, they found that NDSI yielded the most acceptable results in identifying different salt classes.

Another study conducted by Vidal *et al*.(1996) as cited in Allbed and Kumar (2013) looked at salinity by differencing vegetated from non-vegetated areas using NDVI; then the BI was computed to identify the moisture and salinity status of fallow land and deserted fields. Furthermore, three different salinity indices, SI-1, SI-2SI-3 from the EO-1 ALI spectral bands, have been proposed by Bannari *et al.* (2008) to discriminate slight and moderate soil salinity and sodicity in Morocco. Although the results showed that SI-3 had the highest correlation (46.9%), the result from this index was not adequate to provide precise information. Therefore, they devised another two Soils Salinity and Sodicity Indices (SSSI). Their results indicated that these SSSI indices were likely to increase the identification accuracy in areas with low and medium salinity because they offered the most significant correlation (52.9%) with the ground EC measurement.

Moreover, Abbas and Khan (2007) have suggested an integrated approach based on the spatial analysis of both ground and satellite data to assess soil salinity. Remotely sensed data based salinity indices and a Principal Components Analysis (PCA) was developed to detect soil salinity. Their result showed that out of the six salinity indices S3 produced the most promising result compared to ground measurements, they concluded that PCA and salinity indices are promising techniques for soil salinity prediction based on satellite images.

Looking at these vegetation and soil salinity indices in the literature, a number of results stand out. Utilizing vegetation indices in the assessment and mapping of soil salinity in areas of densely vegetated soils will yield promising results, whereas on bare soils, the identification of salt based on vegetation indices will not work. Thus, soil salinity indices will be the appropriate method in the case of bare soils or soils with very low scattered vegetation cover, providing super results.

These observations are in agreement with Bouaziz *et al.* (2011), who found that vegetation indices such as SAVI, NDVI and EVI had a low correlation with EC due to an insufficient density of vegetation cover, whereas soil salinity indices exhibited higher correlations with EC. Additionally, Fan *et al.* (2012) found that NDVI values had a significant negative relationship with soil salinity in soils covered by vegetation, whereas this relationship was not clear on bare soil.

2.2.3 Salt features at the soil surface reflectance

The dynamic processes at the surface of saline soil limit the monitoring and assessment of the salinization process because they influence the spectral, spatial and temporal behavior of the salt features (Metternicht and Zinck, 1997).The physical chemical properties of soil such as soil moisture content, organic matter, soil texture, types of clay color and surface roughness soil spectral reflectance is determined (Dematte *et al.*, 1996) as cited in (Allbed and Kumar, 2013).

Due to salinity these soil properties change which affect the spectral reflectance of features that occur at the soil surface, including salt crusts and efflorescence besides variations in surface texture and structure. For example, Schmid *et al.* (2008) as cited in Allbed and Kumar (2013) found that crusted saline soil reflects strongly in the visible and near infrared (NIR) bands. Moreover, Panah and Zehtabina (2002) noted that a crusted saline soil surface is generally smoother than a non-saline surface and exhibits high reflectance in the visible and NIR bands.

On the other hand Metternicht and Zinck (1997), found that the reflectance in the visible and NIR bands is highly affected by both the crust color and surface roughness factors. Despite the effects of salt features on the soil surface on the spectral reflectance, they have been considered good direct indicators of soil salinity. For example, Fernandez Buces *et al.* (2006), used surface features to predict soil salinity. They found that the correlation coefficient between surface colors, EC and the sodium adsorption ratio (SAR) were statistically significant, which suggested that efflorescence color is a promising surface indicator with which to estimate soil salinity.

2.2.4 Soil Salinity Modeling using Remote Sensing

An integrated approach using remote sensing in addition to various statistical methods has great potential for developing soil salinity prediction models. In the case of soil salinity, statistical analysis, in particular linear regression has created a tremendous potential among other techniques for improvement in the way that soil salinity is modeled, because of its rapid, practical and cost effective manner (Weiss, 2010).

A variety of statistical models based on remote sensing data has been developed and has revealed reasonable predictors of soil salinity. For example in Thailand, Shrestha, (2006), developed several salinity prediction models containing spectral variables, including Normalized Difference Vegetation Index (NDVI), Normalized Difference Salinity Index (NDSI), the eight original bands of Landsat Enhanced Thematic Mapper plus (Landsat ETM+) and soil properties. The results indicated that mid infrared (band 7) and near infrared (band 4) had the highest association with the measured EC. Combining these variables yielded salinity prediction models to infer soil salinity over a large area.

In contrast, Mehrjardi *et al.* (2008), found that among the Landsat ETM+ bands 1–5 and 7, band 3 (red band) had the highest correlation with EC and based on that result, a regression model fitted to relate EC to band 3 and the exponential relation was found to be the best type of model. A regression model based on image enhancement techniques (spectral indices, Principal Components Analysis (PCA) and Tasseled Cap Transformation (TCT)) have also been extensively used to predict soil salinity and to improve the characterized variability of salinity.

Combined Principal Components Analysis (PCA) techniques and regression analysis to predict and map soil salinity from data collected by the Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) at the north of the Aq-Qala Region in northern Iran. From this study, a suitable regression model was developed with electrical conductivity (EC) to predict and map soil salinity (Tajgardan *et al.*, 2007). Other researchers found that incorporating satellite images spectral bands with enhanced images has great promise for soil salinity modeling and mapping. Bouaziz *et al.* (2011), conducted a study to detect soil salinity based on the Moderate Resolution Imaging Spectro radiometer (MODIS) and a multiple linear regression.

They found that incorporating Salinity Index SI2 with near-infrared (NIR) (band 3) into a statistical model allowed researchers to gain great insight into the spatial detection of the spread of soil salinity.

2.3 Groundwater associated soil salinity

In discharge areas of the landscape, water exits from groundwater to the soil surface bringing the salts dissolved in it. The driving force for upward movement of water and salts is evaporation from the soil plus plant transpiration. Generally, the water table in the landscape is at or very close to the soil surface and soil properties at the site allow a maximum rate of water movement through the surface layers. Salt accumulation is high when the water table is less than 1.5 m below the soil surface (Rengasamy, 2006). However, this threshold depth may vary depending on soil hydraulic properties and climatic conditions. Unpredicted environmental problems could arise when the consumptive water demand of crop and water supplies mismatch. This could cause abnormal hydrological flow situation such as rising of shallow groundwater table induced by excess recharge from irrigation, a condition which violates the natural recharge discharge system of the watershed environment (Furi *et al.,* 2011).

2.4 Irrigation associated soil salinity

Irrigation is fundamental for economic development and plays a vital role in improving the welfare of a society. However, irrigation is not always a blessing as it can create problems due to mismanagement of land and water, which results in salinization of land and water resources, as well as adverse environmental damage. The world's demands for food is increasing at such a rate that the ability to meet anticipated needs in the next several decades is becoming questionable. Irrigated agriculture presently accounts for about one third of the world's production of food and it is anticipated that it will need to produce nearly 50 percent by the year 2040. This will likely be difficult, because extensive areas of irrigated land have been increasingly becoming degraded by salinization and waterlogging resulting from over irrigation and other forms of poor agricultural management (FAO, 1988).

According to Rengasamy (2006), Salts introduced by irrigation water is stored within the root zone because of leaching. Poor quality irrigation water, low hydraulic conductivity of soil layers as found in heavy clay soils and sodic soils and high evaporative condition accelerate irrigation induced salinity. Use of highly saline effluent water and improper drainage and soil management increase the risk of salinity in irrigated soils.

In many irrigation regions, rising saline groundwater interacting with the soil in the root zone can compound the problem. Al-Khaier (2003) stated that, salts will tend to accumulate on the soils as a result of evaporation. With this in mind; it was thought that those areas showing a deficit in the difference between precipitation and potential evapotranspiration would eventually help in further discriminating salt affected soils. Such a consideration has its basis on the fact that whenever there is excess in the aforesaid relationship, salts will less likely accumulate because they will be washed away more easily.

2.5 Multispectral satellite sensors for mapping and monitoring soil salinity

Extensive research using satellite imagery for mapping and monitoring soil salinity has been conducted over the last three decades, mostly with multispectral sensors. These include Landsat Thematic Mapper (TM), Landsat Multispectral Scanner System (MSS), Landsat Enhanced Thematic Mapper Plus (ETM+), SPOT, Advanced Space born Thermal Emission and Reflection Radiometer (Terra-ASTER), Linear imaging self-scanning sensor (LISS-III) and IKONOS. For example, in the United States of America (USA) Elnaggar and Noller (2009) used Landsat TM imagery integrated with decision tree analysis (DTA) to map soil salinity in central Malheur County. They found that there was a significant relationship between EC values and reflectance in Landsat bands 1, 2, 3 and 4 as well as the Brightness (BI) and Wetness (WI) indices, Maximum likelihood supervised classification was used to classify the image into non-saline soils (EC < 4 dS/m) and saline soils, with accuracies of 97% and 60% respectively, whereas DTA predicted five classes of soil salinity with an overall accuracy of approximately 99%. Their results indicated that the use of Landsat TM imagery effectively identified bare soils that were characterized by high spectral reflectance due to a high salt content on the surface, and the approach of integrating

DTA with remote sensing data was more accurate and effective compared to using remote sensing analysis alone.

Many researchers, including Nwer *et al.* (2013); Jabbar, *et al.* (2012); Katawatin and Kotrapat, (2005) have investigated the utility and effectiveness of ETM+ data for soil salinity mapping and monitoring. For example, Katawatin and Kotrapat (2005) investigated the use of landsat 7 ETM+ with different combinations of three sources of ancillary data (topography, geology, and underground water quality) for soil salinity mapping. A maximum likelihood classification method was employed in this study. Their results showed that the use of landsat ETM+ data bands 4, 5 and 7 in combination with all three types of ancillary data yielded the most accurate soil salinity map, with 83.6% overall accuracy. According to Douaoui *et al.* (2006); Farifteh (2007); Eldeiry and Garcia (2008), agreed that an integrated approach using remote sensing techniques in addition to ancillary data such as field data, topography and spatial models geophysical surveys can improve the development of high quality soil salinity maps.

Using multispectral sensors for soil salinity research has also been studied by Goossens *et al.* (1993). Their study examined and compared the accuracy of landsat TM, MSS and SPOT XS imagery for soil salinity mapping. They found that landsat TM was optimal for soil salinity mapping.

Another comparative assessment of the suitability of multi sensor data for soil salinity studies was conducted in Pakistan by Ahmed and Andrianasolo (1997) as cited in Allbed and Kumar (2013). They compared the performance of landsat TM and SPOT XS in mapping salinity at a semi-detailed level. Their results were completely opposite to that of Goossens *et al.* (1993).They found that the SPOT XS data were more helpful than landsat TM as it provided finer details of various thematic variables.

2.6 Application of Remote sensing and GIS for waterlogging

Excess soil moisture can cause a change in soil color and a change in soil reflectance properties, which can be easily detected by remote sensing. Plant response is a more accurate means of detecting poorly drained soils in California mainly because of a buildup of the water table. He also indicated that due to the accumulation of organic matter, soil color is generally darker in poorly drained areas than well drained soils (IDNP, 2002).

Moreover, Baber (1982) as cited in IDNP (2002) pointed out that color infrared photography could indicate drainage problems by soil moisture saturation or plant stress. Shallow water tables exhibit an increase in surface moisture, which can be detected from visible reflectance and microwave emissivity. The information about drainage basin area and drainage pattern can be obtained from satellite imagery. GIS helps in assessing waterlogging and drainage problem by identifying the drainage network and its characteristics in a basin, besides the information on the presence of high water table, high morphology, soil color, plant stress and drainage water collection in lower spots. Waterlogging has a number of effects on plant and soil processes (physical, chemical and biological) that can significantly affect crop production and productivity (Dinka and Ndambuki, 2013).

CHAPTER THREE

3.1 Description of the study area

Wonji irrigation farm established in 1954 is one of the largest commercial farms in Ethiopia which irrigates about 8000 ha of land by diverting Awash River to the irrigation field. Wonji Sugar Estate lies downstream of the Koka Dam in the Central Rift Valley of Ethiopia in the Awash River Basin, 110 km southeast of Addis Ababa and 10 km south Adama road. Geographically, it is bounded by latitude 8°21'00"−8°29'00" N and longitude 39°12'00"−39°18'00"E (Fig 3.1) with the total study area of the estate is 6,162.8 ha, from these 5,905.13 ha is under cultivation, while 257 ha are occupied for canals, roads and living quarters.

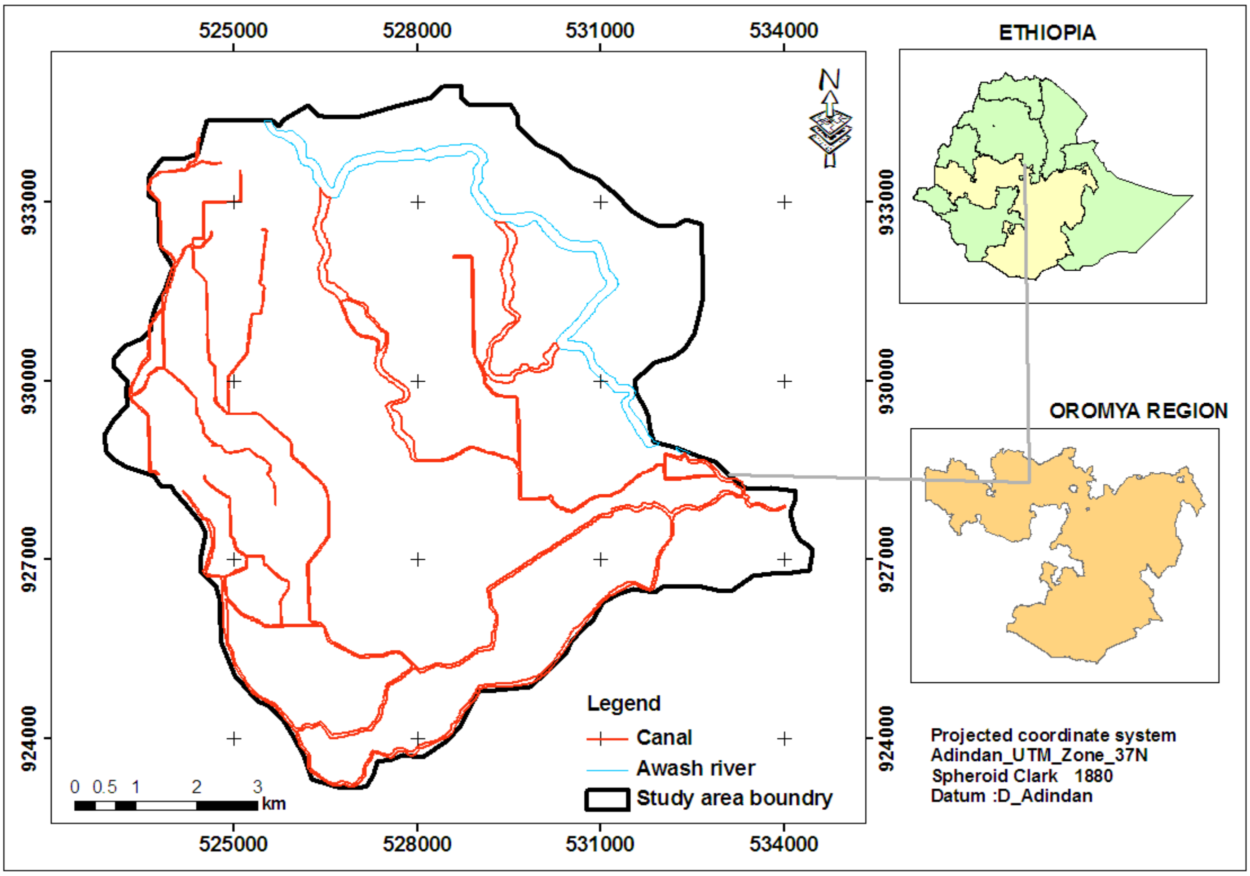
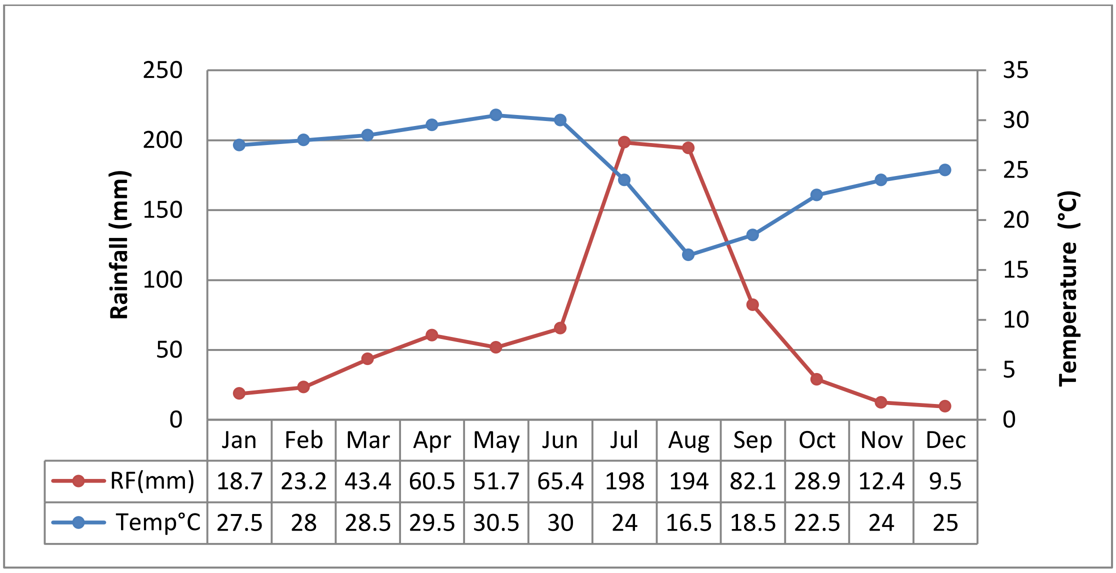


Figure 3. 1 Location map of the study area.

