A Land Evaluation Model for Irrigated Crops using Multi-Criteria Analysis

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Doctor of Philosophy

By

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Abstract

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This thesis investigated the optimal land suitability for irrigated crop production of barley and wheat in Benghazi region of Libya using multi-criteria analysis (MCA) of fuzzy logic and the Analytical Hierarchy Process (AHP). In the MCA, fourteen land suitability factors including twelve soil characteristics, topography and erosion hazard were evaluated. Local experts used their experience and assigned different weights based on crop requirements through pairwise comparison matrix. The combination of these methods was aimed at developing existing land evaluation model in the study area that was based on Boolean logic. Three models were developed based on Food and Agriculture Organization Framework: Model 1 was based on existing land evaluation model of Boolean and equal weights; Model 2 was based on Boolean but with difference in weights assigned using AHP; and Model 3 was based on Fuzzy and AHP. The results of these models were compared using crosstab classification (Kappa statistic and overall agreement). On comparison, Model 2 and Model 3 demonstrated higher agreement in spatial distribution of land suitability class than Model 1 for both barley and wheat crops. However, Model 3 is more realistic than the other two models when tested by linear regression. This implies that the application of fuzzy logic and AHP in MCA produces areas that are most suitable for barley and wheat production than would other methods. In practice, however, land management practices by farmers may lead to different yield in the selected suitable area. This thesis makes original contributions in the field of identifying the most suitable land evaluation model for application to crop production improvements. Furthermore, the results of this research will be useful to the Libyan authorities in planning for the optimisation of available land-use for strategic production of barley and wheat crops. This is pertinent to issues of food security. The approaches are transferable to other regions of the world which face similar challenges in domestic food production.

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Abbreviations and Acronyms

AHP	Analytical Hierarchy Process
AIJ	Aggregate Individual Judgment
AIP	Aggregate Individual Priority
ALC	Agricultural Land Classification
ALES	American Land Evaluation System
ARC	Agricultural research centre
CIA	Central Intelligence Agency
CLI	Canada Land Inventory
CR	Consistency Ratio
ESRI	Earth Systems Research Institute
FAO	Food and Agriculture Organisation
FAOSTAT	Food and Agriculture Organisation Statistics
FCC	Fertility Capability Classification of Sanchez
GIS	Geographic Information Systems
GMRP	Great Man-Made River Project
GWA	Groundwater Authority
GAHP	Group of Analytical Hierarchy Process
LCs	Land Characteristics
LCAS	Land Capability for Agriculture in Scotland
LCC	Land Capability Classification
LUCIE	Land-use Capability Investigation and Evaluation
LUTs	Land Utilisation Types
LQs	Land Qualities
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
MCE	Multi-Criteria Evaluation
PCM	Pairwise Comparison Matrix
ICARDA	International Centre for Agricultural Research in the Dry Areas
UNESCO	United Nations Education Scientific and Cultural Organisation
UN-Habitat	United Nations Habitat
UNICEF	United Nations Children's Fund
USBR	United States Bureau for reclamation
USDA	United States Development Agency
WLC	Weighted Linear Combination
WOT	Weighted Overlay Techniques

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Chapter One

Introduction

1.1 Research Problem

In many countries, land resources are being used with an increasing intensity to meet the needs of growing populations. Increasing demands for food and increasing material expectations have led to the urgent need for the optimisation of land resources (Kutter et al., 1997). According to the Food and Agriculture Organisation (FAO) (1993), land use planning involves making decisions regarding the use of land resources with the primary aim of achieving the best use of land for maximum food production and profit. This is often driven by the needs of future generations in terms of productivity and environmental sustainability. However, sustainable land management in agriculture is a very complex and challenging concept, encompassing biophysical, socioeconomic and environmental issues that must be viewed as part of an integrated system (FAO, 1976; 1985; 2002). Therefore, effective land management information and land evaluation are prerequisites to achieving optimum utilisation of available land resources for agricultural production of particular importance to developing countries (Dale and McLaughlin, 1988; Nwer, 2005). Libya is one of these developing countries whose most important present-day agricultural policies are to use available land and water resources for the maintenance of food security, as evidenced in the man-made river and irrigation project (ARC, 2000; GMRP, 2008).