3.1.1 Climate

The Wonji Irrigation Scheme is found at an altitude of approximately 1,500 m asl. The slope of the farm is very gentle and regular. It has a semi-arid climate; it receives an average annual rainfall of 831.2 mm, and peak daily evapotranspiration of the area is 4.5 mm and mean annual maximum and minimum temperatures of 27.6°C and 15.2°C, respectively (Fig 3.2).



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
RF(mm)	18.7	23.2	43.4	60.5	51.7	65.4	198	194	82.1	28.9	12.4	9.5
Temp°C	27.5	28	28.5	29.5	30.5	30	24	16.5	18.5	22.5	24	25

Figure 3. 2 Mean annual temperature and Rainfall of the study area.

3.1.2 Geology

The geological framework of Wonji sugarcane irrigation is part of the geological architecture of the MER (main Ethiopian rift) which was propagated during the Miocene Quaternary period. The main features of these geological and structural events are the intersecting and interrupting features of several fault systems with interacted volcanic products. Localized piles of basaltic flows and caldera are widespread in the area, which are associated with extensive faults and fractures, important for groundwater recharge. The lacustrine rift sediment is contemporaneous with the Wonji volcanic, mainly of volcano, clastic sediments and tuffs with silts, clays and diatomite, silts and clays are the dominant ones. Alluvial deposits are also common in the area, in some cases mixed with volcano clastics (Alula *et al*, 1992).

3.1.3 Soil

The major predominant soil types in the area of Wonji sugarcane plantation are described as Fluvisols, Andosols and Laptosols according to FAO soil classification. Soils of Wonji are alluvial colluvial origin developed under hot, tropical conditions. In the region diverse soil types are observed which also vary in their production potential. In general, soils of Wonji can be described as a complex of grey cracking clays in the topographic depressions and semiarid brown soils. On the basis of texture they are categorized into light (coarse textured) soils and heavy soils (clayey black types) which are more common in Wonji Sugarcane Plantation (Ambachew and Girma, 2000).

3.1.4 Irrigation water management

Irrigation water is diverted to the irrigation canals from the Awash River using eight centrifugal pumps, which operate continuously for 24 hour. Irrigation usually persists for 8 hour, hence excess pumped water is stored in different night storage reservoirs (7 main and 12 tertiary) distributed across the plantation. There are networks of irrigation and drainage canals of varying sizes and carrying capacities. There are also different hydraulic (small canal) structures such as distribution tanks, flow divisors, a Romjan weir, road crossings, turnouts, canal falls, regulating and measuring structures. The irrigation system consists of a complex network of canals of varying sizes, 480 m masonry-lined primary canals, 77 km (very big) secondary canals and 198 km (small and medium) tertiary canals. The network of the drainage system consists of about 200 km of canals (collectors, laterals, border and main drains). That means that the irrigation systems transport water for a considerable distance (from the Awash River to individual fields), while drainage systems carry away water not used by plants back to the Awash River (Dinka and Ndambuki, 2013).

3.1.5 Land-use/land-cover

According to local witnesses and other reports the Wonji Plain and surrounding plateaus were rich in vegetation cover before the introduction of irrigated agriculture into the region (in the 1950s). Different categories of land-use/land-cover (LUC) conditions were present with a variety of animal and plant species. The area was mostly known as grazing land for semi pastoralists.

Over the past five to six decades, the Wonji area has undergone a significant change in its land use land cover conditions. Most of the grazing lands were changed to agriculture; forests were destroyed by the in-migrants from other parts of Ethiopia (mostly from the south) because of the job opportunities created. Changes in LUC (due to the Koka Dam construction, irrigation development, settlement, etc.) have resulted in unwanted consequences of eviction of pastoralists from their wet grazing lands, conflicts between different societies (ethnic groups and clans), and drought insecurity due to loss of access to the river (Dinka and Ndambuki, 2013).

3.2 MATERIALS and METHODS

3.2.1 Data type and sources

To achieve the objective in this study various data sets of both primary and secondary raster and vector data were collected and used. Primary geographic data sources are captured specifically for use in GIS by direct measurement. While, secondary sources are those reused from earlier studies or obtained from other systems. Accordingly, Primary data, Landsat satellite image having spatial resolution of 30m (Path 168 and row 054), soil data are used (Table 3.1).

Table 3. 1 Data type and sources.

Data type	Path and row	Date of acquisition	Spatial resolution(m)	Data source
Landsat TM	168/054,168/054	1985	30×30	www.usgs.gov
		1995		
Landsat ETM+		2012		
Soil data		2012		WSSE
PH				GIRDC
EC				
Soil texture				
Ground water depth data		2007_2009		WSSE
Toposheet	0839C1 and C2			EMA

3.2.2 Software utility

In order to achieve the intended objective the following materials and soft wares were used in this study at various stages. Arc GIS, 10 Erdas Imagine11, ENVI 4.7 and JMP statistical software Version 11 were used to develop salinity modeling, correlation and statistical graph preparation (Table 3.2).

Table 3. 2 List Software used for the Study.

Type	Name	Utility
Software	ERDAS Imagine 11 and ENVI 4.7	Image processing and data analysis
	Global Mapper	Terrain visualization
	ArcGIS 10	Database creation, dataset preparation, overlay analysis, map and lay out preparation.
	MS Office 2010	Documentation, statistical analysis and presentation
	JMP statistical software Version 11	Used to develop salinity modeling, correlation and statistical graph preparation.
	Stata/SE version 11	Multivariate Analysis

3.3 Methods

This study used different analyses which involves Remote Sensing analysis for salinity change detection, GIS assisted spatial modeling, regression analysis and finally validation and comparison of the methods were used. The study was aimed at determining the feasibility of using remote sensing and geographical information system to map soil salinity directly from bare soil, indirectly from vegetation and salinity change analysis using satellite images. It involves the integration of thematic layer such as geological information, elevation, ground water table level, soil texture and Vegetation density in mapping soil salinity.

3.3.1 Modeling vegetation and salinity indices

In salinity and sodicity mapping, vegetation can be used as an indirect indicator of salt affected soils and hence stressed vegetation could be an indirect sign for the presence of salt in the soils. Salt affected soils are usually characterized by poorly vegetated areas and such state of stressed vegetation could be and indirect sign of the presence of salt in the soils. Six indices were used, which is Salinity Index (SI) and Normalized Difference Salinity Index (NDSI) Brightness index (BI), Normalized differential vegetation index (NDVI), Vegetation Soil Salinity Index (VSSI) and soil adjusted vegetation index (SAVI) used to discriminate and map salt affected soil (Table 3.3). SI is the ratio of red band to near infrared (NIR) band while NDSI is the ratio of the difference of the red to NIR and divided by the summation of the two. SI, NDSI, BI, NDVI, VSSI and SAVI are computed as follows.

Table 3. 3 List of soil salinity and vegetation index model.

No	Index Name	Formula	Reference
1	Salinity Index (SI)	$\sqrt{Band3 * Band4}$	Dehni and Lounis (2012)
2	Brightness index(BI)	$\sqrt{B3^2 + B4^2}$	Khan *et al.* (2005)
3	Normalized Difference Salinity Index (NDSI)	[(Band 3 - Band 4) / (Band 3 + Band 4)]	Khan *et al.* (2005)
4	Vegetation Soil Salinity Index (VSSI)	2 * band2 – 5 * (band3 + band4)	Dehni and Lounis (2012)
5	Normalized differential vegetation index (NDVI)	[(Band4 – Band3) / (Band3 +Band4)]	Khan *et al.* (2005)
6	Soil adjusted vegetation index (SAVI)	SAVI=(1+L)Band4-Band3/L+Band4+Band3	Alhammadi and Glenn (2008)

Accordingly using the selected index Soil salinity model was developed using Landsat image of 2012 and measured ECe data. To develop the model for soil salinity levels mapping from satellite images, spectral reflectance and ECe sampling points were used. Identification of the location of sampling point on satellite image was executed. The corresponding reflectance of soil samples from different sampling zones were retrieved for different bands and indices. Prediction model for SI versus salinity level (ECe) was prepared using regression analysis.

3.3.2 Mapping spatiotemporal salinity change

Soil salinity changes were analyzed by mapping salt affected soils of 1985, 1995 and 2012 from landsat ETM+ image through best correlate salinity index. Temporal and spatial distribution of saline soils of the area for the specified time period was assessed to infer the effect of irrigation on soil salinity rise.

3.3.3 Spatial overlay of environmental factors

Soil salinity in wonji sugarcane irrigation farm was assessed by correlation and spatial overlay of different factors, which contribute to soil salinity as a result of their interaction. These are geological formation, elevation, ground water level, and soil texture and vegetation density (NDVI). Hence, determining the spatial soil salinity potential of wonji sugarcane irrigation farm by integrating GIS functionalities to investigate the interaction of ground water level, elevation, geological information, soil texture and vegetation density is very crucial. Details of the methodology were presented in (Fig 3.3).

Finally Validation of the models was done by plotting the ECe value with the corresponding raster values of salinity map generated from selected remote sensing index and spatial overlay salinity model of the five layers on scattered diagram. Then, the best fit line and equation determines the most accurate prediction of soil salinity modeling and mapping.

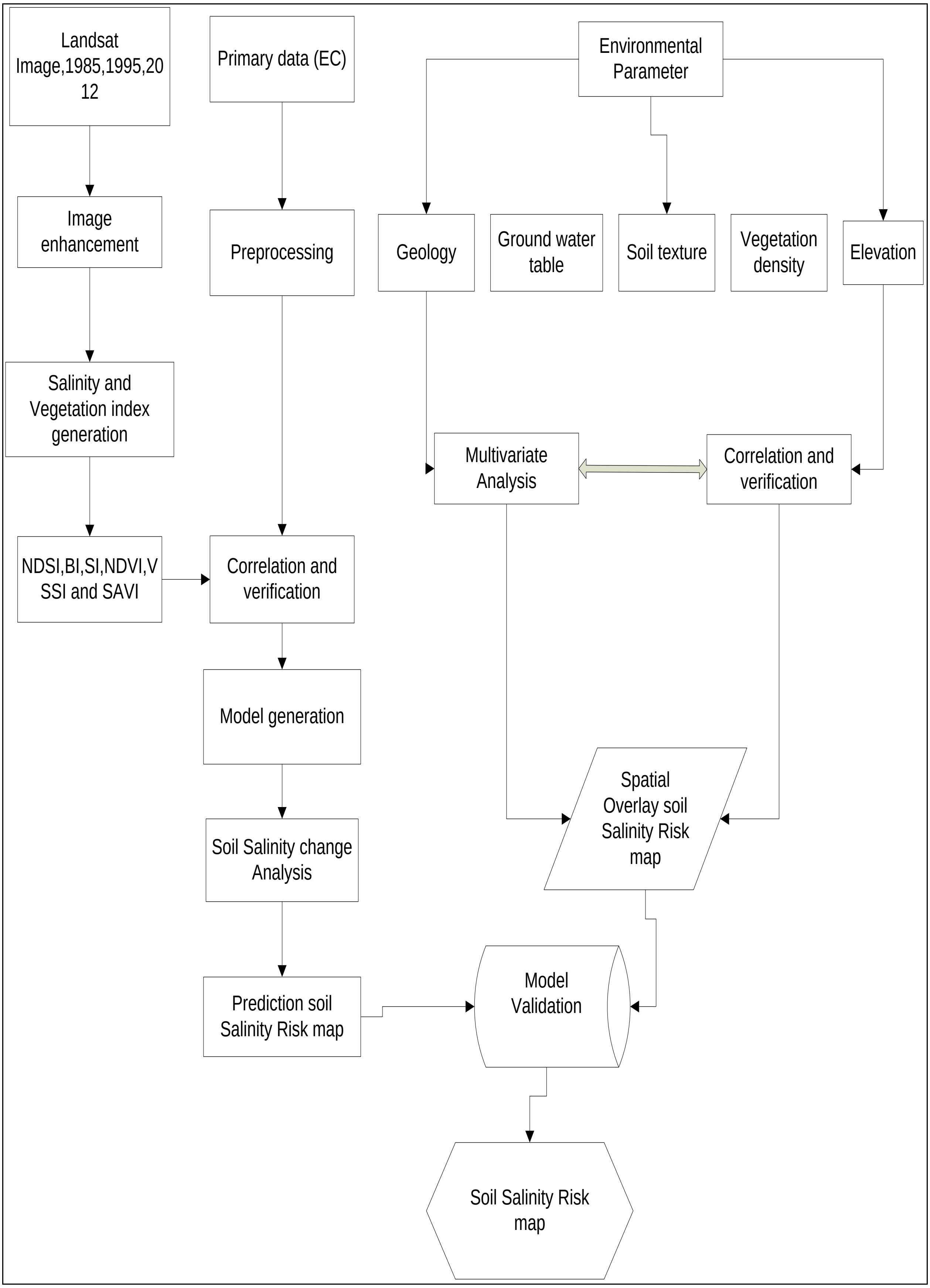


Figure 3. 3 Methodology flow chart

CHAPTER FOUR

DATA ANALYSIS

4.1 Data collection and preparation

Landsat images covering the period from 1985, 1995 and 2012 were acquired for the study area. Layer staking was made for all six bands excluding the thermal band. Geometric correction for the three Landsat images was accomplished using topographic map of the study area. The Landsat images were registered to the topographic map using control points, which were easily recognizable on the satellite image. Image enhancement was made to improve the interpretability of the images. All maps in this study were projected to UTM Zone 37 North using Adindan as a datum. Salt affected areas were clearly identified from other features by higher reflectance in many bands. However, it was difficult to differentiate salt affected area from sand soils. Therefore, sample sites that were identified as salt affected were used for image analysis, followed by model site verification. Topographic maps, 1: 50,000, that were used in digitizing thematic layers for the overly analysis. Soil map, 1:10,000 and geology map, 1:250,000 of the area were obtained from FAO soil classification and Geological Survey of Ethiopia respectively. To assess the spatial distribution of salt affected area with respect to ground water table, the piezometric data were collected and interpolated to generate a continuous surface. For the purpose of interpolation, a total of 32 piezometric data distributed throughout the study area were used.

4.1.1 Band selection and true and false color composite

In this research, band selection was done through the analyses of reflectance properties of features, correlation matrix of the bands and spectral reflectance curve of known features in all bands. Spectral profile was generated from the image using ERDAS Imagine 11. To increase the accuracy of image interpretation and classification of different feature class, band selection was done through the analyses of reflectance properties of features. To enhance visual interpretability of salt affected areas from the satellite image and classification of other features, various color compositions was tested. True color composition and other three false color composition were found to be helpful for feature discrimination from the satellite images. True color composition and one false color composition (TCC: 3-2-1 and FCC: 4-3-2) were found to be the best combination for identification of different features for landsat ETM +images of the study area (Fig 4.1).

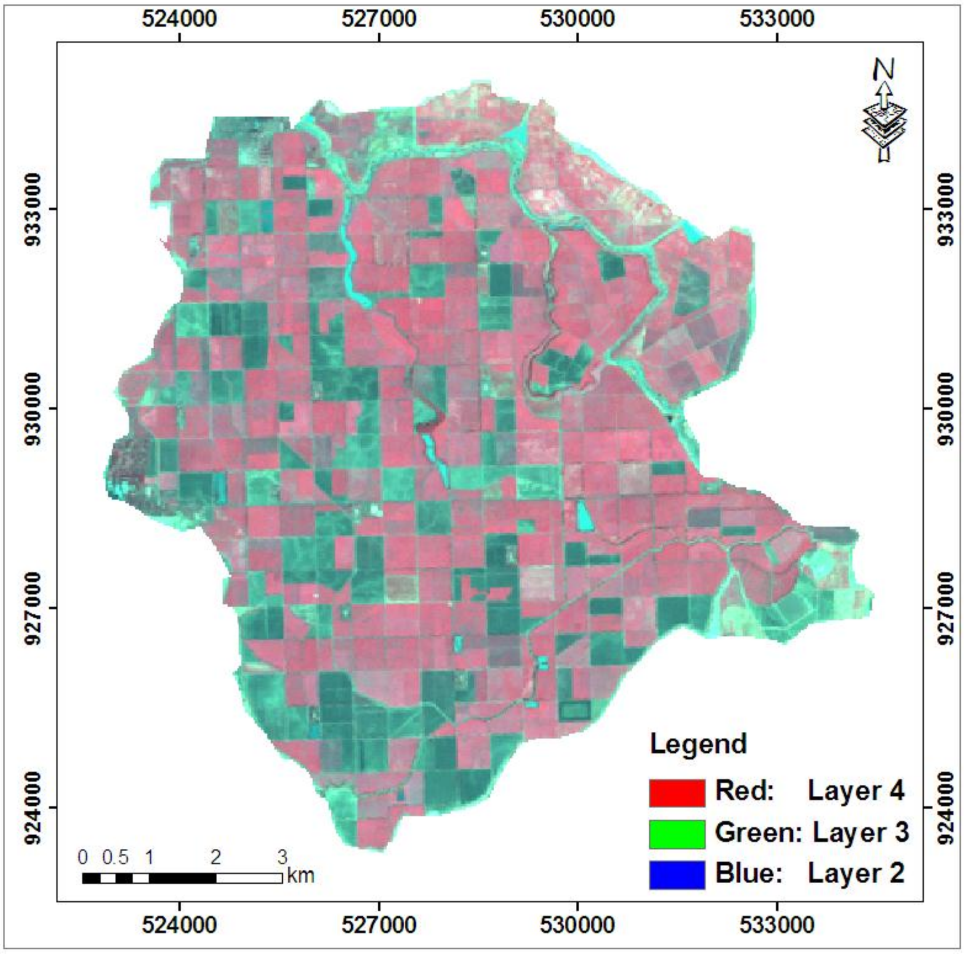


Figure 4. 1 False color composite of 2012.

4.1.2 Spatial distribution of ECe

An attempt was made to predict the salinity level at different locations from a number of points Observations. A total of 53 EC values from a known points locations were used (Table see Appendix-I). The total number for EC/pH and Water table are 53 and 32, respectively and prediction values were calculated using various interpolation techniques. The locations of the EC values were spatially distributed evenly all over the study area (Fig 4.2).

The procedure employed to predict the salinity level at an sample locations was using the scatter plot of point locations of EC *vs* the corresponding raster values of remote sensing salt induces map extracted using GIS environment. Based on the scatter plot, the best fit line which can model the interdependence of EC and salt induces raster value was determined.

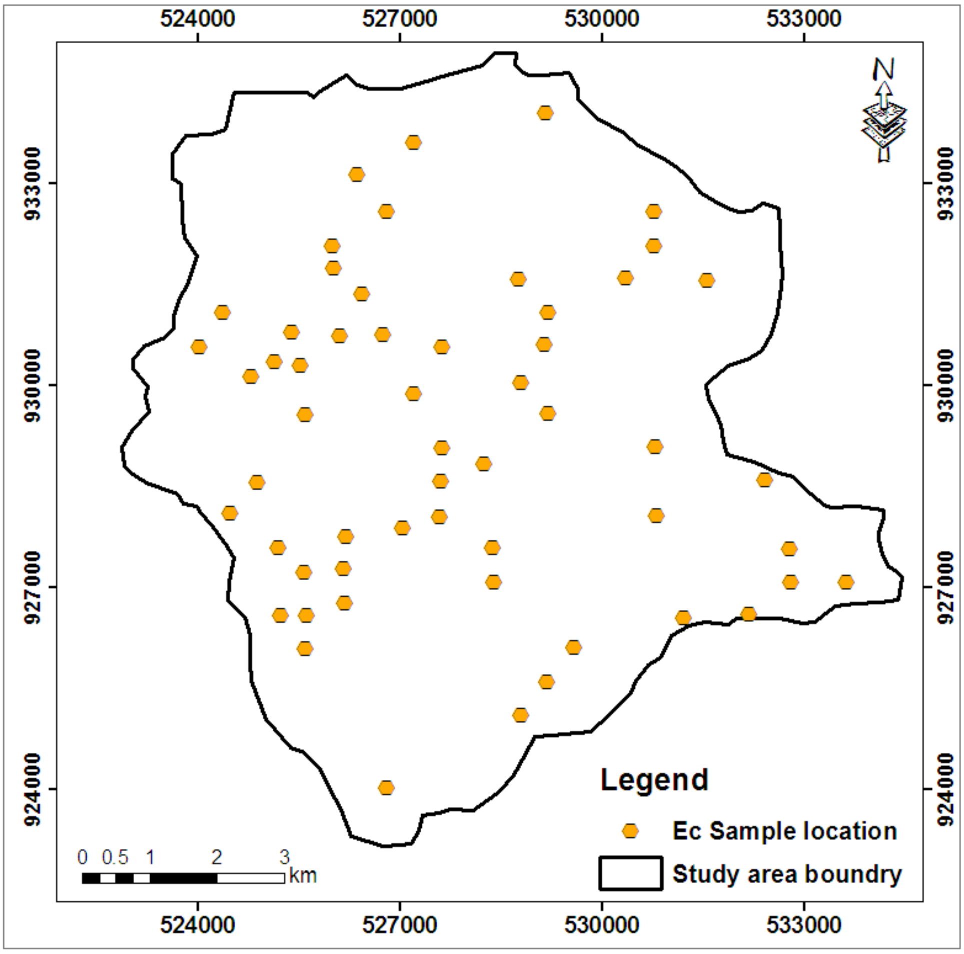


Figure 4. 2 EC sample Locations.

4.1.3 Integration and best band combination

The spectral reflectance of saline soils and other categories that cover the study area have been obtained from six bands of ETM+ 2012 image (Fig 4.3). Generally, it can be observed that the spectral response increases with increasing salts content at the terrain surface. In addition, there is a spectral response contrast between Visible and NIR bands and between NIR and MIR band in salt existing soil. So, these effective band intervals have to be considered to differentiate the background of completely bare and salt affected soil. Accordingly, the correlation coefficients have been computed between the soil variables, the spectral values illustrated in (Table 4.1).

Table 4. 1 Correlation between Landsat ETM+ band and EC.

	EC	Band1	Band2	Band3	Band4	Band5	Band6	Band7
EC	**1**							
Band1	-0.573	**1**						
Band2	00.641	0.742	**1**					
Band3	0.480	-0.737	-0.839	**1**				
Band4	0.502	-0.667	0.506	0.821	**1**			
Band5	0.481	0.526	-0.769	0.968	0.742	**1**		
Band6	0.441	-0.702	-0.469	-0.834	0.683	0.988	**1**	
Band7	-0.693	-0.693	-0.672	-0.872	0.555	0.568	0.67	**1**

The spectral reflectance of soil is governed by many factors. In the present study, the area was relatively homogenous in terms of topography, surface soil color, texture, mineralogy and agricultural practices. The only major difference was soil chemistry, expressed in the form of surface accumulated salts. A substantial increase in the spectral response of salt affected soils was noted. The spectral value of salt affected soils was substantially higher than the normal soils in all the bands (Fig. 4.3).It was observed that saline soils and bare land/fallow have similar spectral response in all the bands but saline soils had significantly higher reflectance in band 3, 5 and, 6 which makes discrimination of saline soils and bare land easier.

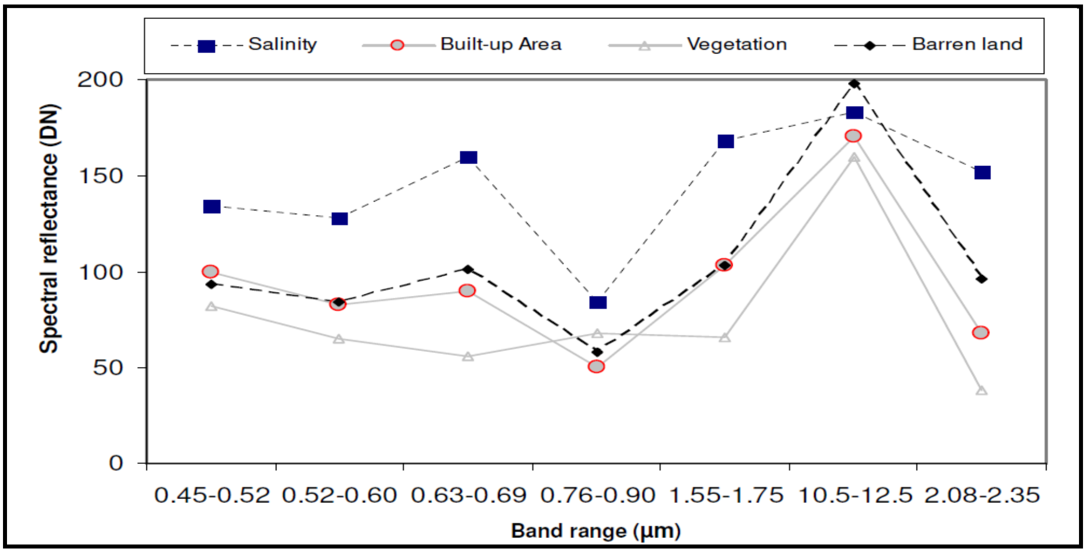


Figure 4. 3 Spectral profile for land covers classes.

4.1.4 Model frame work and approach

The approach used involved integrating remote sensing data, GIS, and spatial analysis to predict soil salinity. The field locations of the sampled soil salinity were retrieved from farm plot centers (the EC values used were representative of single farm plot) and a point map was generated. The location of the soil salinity data were tied to the corresponding points on the image. The soil salinity data were tested against the band 4 and band 5 as well as the remote sensing index. Finally, the EC value and the corresponding raster value were plotted on a scatter diagram and the best fit lines of the equation were determined.

4.1.5 Model generation and selection

Initially; the EC data was tested to establish whether it conformed to a normal distribution. As part of the model generation process, various spectral soil salinity indices were tested for assessing and enhancing the variations in surface soil salinity. Out of all indices tested, the Salinity Index (SI) (Equation 1) which has been proposed by (Dehni and Lounis 2012), was used to create enhanced images for soil salinity in this study, due to its very highly significant correlation with EC. To ascertain the spatial location of the soil samples; a convolution low pass filter with a kernel size of 5 × 5 was applied to the enhanced images, then digital values were extracted at the location of sample points over those enhanced images.

SI = $\sqrt{(Band3 * Band4)}$……………………………………………………Equation (1)

Subsequently, Pearson Correlation analysis between the bands and SI, NDVI, NDSI, BI, SAVI with EC was conducted to reveal the relationship between these variables and assess their efficiency in predicting soil salinity. The explanatory variables chosen were those showing the highest significant correlations with EC (Table 4.2).

Table 4. 2 Correlation between remote sensing induces and EC.

Measured EC	**Measured EC**	**BI**	**NDSI**	**SAVI**	**SI**	**VSSI**	**NDVI**
	1						
BI	0.795	**1**					
NDSI	0.626	0.410	**1**				
SAVI	0.611	0.689	0.040	**1**			
SI	0.897	0.817	0.542	0.576	**1**		
VSSI	0.379	-0.344	0.067	0.346	0.166	**1**	
NDVI	0.673	0.611	0.398	0.461	0.665	-0.216	**1**

Deciding which explanatory variable to include in the regression model is not always easy, and increasing the number of variables in a model may lead to an over fit and provides poor prediction when used with a different data set (Royston, 2008). To overcome these issues, stepwise regression was used to determine the variables that best explained most of the variability of the dependent variable, which is EC.

Once all the developed regression models were tested, models with (i) a high R^2, signifying a strongly linear relationship, (ii) low standard errors of the model's variables and (iii) few variables with a p-value of <0.05 were selected for evaluation using the testing data. Consequently, the best performed regression model that met all the model selection and validation criteria was chosen and used to predict and map the spatial variation in soil salinity.

4.2 Spatial overlay soil salinity model analysis

4.2.1 Environmental model parameter

Soil Salinity Modeling is a methodology or a set of analytical procedures that simulate real world conditions within a GIS using their spatial relationships of geographic features to locate the problem of salinity geographic areas for a specific land use.

The basic reason for developing models is to understand the causes of soil salinity and devise management practices required to control its spread. It is a rapid and reliable method of obtaining information on the spatial distribution of salinity (Madyaka, 2008).

The effectiveness and efficiency of the method depends on the understanding of the dynamism of water and solute movement in the soil. There are several approaches for modeling soil salinization in practice, all attempting to better understand its extent and dynamics. Some of these approaches involve mathematical models, which describe and quantify the basic hydrological processes and phenomena under a range of conditions. In this study, the modeling functions include spatial overlay by using multivariate analysis and correlation of different environmental factors with EC. To develop soil salinization model, parameters were identified which have significant influence in the salinization process. These are ground water level, elevation, soil texture, Vegetation density and Geology of the area.

4.2.1.1 Ground water level

Ground water level was considered as one of the parameters in the analysis of soil salinization model as ground water is the most contributors in salinity rise. 32 point data with coordinate references were acquired and converted in to point shape file in GIS environment (Fig 4.4).

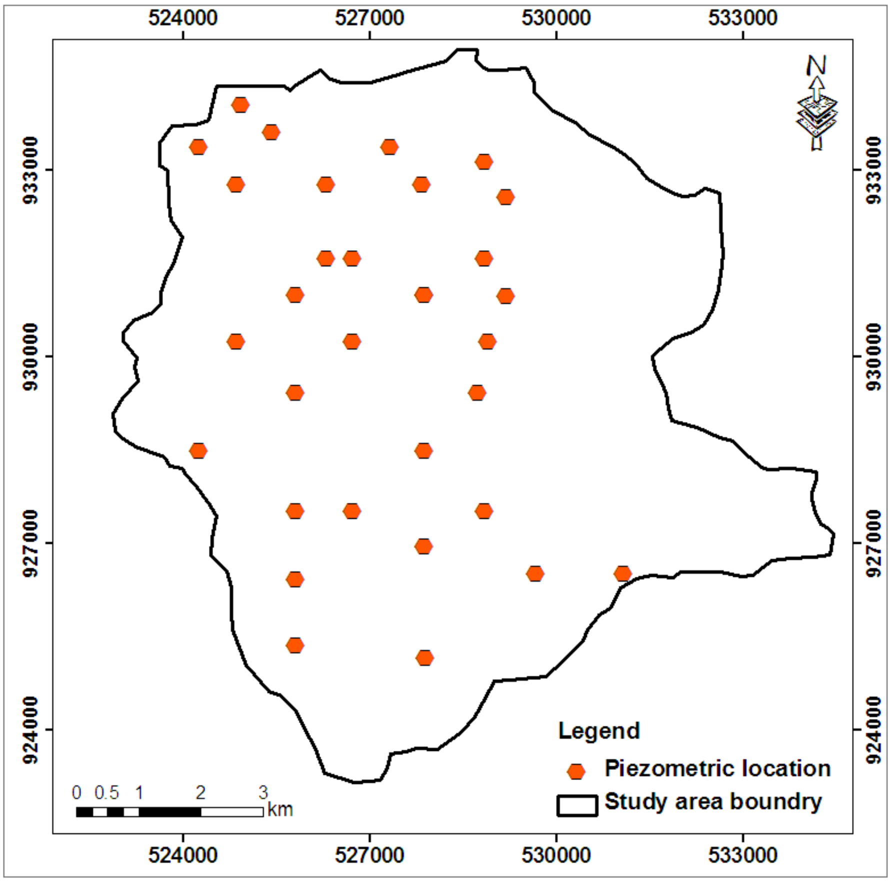


Figure 4. 4 Location of Piezometric data.

In order to have area distribution of ground water level, various geo statistical methods completely regularized spline interpolation (CRSI), inverse distance weighting, Radial basis functions and kriging were tested. Kriging has the lowest root-mean-square prediction error when performing cross validation was adopted. Indeed, the smaller the root mean square prediction error, the closer the prediction is to their true values and better to the interpolation method (Fig 4.5). For the spatial overlay analysis, the ground water table point data were interpolated to generate continuous surface water table using regularized Kriging interpolation in spatial analysis tools in GIS environment.