Furthermore, the most current and future challenge facing the development of agriculture is how to ensure the sustainability of land resources through efficient exploitation of what is available. Again, due to rapidly increasing population and urbanisation, arable land needs to be evaluated in order to achieve self–sufficiency and reduce vulnerability to food insecurity (FAO, 2011). This is particularly relevant for the two main areas of human settlement and food production in Libya's Jeffara and Benghazi regions, which both have significant human and natural resources (Ben Mahmoud, 1995; Ben Mahmoud et al., 2000; GMRP, 2008). These regions are targeted to receive water from the southern aquifers (Al Kufrah, Al Sarrir and Fazzan) through a network of concrete pipes. According to GMRP (1990), the main objective of Libyan agricultural policy in this region is to create all year round irrigation projects for the production of food and cash crops (e.g. barley, wheat and maize). However, currently the contribution of crops to the local economy also remains substantially low, with potential for future increases when suitable land suitability methods are developed and adopted. To sustain agricultural production, special attention needs to be given to spatial models that can illustrate stronger linkages between data derived from land characteristics and crop yields, which can predict land suitability for crop production on specified farmland management in the Libyan context. Similarly, Al-Mashreki et al. (2011) suggest that increasing food production for self-sufficiency and national economic growth could be met through systematic survey of the soils, evaluating land use options and formulating land use plans based on local peculiarities, but which are viable economically, socially acceptable and environmentally friendly.

In addition to the previous works undertaken by Nwer (2005) and Elaalem (2010), this thesis used GIS-based multi-criteria decision making (MCDM) of fuzzy logic and the Analytical Hierarchy Process (AHP) to identify and map optimal land suitability for barley and wheat crop production in the Benghazi region of Libya. Section 1.2 shows previous works that have developed land evaluation models for a number of cash crops in the Benghazi and Jeffara region of Libya.

1.2 Land Suitability Evaluation in the Study Area

Traditional land evaluation methods (the FAO Framework and Boolean Logic) were applied by Nwer (2005) using the concept of a limiting factors to produce land suitability maps for barley and wheat crops in the study area. One of the limitations of Nwer's (2005) land evaluation model, in the context of the selected study area, is that it applies the Boolean methodology. The Boolean method usually refers to a number of related elements as a crisp set (Baja et al., 2011). In Boolean logic, the boundaries between land mapping units are sharply defined, whereas they should actually be set according to transition zones (e.g. Baja et al., 2002; Burrough, 1989; Christoffel, 2006; Davidson et al., 1994; Dobermann and Oberthiir, 1997; Elaalem, 2012; Sarmadian et al., 2010). According to McBratney and Odeh (1997), Boolean logic application in land evaluation often leads to the loss of useful information that is relevant in the study area as occurred in Nwer's (2005) study. Davidson et al. (1994: 383) were some of the early authors to describe the disadvantages of applying Boolean logic, stating for example: 1) "masking of key and positive land properties by less important ones may depress the overall suitability class", and 2) inabilities to take into account the effect of properties which happen to have values near to class boundaries". In recent times however, fuzzy-set theory in land evaluation is gaining popularity as a remedy for Boolean limitations (De la Rosa and Van Diepen, 2002).

The first limitation of existing land evaluation in the study area is the imprecision caused by the method used to select the weighting for all criteria or factors that affect the suitability of land for barley, as it ascribes equal weighting to each factor, and each criterion selected contributes towards the overall suitability selection process (Feizizadeh, and Blaschke, 2013; Ceballos-Silva and Lopez, 2003; Paraksh, 2003). Secondly, many studies (such as Davidson, 1994; Groenemans et al., 1997; Braimoh et al., 2004; Elaalem et al., 2010; Sarmadian et al., 2010) clearly affirm that the selection of weights have a major effect on the model outputs. However, a major issue confronting land evaluation methodologies is the prediction of the weights placed on land characteristics and/or land qualities against the eventual crop performance required. The accuracy of land evaluation methods also depends on the weighting values of the attributes of land based on their effect on crop production. It is therefore, necessary to assign appropriate weights to them. The third limitation is the choice of technique used to identify the land that is suitable for each crop i.e. weighted overlay technique (WOT).