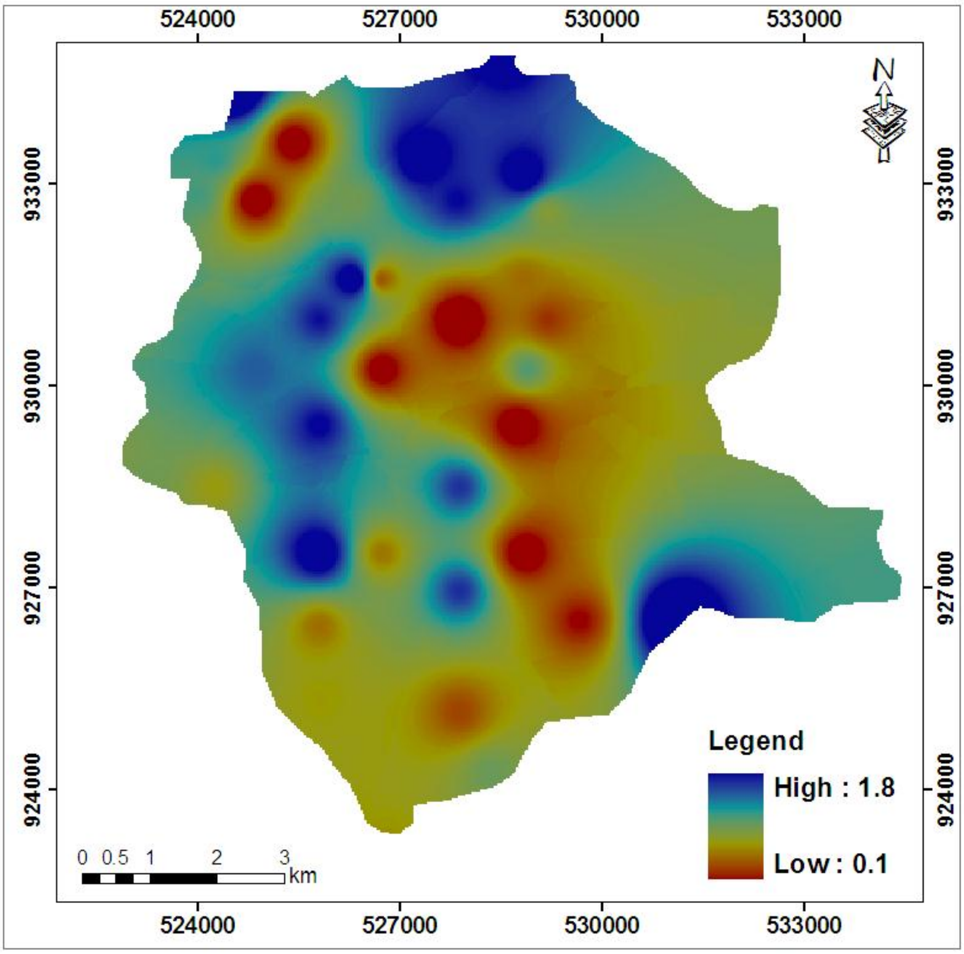


Figure 4. 5 Interpolated ground water level map of wonji Sugarcane estate.

During interpolation, the raster data were sampled to 30 m cell size to make compatible with other layers in the analysis (Fig 4.6). After interpolation, the continuous surface water table data were reclassified in to three classes based on its contribution to the salinization process.

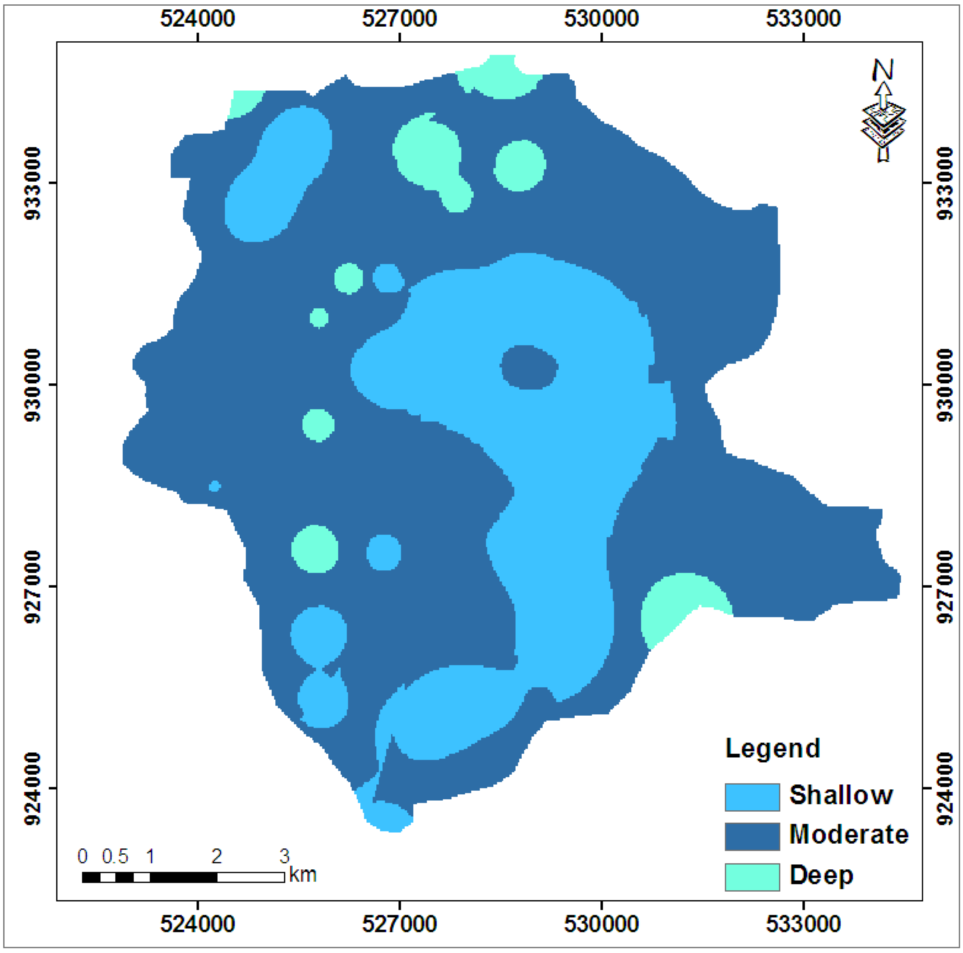


Figure 4. 6 Reclassified Interpolated ground water level map.

The Ethiopian rift is characterized by high salinity due to high degree of water rock interaction, evaporation and the discharge of thermal water. Most waters in the highland volcanic have well to excellent chemical quality, while waters in rift valley are characterized by high Na, HCO3 and F content (Tamiru Alemayehu, 2006). Therefore, the shallower the ground water depth is the higher influence to soil salinity model and higher depth of ground water the lower its influence to soil salinity model. As the dissolved ions come to the surface through capillary rise and only H2O is evaporated and the dissolved ions remain in the soil.

4.2.1.2 Digital elevation model (DEM)

Wonji sugarcane estate is a flat topography and it surrounded by steep topography and has very flat slope, predominantly varying from North West to south east. Physiographically, the area can be viewed as a topographic depression. This topographic characteristic of the plain is the bottleneck in the management of excess irrigation and surface runoff. The elevation shows a range of very low altitude 1515 meter and peaks up to 1573 meter above sea level (Fig 4.7). Elevation has significant effect in the process of soil salinization and hence classifying the landform and assigning proper scale value to the landform classes to make compatible with other model parameters is very important. Therefore, the lower elevation value, which was very susceptible to soil salinization, whereas the higher the value it had the least influence in the process.

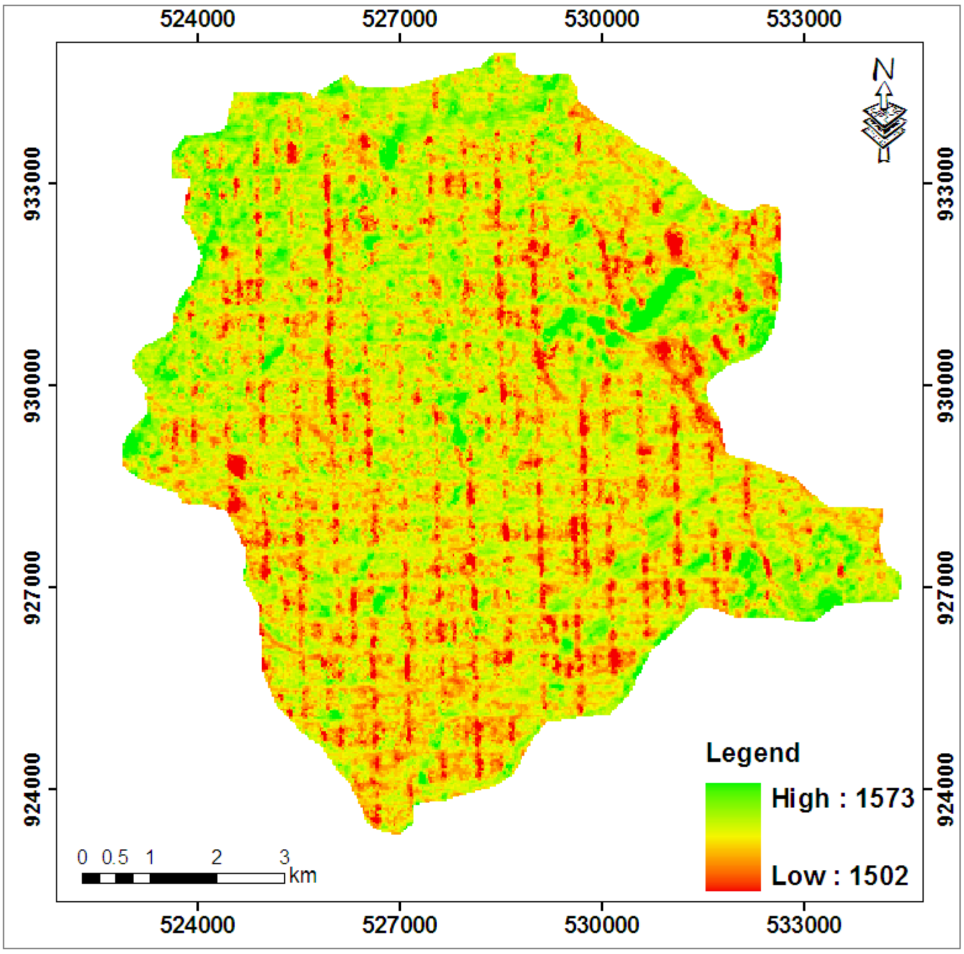


Figure 4. 7 Elevation of the area.

4.2.1.3 Soil texture

Soil textural analysis carried out by Dinka and Ndambuki, (2013) indicated that most (> 70%) of the plantation soils are classified to be clay type, of which about 70% are heavy black clay type (Fig 4.8). These soils are characterized by inherent problems such as compaction, poor structure, shallow water table and poor organic matter status.

The rates of soil salinity are affected by the texture, structure and water holding capacity of the soil. The pores of clay soils are less well connected than those of sandier soils, thus drain slowly because of their low hydraulic conductance (Jackson, 2012).

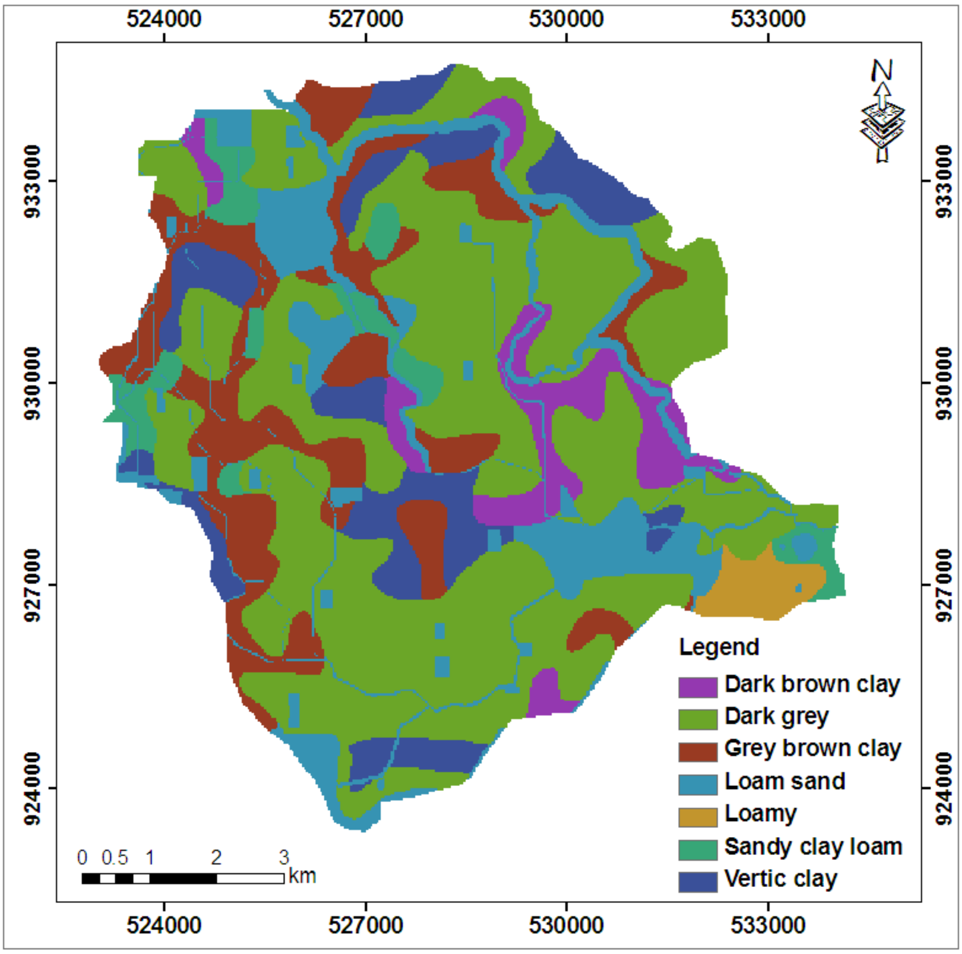


Figure 4. 8 Soil texture map.

Generally, capillary rise is larger in a medium textured soil than in a fine textured soil. The surface soil salinity was more important in medium textured soil as compared to that of fine textured soil. Soil stratification also has influence on the capillarity rise of soil salinity. Soils of the study area are characterized by clay, vertic clay, clay loam, sandy clay loam, and sandy loam.

4.2.1.4 Vegetation density

Vegetation density was considered as one of the parameters in building soil salinization model in this research. The land cover maps, based on vegetation density were prepared using landsat ETM+ data taken in 2012.

Salt affected soils were usually characterized by poor vegetation developed areas and such state of stressed vegetation could be an indirect sign of the presence of salts in the soil. Vegetation indices were, therefore, included in classifying land cover layer (Singh and Somvanshi, 2012). High level of soil salinity affects growth of most crops as well as their appearance, and hence the state of stressed vegetation could be an indirect sign of the presence of salts in the soil (Fig 4.9).