The limitation associated with using the weighted overlay technique is that the output of WOT in the raster should be discrete, and the value will typically be rounded to an integer; yet, this is a limitation because converting the decimal value to an integer can result in a loss of information which inaccurately reflects reality (ESRI, 2010). In addition, the weighted overlay tool is applied to solve multi-criteria problems such as location selection and suitability models, and allows for the consideration of geographic problems which may often require the analysis of different factors (ESRI, 2010). Such is the case with land suitability analysis where determination of overall land suitability of an area for a particular agricultural crop will require consideration of many criteria e.g. soil pH, depth and texture (Van Diepen et al., 1991). Each criterion can be represented by a separate map (a single thematic layer) in terms of the degree of suitability for each land unit, but in the existing land evaluation model for the study area, the land characteristics which are related to soil are grouped and represented as one thematic layer. Arguably, this may result in the loss of interaction between factors, particularly when weights are being assigned to each land characteristic. This demonstrates the need to give attention to the testing and development of traditional land suitability models in order to achieve the optimum use of available land in Libya. To overcome the limitations of purely relying on traditional methods, this research explores the potential of using multi-criteria methods (such as the fuzzy method and the AHP integrated with GIS functions (such as overlay analysis) to handle these problems.

1.3 Research Questions

In order to address the research aim and to analyse land evaluation techniques to find land suitability in in Benghazi region in northeast of Libya, the following research questions were developed followed by a main aim and objectives:

1. What are the benefits of applying different approaches such as multi-criteria methods to a land suitability model?
2. Is it possible to develop the existing land suitability model by using multi-criteria method?
3. Which land evaluation system is most suitable for Libyan land conditions?
4. How will the newly-developed land suitability model help the Libyan government in the decision-making process for land use planning?

1.4 Research Aim and Objectives

The overall aim of this study is to develop and verify a land evaluation technique for the production of barley and wheat in the study area. This aim was achieved by meeting five specific objectives:

1. Identification, testing and evaluation of suitable available methods for land evaluation to select the appropriate technique.

2. Development of existing land evaluation methods by using Multi-criteria Evaluation (MCE) methods.
3. Identification and assembly of data on land characteristics which affect agricultural growth in the study area, weighted by means of local expert knowledge.
4. Comparison of the outputs derived from both the new model and those from an existing land evaluation model of the study area, with field yield data collected during the course of this research.
5. Derivation of a number of land suitability maps for barley and wheat based on MCE and Boolean methods.

1.5 Thesis Structure

This thesis is arranged into nine chapters, from introduction to study area, followed by methodological issues to results then the conclusion. A summary of the contents of each chapter is presented below.

Chapter One presents a brief introduction to the thesis and provides a brief background to the study including the rationale, research questions, aim and objectives and structure of the thesis. Chapter Two covers most relevant socio-economic and geophysical factors including population, climate, soil and water resources use and management and the interplay between agricultural policies and food security among others. Chapter Three presents a review of land evaluation methods and their applications in land suitability. The second part of this chapter goes on to briefly explain Boolean and Fuzzy theory as the two logics used in land evaluation. Chapter Four is an extension of chapter three reviewing the most widely used land evaluation methods. Chapter Five reviews land suitability analysis that involves GIS and multi-criteria evaluation. Chapter Six document the methods employed in the research from selection of study areas to data validation, covering data requirements, database construction, deriving weights, fuzzy set theory applications and deriving land evaluation models. While Chapter Six shows the different models used to produce land suitability maps for Barley and Wheat, Chapter Seven shows the results (in the form of three models). The latter are based on FAO framework and weighting local experts' opinions. Chapter Eight compares the three models and their implications in practice. Chapter Nine links the aims and objectives, the literature review, and the research results to present the conclusions to this research project. This last section of the thesis provides recommendations based on the findings and suggest possible areas of future research.

Chapter Two
Research Context

2.1 Introduction

Compared to its North African neighbours, Libya is for the most part an arid country, which account for why the agricultural sector's contribution to the national economy in terms of Gross Domestic Products is low. The constraint to agriculture is caused by fresh water scarcity, low soil fertility coupled with limited arable land. Consequently, this has resulted in an extensive production system that suffers from low productivity. However, the productivity along the coastal areas of the Mediterranean climate which covers a narrow belt of about 25 square kilometres is an exception due to year round adequate rainfall. To overcome limitations in land scarcity robust scientific analyses for evaluating land suitability are required to increase output of crop production for self-sufficiency in food supply. This chapter is therefore aimed at contextualising these issues in the country of study. Section 2.2 starts with the background and general characteristics of Libya, including the geography and the population. This is followed by an examination of the major natural and land use conditions associated with agriculture but are relevant to the research topic such as soil and water management. The Libyan economy, agriculture and food security problems are also examined in Sections 2.5 and 2.6 respectively.