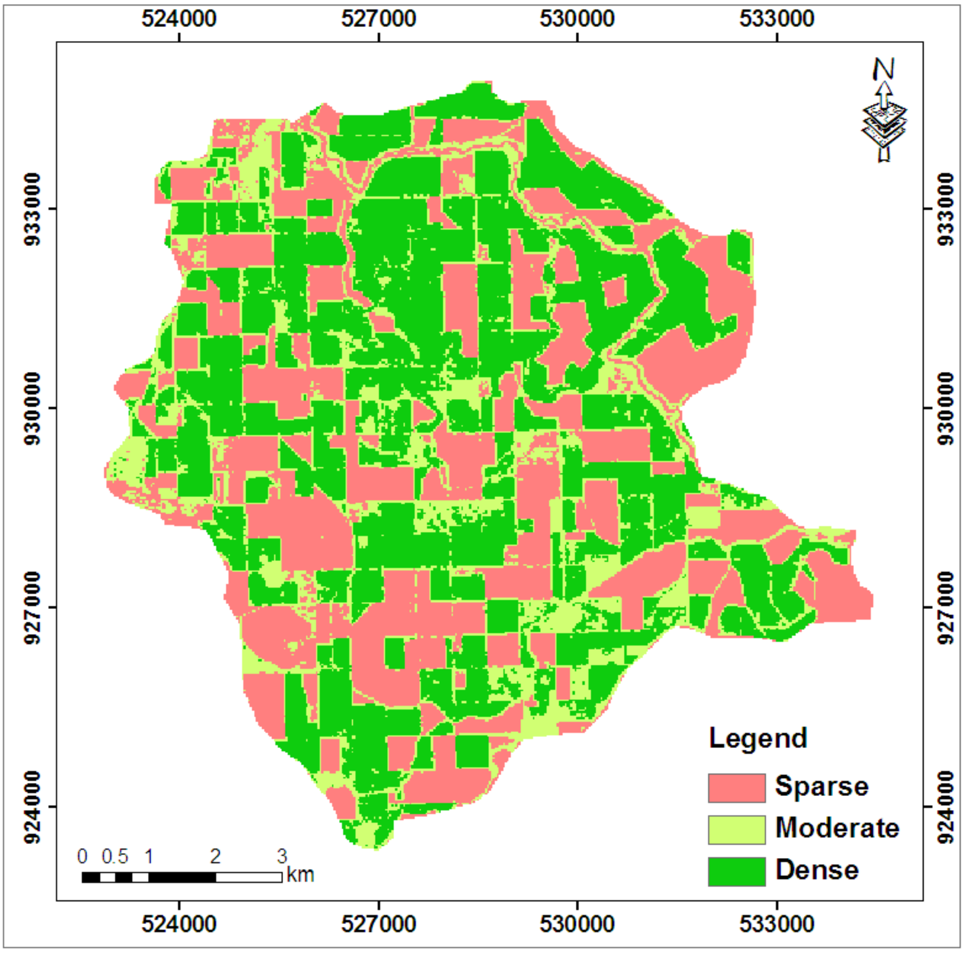


Figure 4. 9 Vegetation density map.

This can be detected remotely using satellite imagery where vegetation conditions can be separated into several classes from satellite images. To map vegetation density and land cover of the area from image, NDVI was generated from landsat image of 2012 and categorized in to three classes, as sparse, moderate and dense vegetation class, which express the density of vegetation. The land cover derived from NDVI was reclassified and scale values were assigned to each class to make it ready for correlation and spatial overlay analysis with other model parameters.

4.2.1.5 Geology

There are three types of geological formation on the study area namely, lacustrine sediment, Pleistocene sub recent basalts and alluvium (Quaternary sediment). The lacustrine deposits were purely lake or swamp deposits or those of volcano lacustrine type of the rift valley. The most extensive lacustrine sediments were located around all the area. According to Tamiru Alemayehu, (2006), Salinity and high fluoride content in the rift valley was the main problems in developing groundwater in lacustrine sediments. The lacustrine sediments were situated in low lying areas and they store large quantities of saline ground water (Fig 4.10).

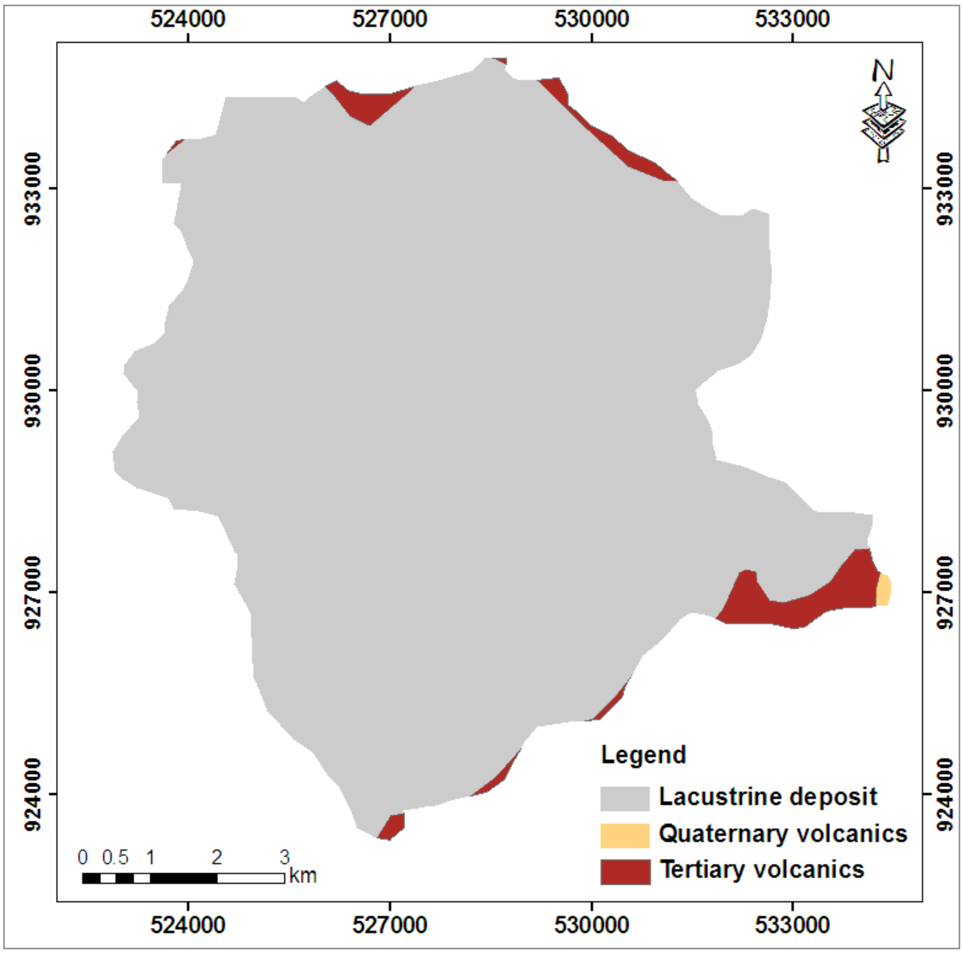


Figure 4. 10 Geology of the area

Ground water in the basaltic formation is known to have low concentration of fluoride as it has been found. For example, in the Bishoftu area, it was 0.3 - 1.8 mg/l. Hence, it was possible to hypothesis that even in the other parts of the Rift; groundwater in the basaltic aquifers would have low fluoride content. High fluoride content of the groundwater in the Rift was related with high salinity and alkaline environment, where it favours high concentration of fluoride in the water (Tamiru Alemayehu, 2006).Therefore, lacustrine sediments were contributing salinity to soil higher than the rest of geological formation in wonji area. Alluvium (quaternary sediment) was moderately contributing salinity whereas tertiary volcanic contribute least.

4.3 Spatial overlay multivariate analysis

The potential of soil salinity level was obtained by creating spatial overlay analysis, which involved weighting of values of all data sets such as ground water table, elevation, soil texture, Vegetation density and geology. Each criterion was weighted according to their importance in influencing soil salinity. Multivariate Analysis was used in weighted each environmental parameter layers, so as to avoid the biasness in assigning weight value for every parameter in the model. According to Lesch *et al*. (1995), Multivariate analysis models have been successfully employed to improve the estimation accuracy of a number of soil physical properties and salinity during various types of soil survey and water resources work. This methodology is specifically designed to handle spatially correlated random variables and hence is often suggested as an ideal procedure for analyzing multivariate soil salinity detection parameter.

Therefor multivariate analysis based on the probability value (p) of each layers by multiply with the coefficient value of the parameter taken based on the relative importance of the criteria involved in determining salinity vulnerability of the area. The probability value should be less than ($p<0.05$) to consider the coefficient value of each layer in the model. The result of cell values is added to produce the final output raster that represent salinity risk areas. Higher sum values represent a greater potential for salinity (Appendix-III).

4.4 Salt affected soil against different factors analysis

The spatial distributions of salt affected areas were evaluated based on overlaying with different features. Among the factors considered were canal and ground water level data.

4.4.1 Canal layout *vs* soil salinity map

For the purpose of overlay analysis, the digitized canal was buffered with 100 m distances. Since the problem associated with malfunctioning of canal and drainage was not confined to only along the line, rather their effects were manifested some distance along the canal line. Therefore, the overlay analysis was done using 100 m buffered canal layout (Fig 4.11).

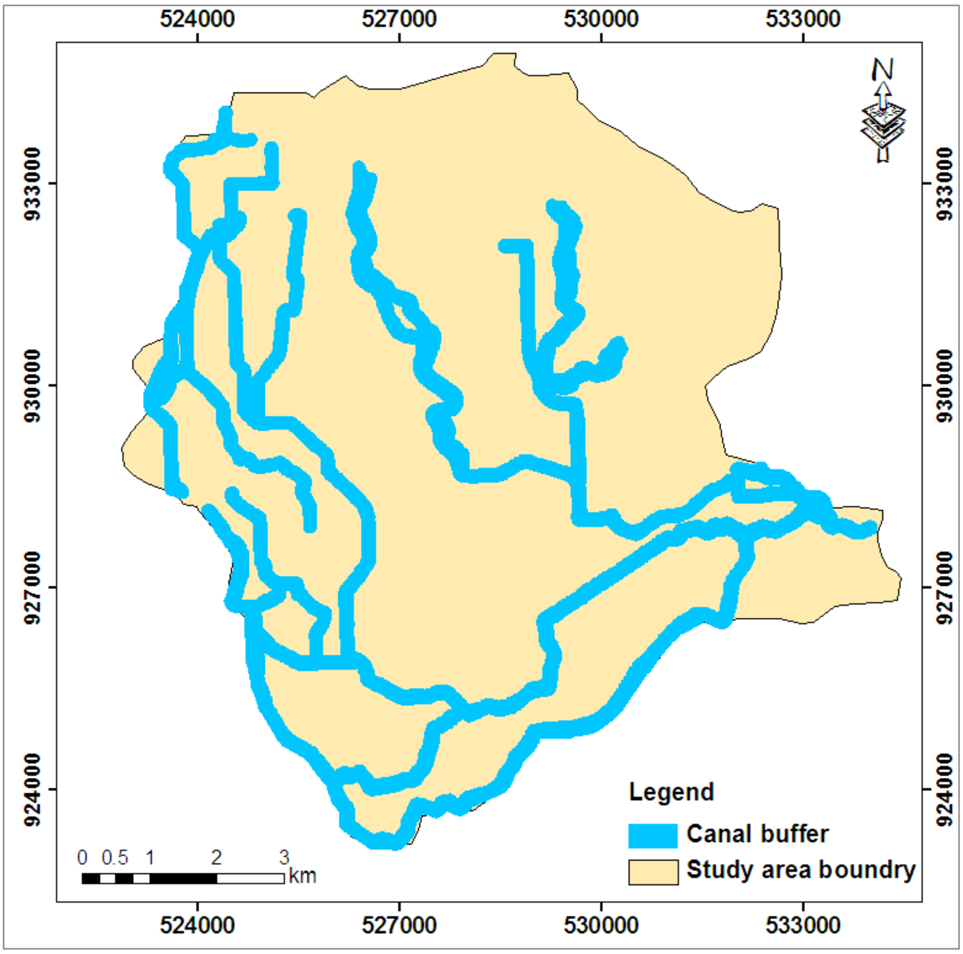


Figure 4. 11 Buffered Canal layout map.

4.4.2 Ground water table data *vs* soil salinity

As soil salinity problem was closely related with shallow water depth, the salt affected areas mapped were overlaid with the ground water table depth. The Ground water table depth of the area is within the range of 0.3–2.47 m below the ground surface (Table 4.3). As per the FAO/UNEP (1984) guidelines cited in Masoudi *et al.* (2006), all of the area is classified as shallow (i.e. waterlogged). Almost all piezometers have a mean Ground water table depth value less than 1.50 m below the ground surface, exceeding the critical level (1.5 m) recommended for a sugarcane crop. Accordingly, about 94% of the plantation areas are classified as critically waterlogged. About 15% of the piezometers have extremely shallow Ground water table depth (< 0.5 m), almost at the ground surface. Based on this, the groundwater table depths of the entire area were classified as critically waterlogged, potentially waterlogged and safe area (Fig 4.12).

Table 4. 3 Classification of ground water table depth.

No	Water table depth(cm)	Risk of waterlogging	Reference
1	< 0.5 m	Critically waterlogged	FAO/UNEP,1984
2	< 0.8 m	Potentially waterlogged	
3	>1.5m	Safe area	

Shallow ground water table leads to high capillary movement of water and increases the risk of salinization (Khorasgani and Karimi ,2008). Based on this view, to assess the distribution of saline soils, the water table map was overlaid with map of salt affected soils.

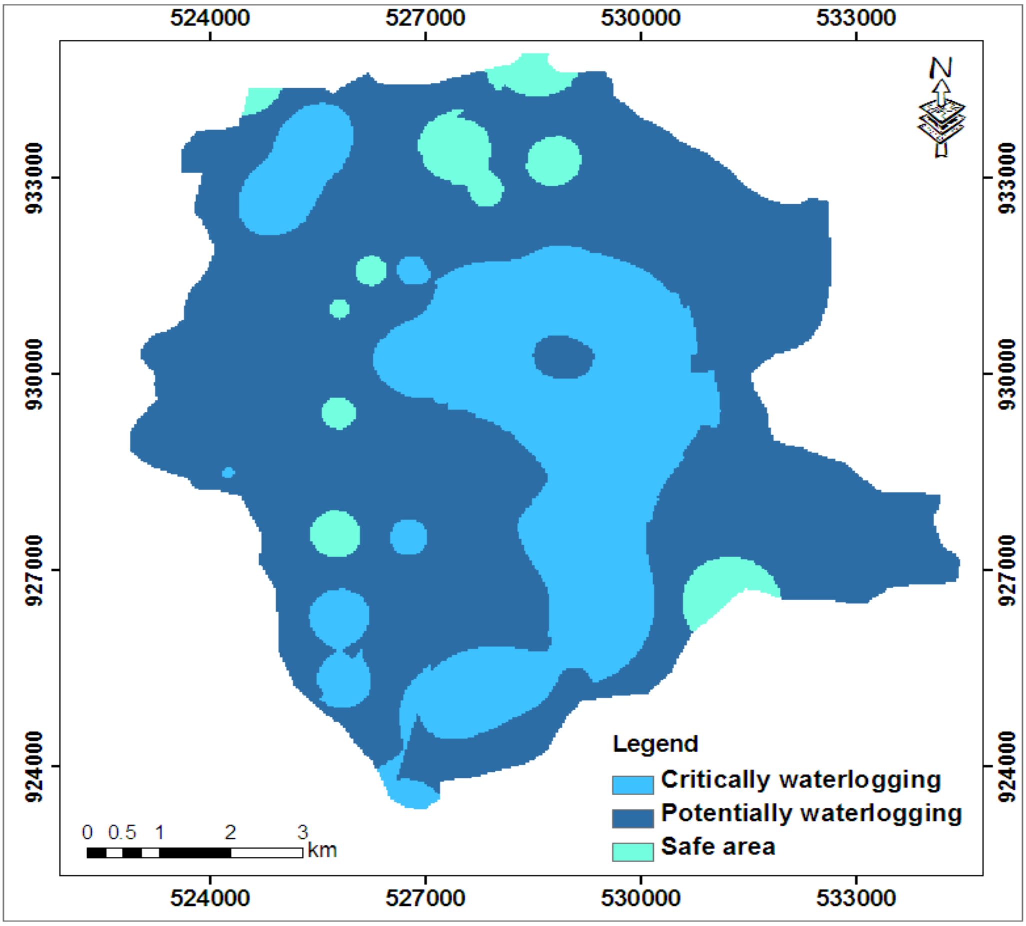


Figure 4. 12 Interpolated ground water level classes map.

CHAPTER FIVE

RESULTS AND DISCUSSION

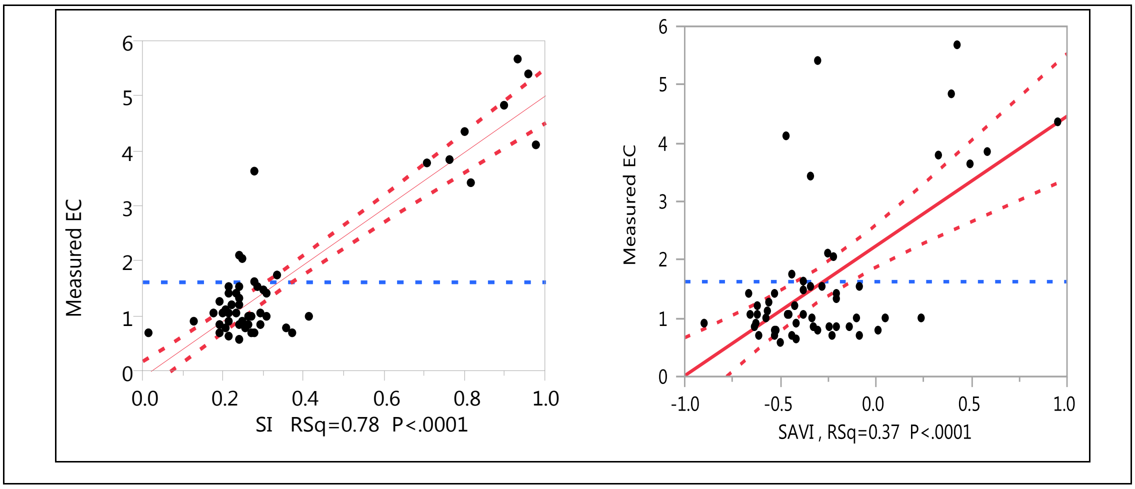
5.1 Result from Remote sensing soil salinity model

Remotely sensed data with a significant correlation to EC were considered for developing the regression models. The developed regression models are shown in (Fig 5.1) and their statistical results are summarized in Table 5.1, showing how well spatial variation in soil salinity can be predicted by applying different developed regression models. All the developed regression models were highly significant; however, soil salinity index (SI),Brightness index (BI) and normalized difference salinity index (NDSI) models were best able to predict soil salinity spatial variation, as they met all the model selection criteria. Among this model, model one, which combine salinity index (SI) and EC, provided the best fit overall.

It had the highest R^2, signifying a strongly linear relationship between estimated and predicted EC and indicated that 78 % of the variance in the EC values could be explained by this model with relatively low standard errors for its variables at 0.54. Each of these variables had significant p-values, indicating a strong correlation with EC (Fig 5.1).

Table 5. 1 Regression models to predict EC based on remotely sensed data.

Model	Variable	Regression Coefficient	Standard Error	P-Value
	Intercept	-0.705575	0.220087	<.0.0023*
1	**SI**	7.5189111	0.541522	<.0001*
	R 0.9,R^2 0.78			
	Intercept	2.2375466	0.179712	<.0001*
2	**SAVI**	2.223279	0.399486	<.0001*
	R1.04, R^2 0.37			
	Intercept	1.6082391	0.174729	<.0001*
3	**NDVI**	-4.045224	10.16913	0.6923
	R1.6, $R^2$0.002			
	Intercept	0.7626517	0.204428	0.0005*
4	**NDSI**	2.793508	0.482298	<.0001*
	R1.02, R^2 0.39			
	Intercept	-0.163753	0.21785	0.4556
5	**BI**	5.7966769	0.611587	<.0001*
	R0.79,R^2 0.63			
	Intercept	1.4605214	0.175235	<.0001*
6	**VSSI**	0.6981626	0.236018	0.0046*
	R1.2, R^2 0.14			



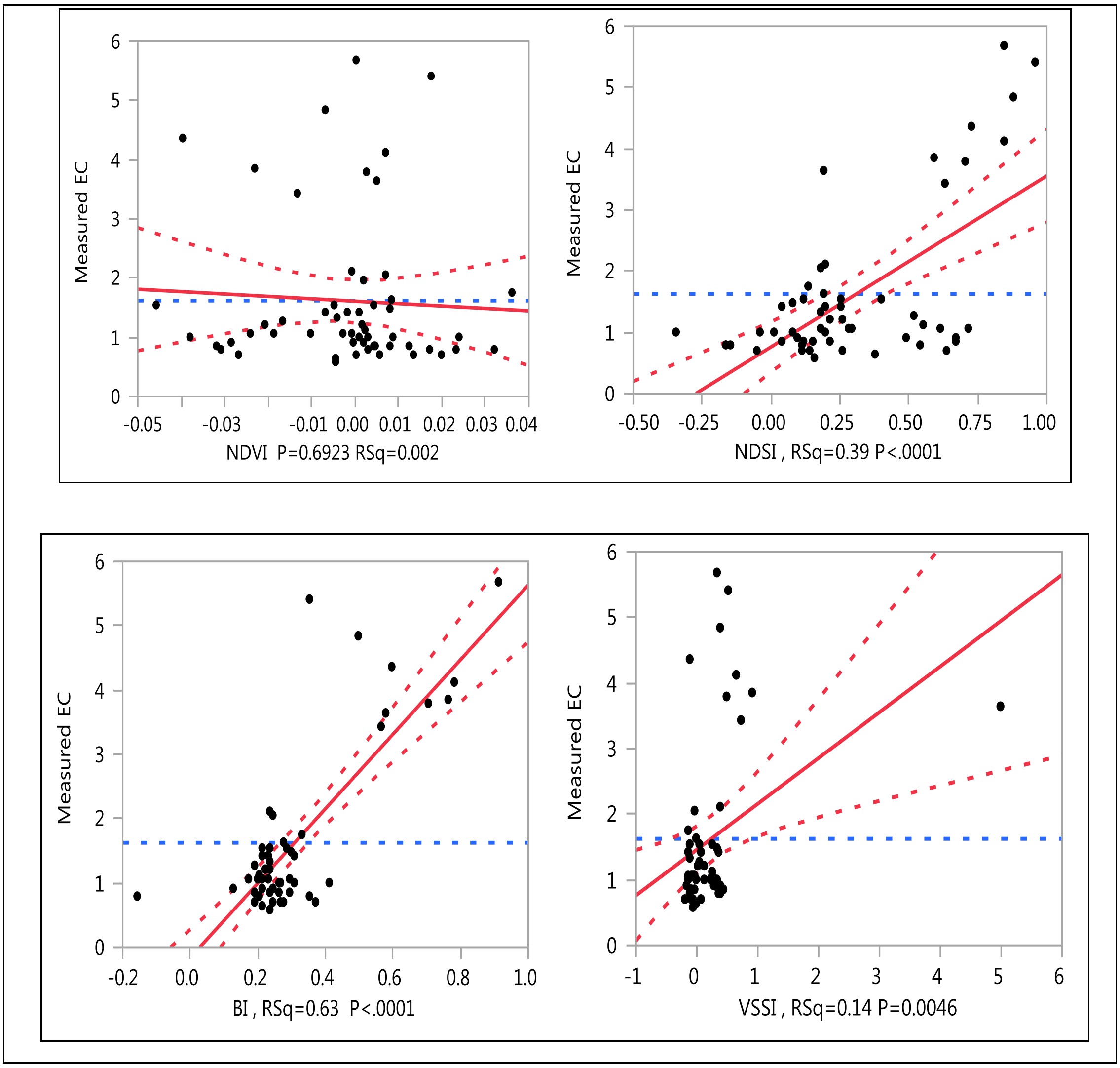


Figure 5. 1 Scatter plots of predicted vs measured EC using the developed regression models.

5.1.1.1 Salinity Prediction Model using Salinity Index (SI)

Prediction model for ECe *vs* SI was prepared using regression analysis. It was observed that the model of ECe *vs* SI offered coefficient of determination 78% (Fig 5.2). This model was extended for the whole image and salinity levels were divided into three groups. This model directly gives the salinity level at any point in the image. This prediction model enhances areas of moderately, slightly saline soil. From the predicted salinity map three ranges of salinity level was generated. The summary of salinity level, extent of the area in hectare and percentage are given in Table 5.2.

Salinity = **-0.705575 + 7.5189111***X……………………………………Equation 2

Where x is spectral reflectance/SI

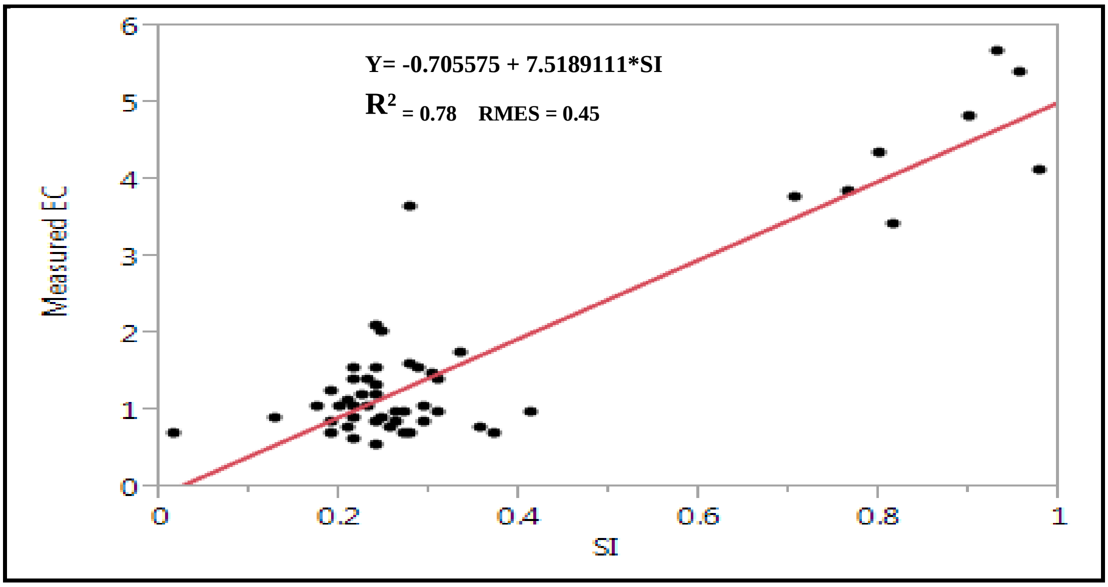


Figure 5. 2 Regression analyses between EC and Salinity index (SI)

The model result in three salinity classes with varying degree of salinity, namely, moderately saline and slightly saline and non-saline which covers 18.8%, 23.4% and 57.7% of the total area respectively (Table 5.2).

Table 5. 2 Area extent of soil salinity level derived from prediction model.

No	Salinity Extent	ECe value mScm	Area (ha)	Area (%)
1	Non-saline	<2	3778	57.7
2	Slightly saline	2-4	1530.7	23.4
3	Moderately saline	4-8	1230.3	18.8
4	**Total**		6539	100

From the output map, one can easily see that those areas categorized as moderately saline are located in central part of the farm and flat slope areas of the estate (Fig 5.3). The spatial distribution of salt affected land derived from prediction model were checked by comparing it with salt affected area derived from spatial overly model, in order to show the relationship between each environmental parameter for occurrence of salinity in the area.

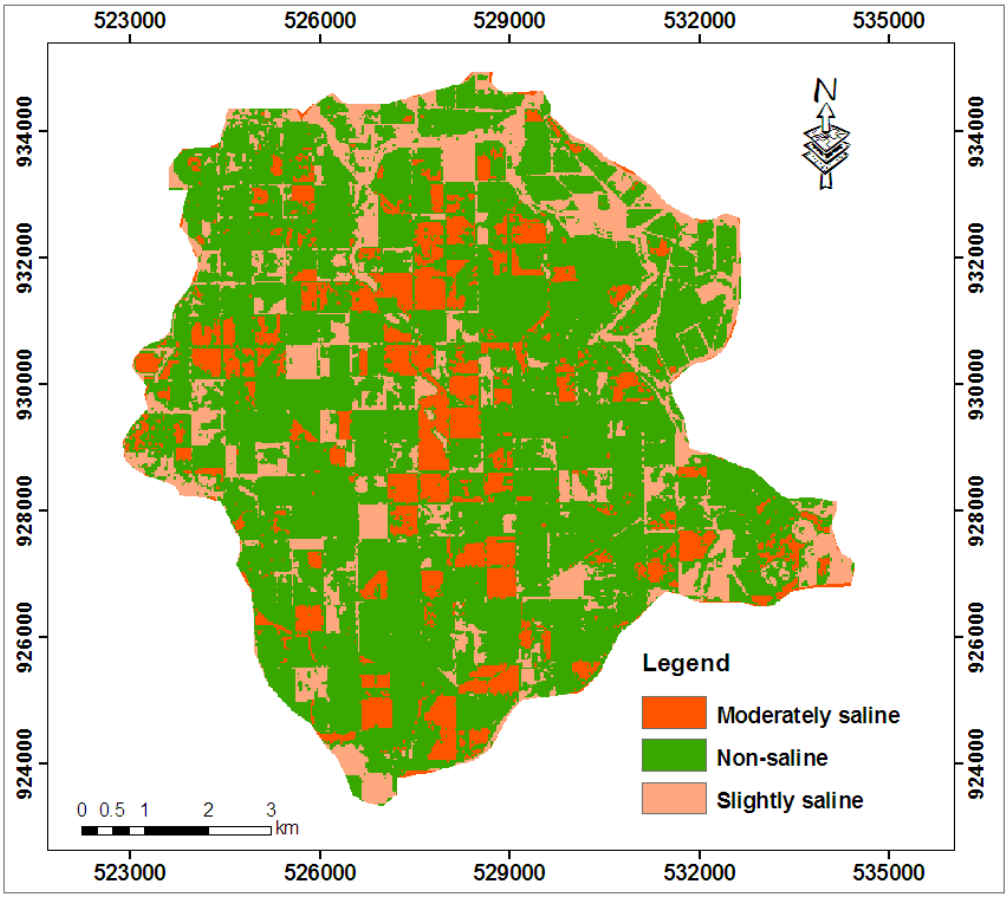


Figure 5. 3 Salinity map from prediction model.

5.1.2 Spatiotemporal variation of soil salinity

From the result of Salinity index (SI) it was observed that an area with high raster value or high reflectance was delineated as area affected by salinity problem. Once areas having high reflectance value were identified, based on their reflectance value the level of the salinity was determined.

In the salinity index image salt affected areas depicted in gray color, could be roughly differentiated from those of non-salt affected areas, waterlogged (in cyan color) and vegetation (in green color).In this study Maps of the study areas generated using the selected model.

Landsat image of 1985, 1995 and 2012 was analyzed for temporal and spatial detection of salt affected areas. Salinity index was used to enhance the saline zones and suppressing the vegetation which is calculated as the ratio of the difference of red band to NIR band. The value of Salinity index (SI) ranges between 1 and –1, from these areas with value 0 and less than 0 were classified as none saline.

Areas with SI value of greater than 0 were classified as slightly saline to moderately saline (Shegena *et al.*, 2014). Therefore, to detect temporal variation of salt affected areas, the SI for images of 1985, 1995 and 2012 were classified and hence four classes were identified; non-saline, slightly saline, moderately saline, and waterlogging (Fig5.4 and 5.5).

The result shows that about 65.9% of the areas were non-saline in 1985, which gradually decreased to 44.9% in 2012 (Table 5.3). Out of this 4312 ha under non-salinity in 1985, only 2940ha remained as non-saline, whereas the rest 1372 ha areas were converted to slightly saline, moderately saline and waterlogging with a large area converted to slightly saline. Large area change was observed in the slightly and moderately saline soil. Moderately saline soil was about 11.4% in 1985, which has increased to 14.4% and 15.6% in 1995 and 2012, respectively.

Table 5. 3 Soil salinity class derived from SI and change rate for 1985, 1995 and 2012.

Soil salinity class	**Year**							
	1985		1995		2012		Rate of Change	
	(ha)	(%)	(ha)	(%)	(ha)	(%)	ha/year	**%**
Non saline	4312	65.9	3230	49.3	2940	44.9	-50.8	-0.7
Slightly saline	1200	18.3	1497.9	22.9	1599.4	24.4	14.7	0.2
Moderately saline	750.1	11.4	945.4	14.4	1020.3	15.6	10	0.1
Waterlogging area	277	4.2	865.7	13.2	979.3	14.9	26	0.39
Total	6539	100	6539	100	6539	100		

Generally, result Indicate that salt affected area were distributed throughout the study area, specifically in the, central and in many part of north part of the farm was found to be moderately saline. As illustrated in Figure 5.5, the north-eastern zones of the estate were clearly marked by lower salinity. Map of salt affected soil for the three different years revealed that moderately and slightly saline soils were concentrated in the central.