2.2 Physical Landscape

With the Mediterranean Sea on the north and the Sahara desert on its south, Libya is located in the north of Africa covering an area of 1,759,540 square kilometres (1,093,327 sq. mi), lying between 20° and 34° N and 10° and 25° E. The vast Sahara desert in the south makes about 95% of its territory, while the coastline covers about

1,770 kilometres (Ben Mahmoud et al., 2000; Johnson, 1973). Libya shares borders with Egypt to the East, Sudan to the south-east, Tunisia and Algeria to the west, and Niger and Chad to the south (Figure 2.1). It has an important physical asset in its strategic site at the centre of Africa's northern rim. Figure 2.1 also indicates the location of the study area which covers the Benghazi coastal line located in the western corner of north-eastern Libya. The Benghazi region is located between longitudes 32^{o} 4′N and 20^{o} 16′ E.

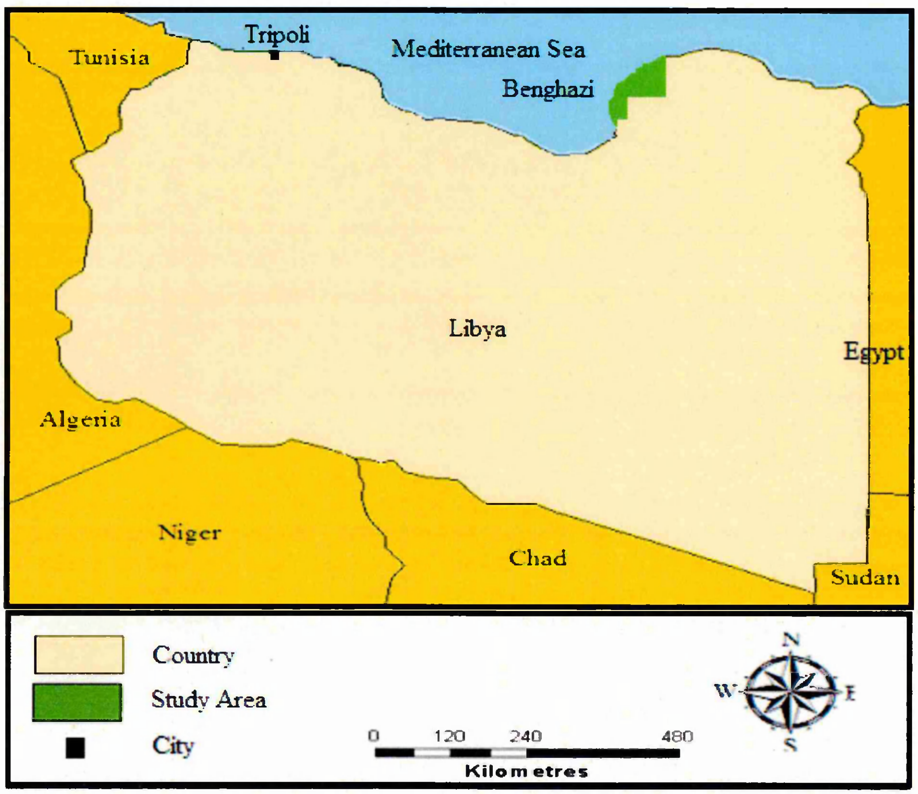

Figure 2.1: Map of Libya.

In Libya, two main land systems were identified, based essentially on geographic location and geomorphological patterns: the barren plains are in the north part and the Sahara desert in the south are the most dominant natural features. The Mediterranean coastal lands stretch from west to east, stretching about 2000 km from the Tunisian border to the Egyptian border. The desert includes rocky outcrops and loose surface materials. Only 2% of the country is cultivable land which is estimated at about 3.8 million hectares (Ben Mahmoud et al., 2000). The majority of the cultivated land and /or rangeland are located along the northern zone. However, there are recent agricultural development projects in the southern desert covering about 35,000 hectares. In 1997, the total cultivated area was estimated at 2.28 million hectares or 60 % of the cultivable area, of which 1.93 million hectares consisted of annual crops and 0.35 million hectares biennial and perennial crops. At present, an estimated 400,000 hectares are under irrigation. These areas include large projects, settlements and small holder farms (Ben Mahmoud, 1995).

In between the Sahara desert and the Coastal shorelines, four physiographic regions can be distinguished: 1) The Coastal Plains that run along the Libyan coast which vary in width; 2) Northern Mountains that run close to the coastal plains and include the Jabal Nafusa to the west and Jabal al Akhdar to the east; 3) Internal Depressions that cover the centre of the Libya and include several oases; and 4) Southern and Western Mountains (Figure 2.2). All of these regions have constrained agriculture due to barrenness, dryness, low soil fertility and difficulty of access.