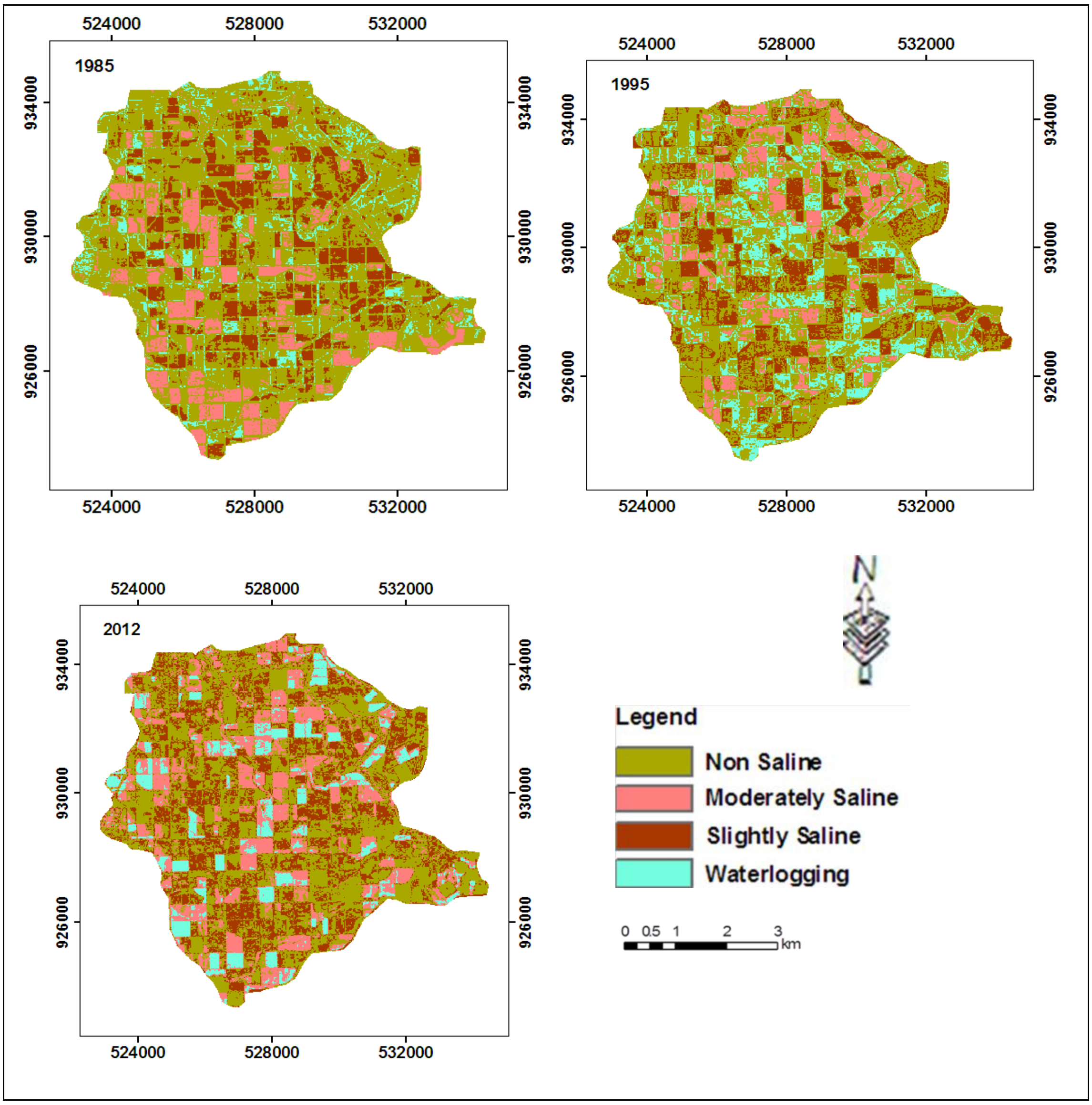


Figure 5. 4 Salt affected areas derived from Salinity index (SI) for 1985, 1995 and 2012.

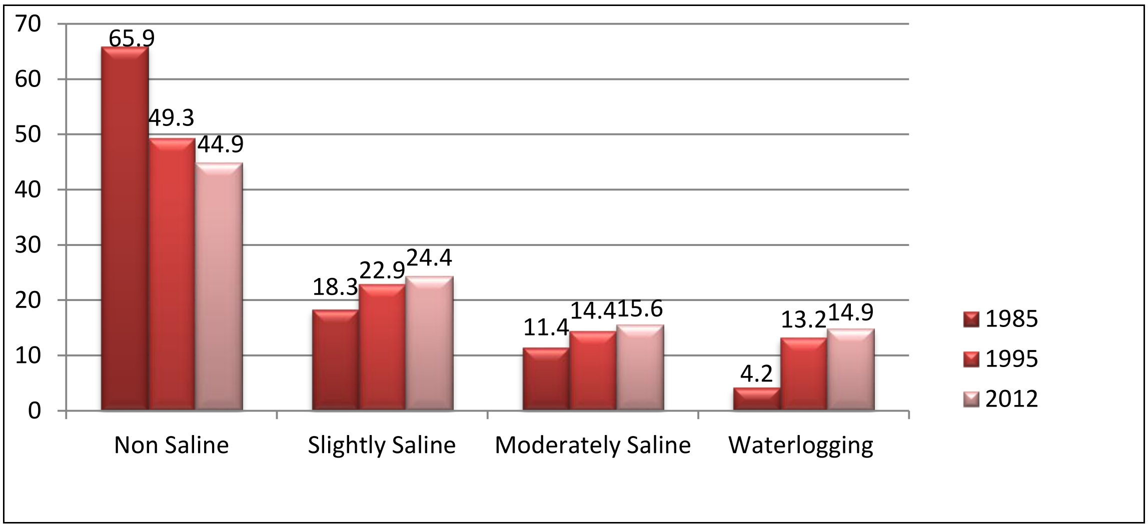


Figure 5. 5 Percentage of Salt affected soil from salinity index (SI) for 1985, 1995 and 2012.

5.1.3 Result from multivariate analysis

The Spatial overly model of salinization in the wonji Sugarcane irrigation farm consists of five environmental factor layers. Salinity model was developed by overlaying factor layers, which have contribution to the occurrence of soil salinity directly or indirectly. This includes; ground water table, elevation, geology, soil texture and Vegetation density (NDVI) with varying degree of influence (Appendix-III).

Probability of presence of salinity in an area= 1/ (1 + e-Z)…………………Equation 3

Where **Z**= 117 + (Geology *0.15)+(Elevation *0.16)+(soil texture *0.22)+(Ground water table *0.28)+(Vegetation density*0.012)

Based on the spatial overly salinity model result, three classes were identified with varying degree of salinity (Fig 5.6). The extent areas of each class of the salinity are shown in Table 5.4. Moderate and slightly soil salinity classes cover approximately 30 % and 33.7 % of the total area, respectively. None saline classes accounted over 36% of the total area.

Table 5. 4 Extent of areas of various salinity levels derived from multivariate analysis

Salinity Extent	**ECe mScm**	**Area (ha)**	**Area (%)**
Non Saline	<2	2362.5	36
Slightly Saline	2-4	2209	33.7
Moderately Saline	4-8	1967.4	30
Total		6539	100

From multivariate analysis result one can clearly identify that, moderately and slightly saline soils were found on the areas underlain by the lacustrine sediments and shallow ground water level. Moreover the low-lying topography and less vegetation cover greatly enhanced the salinization of the area.

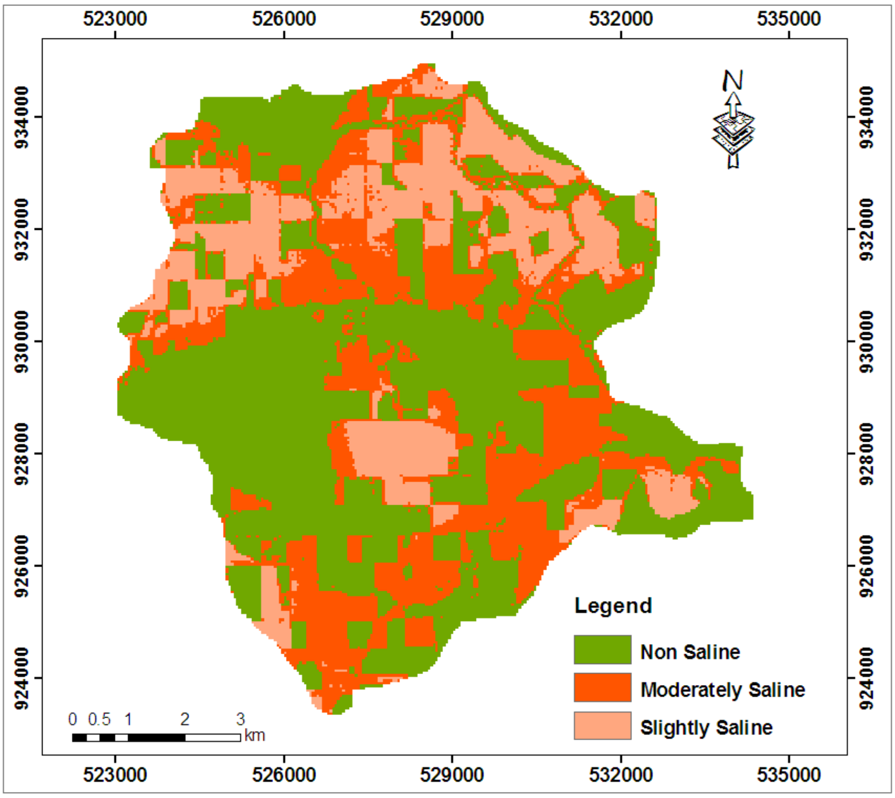


Figure 5. 6 Salt affected area derived from multivariate analysis.

5.1.4 Model validation and comparison of the models

Validation and comparison of the model derived from Soil ECe versus prediction model using salinity index (SI) and spatial overlay model of the factor layers was made. This was done by plotting the ECe value and raster value of salinity map from salinity index (SI) model and spatial overlay factor model on scattered diagram. Then correlation between ECe value and raster value of each of the model was derived.

The result of the validity of salinity model shows that the relation between measured ECe value and salinity derived from the remote sensing index model has high correlation (63%) (Fig 5.7).Validation for spatial overlay model was also made and the correlation between measured ECe value and salinity derived from the spatial overlay was also correlated 23 % of the total area.

The Coefficients value of correlation show that both models have predicted salinity of the area in different level. However, the remote sensing induces from salinity index (SI) model has better validity compared to the spatial overlay factor model.

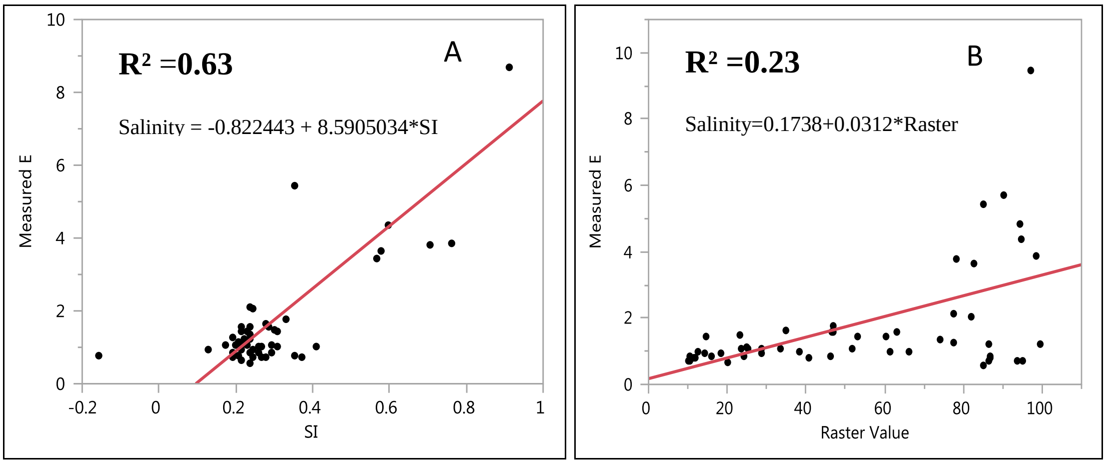


Figure 5. 7 Correlation between Prediction model (A) and spatial overlay raster value (B).

5.1.5 Distribution of salt affected areas with respect to canal layout and ground water table

5.1.5.1 Canal *vs* map of salt affected soil generated from prediction salinity model

The area of salt affected soils that resides within 100m distance of canal is found (Fig 5.8) to be only 3.2% (39.36 ha).According to Rengasamy, (2006), poor Irrigation water management system and small canal structures leads to secondary salinization. Secondary salinity, resulting from modern irrigation occurs because of accelerated redistribution of salt in the profile by high water table or use of insufficient water to leach salts out of the soil.

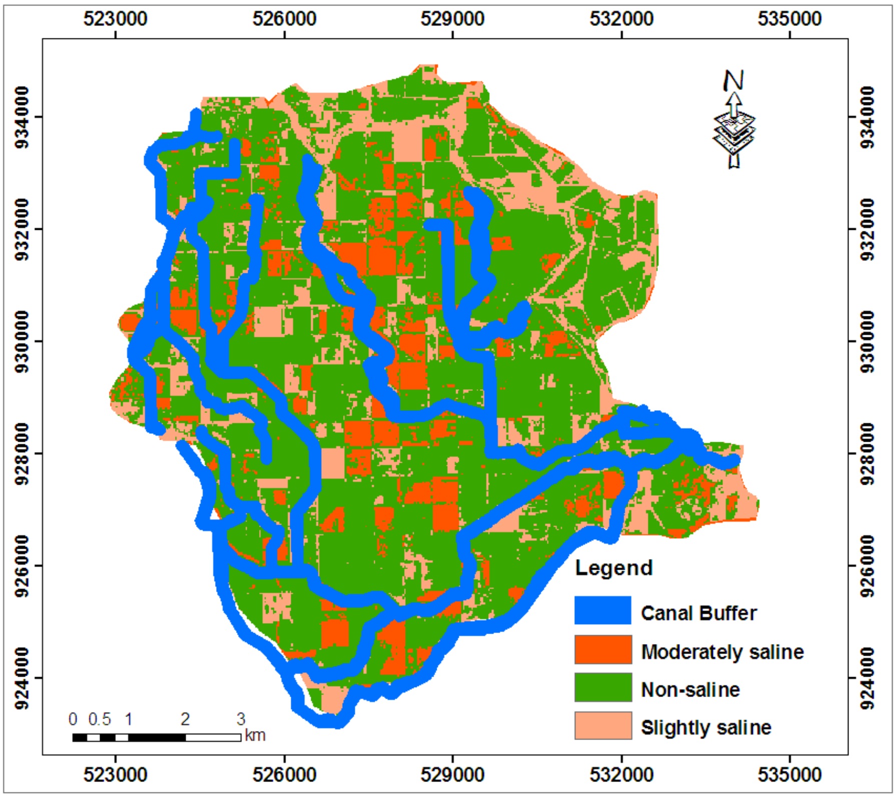


Figure 5. 3 Salt affected area *vs* canal map.

5.1.5.2 Water table *vs* map of salt affected soil generated from prediction salinity model

The spatial distributions of salt affected area were assessed based on the classification of ground water table depth. Irrigation is the main cause of rise in shallow groundwater table under intense evapotranspiration conditions and this led indirectly to soil salinization (Wang *et al.*, 2007).From the prediction model the total area being identified as salt affected soil is 1230.3 ha, out of this 62 % (762 ha) is lying within critically water logging and 31% is lying in potentially water logging class and safe area only 17% of the total salt affected soil exists (Fig 5.9).

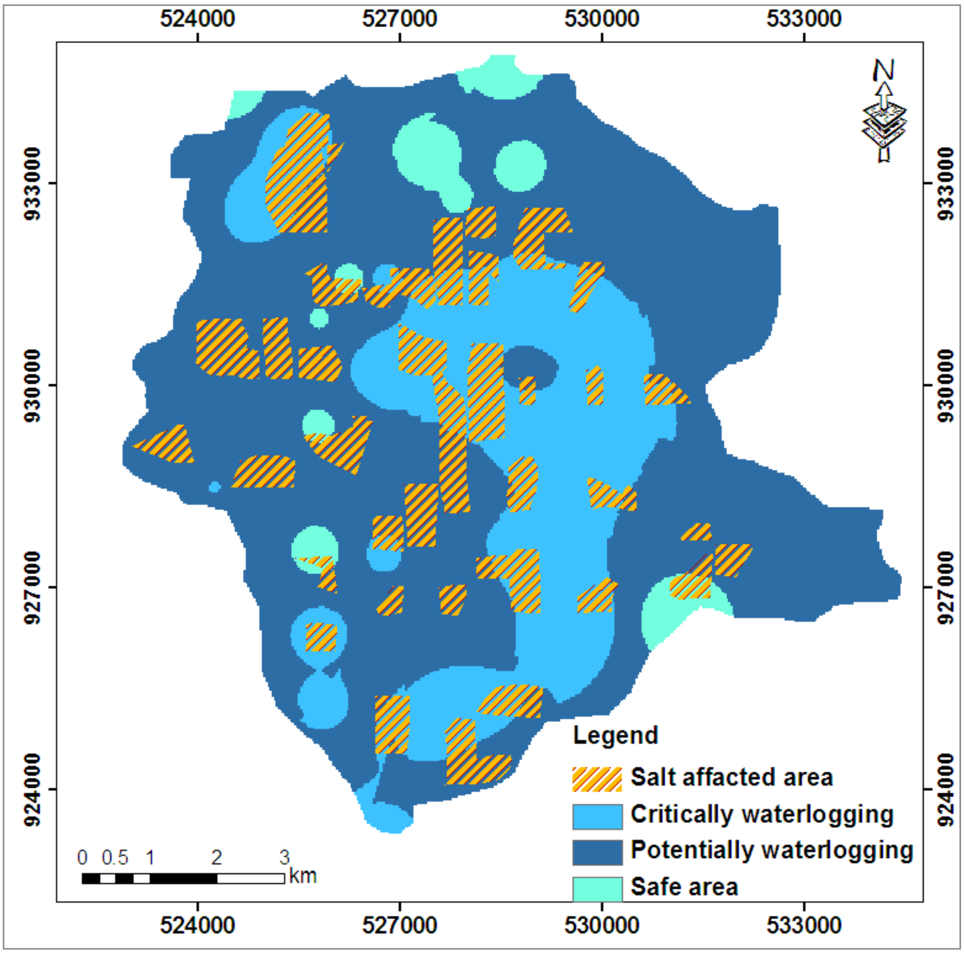


Figure 5. 4 Salt affected area *vs* Ground Water table.

5.2 Discussion

Multi-class soil salinity maps are required for modern management of arid lands, and techniques such as that described here are needed to efficiently develop such inventories. Our results indicate that use of landsat ETM+ images of the study area well identified bare areas that have a high reflectance due to their high salinity content and or salt-efflorescence on the soil surface. This result agrees with that obtained by Elnaggar and Noller (2010), who reported that salt-affected soils with salt encrustation at the surface are, generally, smoother than non-saline surfaces and cause high reflectance in the visible and near-infrared bands.

The efficiency of the selected regression model to predict and map the spatial variation in soil salinity is shown by the strong relationship (R^2 = 0.78) at the 95% probability level, RMSE of 0.54 dS/m and the normality of the residuals. This is in part due to the result of the selected image enhancement method. The selected model in this study showed superiority in the prediction power of soil salinity over those reported by Shrestha, (2006) (R^2 = 0.23).Moreover, the good performance of the selected model in this study is due to the enhanced images efficiency in highlighting information from soil salinity and suppressing the other details. Image enhancement is data processing that aims to increase the overall visual quality of an image or to enhance the visibility and interpretability of certain features of interest in it. Several studies have shown that image enhancement techniques consisting of spectral indices (e.g., NDVI, SI, NDSI) have a great potential in enhancing and delineating soil salinity detail in an image (Noroozi *et al.*,2012).For example, Allbed *et al.*(2014), found and emphasized that identifying salt affected soils based on the image enhancement method, represented by the salinity index, yields better results than individual bands, due to its ability to enhance the saline patches by suppressing the vegetation.

Beside this, the superiority of the visible red and NIR band over the other bands in retrieving soil salinity has contributed to improving the regression model. This result is supported by those of Abdul Qadir and Benni (2010), who found that the visible red band performs best among the Landsat ETM+ bands at characterizing the pattern and features of soil salinity due to its high correlation with EC ground measurements. Soil salinity spectral reflectance is affected by the physical chemical properties of soil quality and mineralogy of salt, together with soil moisture, color and surface roughness. Salt influenced surface features are crusts without or with only a little evidence of salt, thick salt crusts and puffy structures.

Salt causes variations in the surface roughness which induces variation in the soil spectral reflectance (Goldshleger *et al.*, 2013).Most salt affected soils can be identified by a white salt crust that will form on the soil surface, thus, these soils tend to increase spectral reflectance (Crusted soil, which affects soil structure and reduces the soil infiltration rate is characterized with significant spectral changes due to the structural crust formation and color. Salt crust at its inception high infiltration rate presents low spectral reflectance, where as in intense salt crust soil, the spectral reflectance will be significantly higher. Besides, smooth crust surfaces have higher spectral reflectance than rougher crust surfaces (Metternicht and Zinck, 2003*)*.

According to the investigated samples in this study, saline soils with a smooth and light salty crust surface show high spectral reflectance in the red and NIR band, in contrast saline soils characterized by coarse dark puffy surface crust exhibit a decrease in spectral reflectance. These findings are in agreement with (Metternich and Zinck, 1997), confirms the fact that saline soil reflectance results from spectral properties such as the presence of salt crust, soil color and moisture content, which have a combined effect on the amount of reflectance. Thus, it is clear that a combination of spectral bands and image enhancement yield a better result than the actual band used for modeling and mapping soil salinity alone. This finding is consistent with earlier finding, Tajgardan *et al.* (2007) ; Eldeiry and Garcia (2008); Bouaziz *et al.*(2011; Noroozi *et al.* (2012), who found that this method of combining spectral bands with enhanced images in a single model is a promising tool for soil salinity detection and mapping. That is to say, the combination is the key, giving better results than either spectral band alone or image enhancement alone.

Factors causing soil salinity include inappropriate and excessive irrigation without an adequate drainage system, irrigation water quality, a rising water table, climate, rainfall history, local topography and soil composition and farming practices. Therefore, increasing soil salinity at the surface is most likely to vary according to the distribution of these different factors across the landscape.

For example, Bilgili (2013),found that the spatial distribution of saline soils in the Harran Plain, southeast Turkey, is likely due to inappropriate irrigation coupled with high evaporation ,topographical factors and shallow ground water table. A high risk of salinization for the soils with shallow Ground water table (less than 100 cm) seems logic. Elisabeth, (1997) also reported that high and medium salinity hazard occurs, where ground water table is shallow. The risk of salinization is low for soils when the depth between 100 and 200 cm, which could be due to increasing the distance from the Ground water table.

Moreover, Khan *et al.* (2005) reported from Pakistan that seepage and percolation from large irrigation systems gave rise to water table and thus gradually and substantially contributed to the outburst of waterlogging and salinization. The rising water table brings salt from deep in the soil up to the surface, causing salt accumulation Therefore our result also suggested that a rising water table and salt accumulation at the surface combined with a high evaporation rate are one of the most likely factors that have resulted in the spatial variation in soil salinity of the area.

This study shows how regression analysis, coupled with remote sensing images, could successfully predict and map spatial variation in soil salinity over an area vegetated mainly with sugarcane plantation. Thus, the information presented here can help agricultural workers, scientists and engineers to manage soil salinity problems affecting the ecosystem. Additionally, the simplicity of this approach, with its satisfactory accuracy, can contribute greatly to soil salinity prediction and mapping, at lower costs than conventional approaches.

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1. Conclusion

The present study demonstrates that combining the landsat image band and the salinity index into a regression model offers a potentially quick and inexpensive method to map and model the spatial variation in soil salinity. The great capacity of this combined model over the other developed models is attributed to the enhanced images and the band efficiency in highlighting information from soil salinity. The developed model's simplicity and acceptable degree of accuracy makes it a promising tool for continued use in soil salinity prediction.

Soil salinity Prediction models were developed to map salt affected areas, which were derived from the correlation of measured ECe value and salinity index (SI) derived from Landsat image of 2012.The combination of these remotely sensed variables into one model were able to explain with R^2 78% of the spatial variation of salinity in the area. In most of the cases, the areas with the highest reflectance that appeared as brightest on the SI images had the highest ECe. However, there were some areas with high reflectance and corresponding low ECe values. This is because of barren land with high reflectance, but having low ECe. The model was extended to the whole area and map of salt affected area in different level.

The Spatial overlay soil salinity model using multivariate analysis result showed that most of the moderately saline soils are on shallow water table depth. Intensive irrigation practices and excessive use of water and poor irrigation management can cause soil salinization. Areas where ground water table lay above critical depth increased as a result of higher evaporation and this has contribute directly to the occurrence of moderate and slight salt accumulation in the area. The model has good predictability as it considers most of the factors which contribute to soil salinization.

Satellite image indices analysis shows that soils under moderate and slightly saline are increasing at the rate of 10 ha/year and 14 ha/year, respectively. The analyses also show that soil salinity is increasing at significant rate from year to year, which is resulted from long term irrigation as the area is under irrigated agriculture for the last five decades.

From the validation and comparing the model result, it can be concluded that, the prediction model using salinity index (SI) is found to be a better indicator of soil salinity than spatial overlay model. Prediction salinity model method indicates the condition and existence of salt in the entire area of the farm. Even though, the correlation between spatial overlay models is less than the prediction salinity model's correlation coefficient; it could be an efficient parameter for preparing soil salinity maps. The result from overlay analysis between salt affected areas and canal and ground water level show significant relation with soil salinity and influence the spatial distribution of salt affected soil in the area.

The results demonstrate that modeling and mapping spatial variation in soil salinity based on regression analysis and remote sensing data is a promising approach, as it facilitates timely detection with a low-cost procedure and allows decision makers to decide what necessary action should be taken in the early stages to prevent soil salinity from becoming prevalent, sustaining agricultural lands and natural ecosystems.

6.2 Recommendations

Although this study demonstrates that soil salinity mapping and modeling can be undertaken with good accuracy based on multispectral images, further research is needed to focus on investigating the possibility of hyper spectral data in mapping and modeling soil salinity over areas dominated and investigating whether it can increase the accuracy of modeling and the mapping process.

Using landsat ETM+ image, it is possible to map salt affected areas. The spatial resolution of satellite images still limits to detect small patches of salt affected area. Therefore, high-resolution images should be applied to map small areas and increase the accuracy of the prediction of salinity of the area.

In order to apply the soil salinity prediction model to the area, there must be field visits first and adjustment and calibration because of the dynamism of salinity with time and space and sometimes similar reflectance between saline areas and barren land.

In order to assess reliability of the method applied, it is recommended to execute similar studies in the rift valley having similar agro-ecological conditions. Soil salinity processes are highly dynamic. Therefore, the method of detecting soil salinity should also be dynamic.

The result shows the salt affected areas have increased in the time period considered for the study. To show the correlation between ground water level and soil salinity, studies on ground water level and soil salinity should be carried out at regular intervals. Moreover ground water salinity level should be check, before to the ground water table depths apply for analysis of soil salinity of a given area.

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Appendices

APPENDIX-I

Soils saturated extract Electrical conductivity (ECe) and pH data analyzed from auger samples of 2012.

Auger No.	Easting	Northing	pH value	Measured EC
6	527215	933524	8.2	3.33
17	526365	933062	7.9	0.84
31	526816	932507	9.1	5.40
45	526000	932000	7.6	2.77
56	528768	931503	8.3	1.4
68	529203	931002	7.8	3.43
80	524370	931004	8.0	1.05
84	524020	930496	7.6	0.70
92	524794	930055	7.5	1.05
102	527632	930486	8.2	1.05
111	528800	929966	7.8	2.77
118	529200	929500	7.9	1.05
129	525600	929489	7.7	3.78
136	530796	928999	7.5	3.84
147	527627	928990	9.2	3.85
158	527607	928492	8.3	4.26
169	524890	928468	8.1	4.12
175	525201	927501	8.3	1.54
185	527596	927960	8.7	3.64
194	530813	927989	7.6	1.98
209	532430	928522	7.5	1.63
215	528390	927505	8.0	1.54
227	532814	927002	7.8	0.91
228	532802	927494	7.5	0.70
237	528404	926987	7.5	0.91
243	531227	926459	7.4	3.77
261	525240	926500	7.7	5.67
267	525619	926504	7.9	1.12
273	525600	926002	7.7	1.19
293	529596	926032	7.4	0.84
301	529190	925502	7.3	4.70
310	526808	923933	7.9	0.98
320	528804	925010	7.9	1.40

331	530780	931984	7.6	0.56
336	530365	931514	7.8	1.84
341	529148	930527	7.7	0.91
346	525392	930711	9.8	4.83
347	525139	930265	8.1	0.77
348	525530	930210	8.4	1.40
349	527208	929797	8.6	1.61
350	524422	927932	8.0	0.98
351	528262	928756	8.4	4.10
352	526197	927680	8.5	1.75
353	527047	927794	8.5	2.84
354	526026	931669	7.8	4.34
356	526444	931278	9.0	2.03
358	526763	930672	8.6	1.05
359	526123	930652	7.6	1.19
360	526170	927193	8.0	1.54
363	533640	926999	8.3	1.47
367	532200	926522	8.4	3.70
374	525587	927145	8.2	0.70
376	526191	926681	7.7	4.98

Source: Ethiopian sugar corporation research and training center

APPENDIX-II

Ground water table data of the study area taken in 2007 to 2009

NO.	Filed ID	Easting	Northing	Elevation	2007/2009 Change(m)
1	16	524866	932771	1543	0.12
2	18	526319	932772	1549	0.78
3	166	527332	933381	1540	1.5
4	123	525817	926426	1538	0.51
5	177	529204	932575	1543	0.71
6	182	528852	931591	1541	0.5
7	101	526741	927510	1539	0.53
8	202	528754	929424	1541	0.16
9	99	525816	927510	1539	1.5
10	131	529681	926517	1537	0.27
11	25	524261	933379	1539	0.93
12	105	528855	927511	1539	0.16
13	41	525814	930992	1541	1.28
14	189	527895	930993	1541	0.03
15	159	525818	925365	1538	0.62
16	52	526739	930252	1542	0.18
17	76	524263	928493	1539	0.63
18	169	528851	933139	1542	1.45
19	195	528908	930253	1541	0.86
20	170	527861	932773	1541	1.3
21	29	526320	931589	1543	1.5
22	192	529205	930983	1539	0.36
23	22	525427	933612	1546	0.13
24	178	526739	931590	1549	0.45
25	184	527895	930993	1541	0.89
26	69	525815	929422	1540	1.32
27	127	527897	926958	1540	1.21
28	238	531086	926519	1538	1.67
29	198	527899	925156	1538	0.4
30	48	524868	930251	1536	1.1
31	82	527896	928495	1540	1.2
32	WRS	524502	934429	1543	1.87

Source: Ethiopian sugar corporation research and training center and Megersa (Wonji Sugar Factory, 2008).

APPENDIX-III

Result of Multivariate analysis

```
  ___  ____  ____  ____  ____ (R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/   12.0   Copyright 1985-2011 StataCorp LP
  Statistics/Data Analysis            StataCorp
                                      4905 Lakeway Drive
     Special Edition                  College Station, Texas 77845 USA
                                      800-STATA-PC        http://www.stata.com
                                      979-696-4600        stata@stata.com
                                      979-696-4601 (fax)

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       Serial number:  93611859953
         Licensed to:  STATAforAll
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Notes:
      1.  (/v# option or -set maxvar-) 5000 maximum variables

Checking for updates...
(contacting http://www.stata.com)
host not found
http://www.stata.com did not respond or is not a valid update site
unable to check for update; verify Internet settings are correct.

. import excel "H:\ENGDA DATA\INDEX\factor\xls\edited FINAL FACTOR.xls", sheet("edited FINAL FACTOR") firstrow

. mvreg MeasuredEC = soiltexture Vegetationdensity Elevation GEOLOGY Groundwatertable

Equation          Obs  Parms        RMSE      "R-sq"          F            P
----------------------------------------------------------------------------------
Measured EC        53      6     .6212435      0.7526      11.61246        0.0000

----------------------------------------------------------------------------------
       MeasuredEC |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------------+---------------------------------------------------------------
      soiltexture |   0.224      .1096      2.68   0.010     -.5146503   -.0736422
Vegetationdensity |   0.013      .1343      2.46   0.017      .0606217    .6010575
        Elevation |   0.161      .0342      2.23   0.031     -.1449832   -.0073285
          GEOLOGY |   0.158      .3195      2.15   0.036      .0455676    1.331127
 Groundwatertable |   0.288      .0039      2.74   0.009      .0028887    .0188787
            _cons |   117.3499   52.79      2.22   0.031      11.13079    223.5689
----------------------------------------------------------------------------------
```

D E C L A R A T I O N

I hereby declare that the thesis entitled "**Soil salinity Mapping and Risk Assessment using Remote sensing and GIS: the case of Wonji Sugarcane Irrigation farm"** has been carried out by me under the supervision of Dr. K. V. Suryabhagavan, Department of Earth Sciences, Addis Ababa University, Addis Ababa during the year 2014 as a part of Master of Science program in Remote Sensing and GIS. I further declare that this work has not been submitted to any other University or Institution for the award of any degree or diploma

ENGDAWORK ASFAW

Signature: ______________________
Place: Addis Ababa
Date: June, 2014

C E R T I F I C A T E

This is certified that the dissertation entitled **"Soil salinity Mapping and Risk Assessment using Remote sensing and GIS: the case of Wonji Sugarcane Irrigation farm"** is a bonafied work carried out by Engdawork Asfaw under my guidance and supervision. This is the actual work done by Engdawork Asfaw for the partial fulfillment of the award of the Degree of Master of Science in Remote Sensing and GIS from Addis Ababa University, Addis Ababa, Ethiopia

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