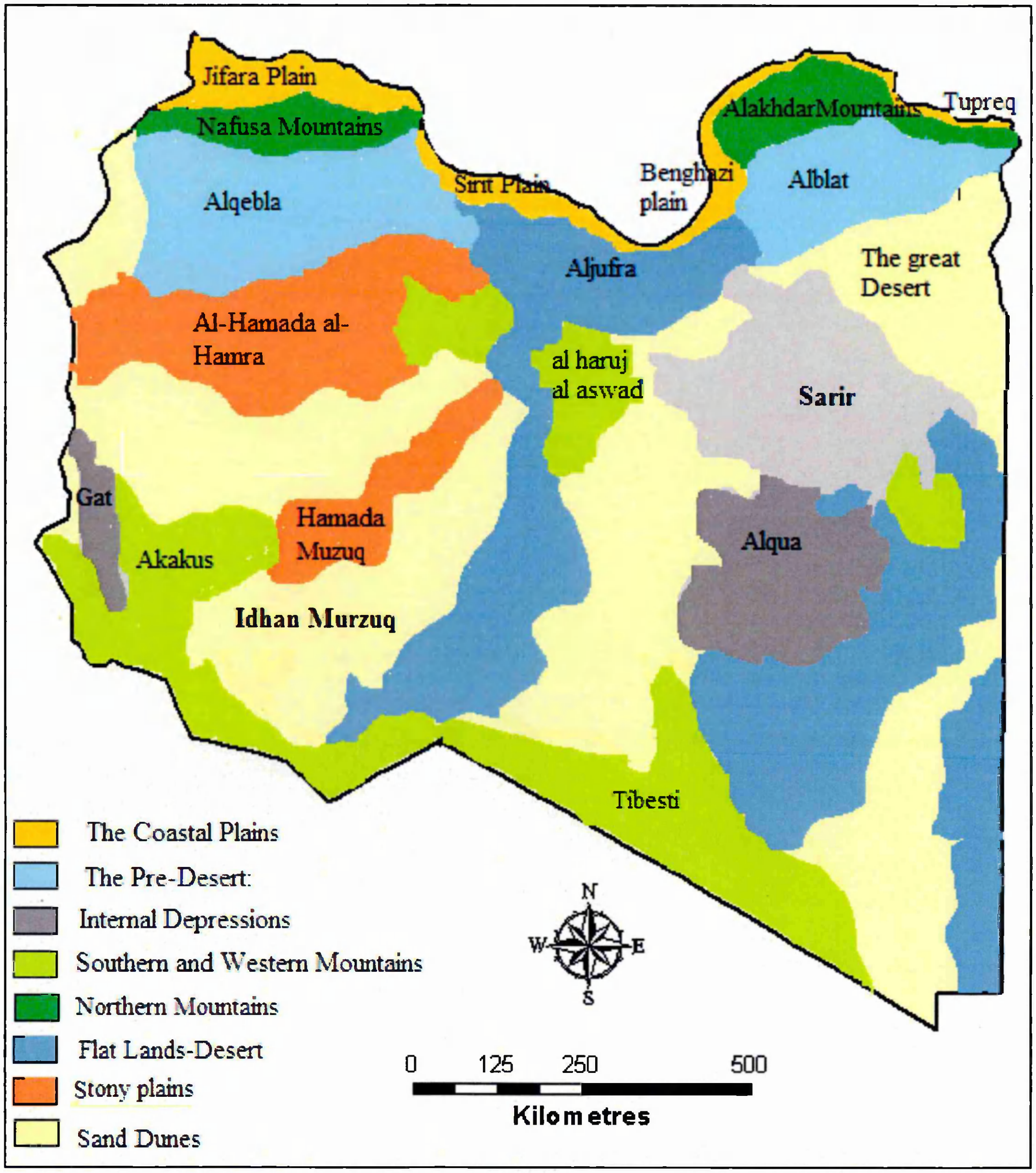

Figure 2.2 : Map of Physiographic regions in Libya

2.2.1 Climatic Conditions

The climatic conditions of Libya are influenced by the Mediterranean climate to the north and the Sahara desert to the south. The coastal region, which contains cities such as Tripoli, Khoms, Alzawia, Shahat and Tubruq comes under the influence of the Mediterranean coastal strip that is characterised by hot and dry summers and relatively wet winters. The inland mountains comprising Jabal Nafusa and Jabal Akhdar highlands experience a plateau climate with higher rainfall and humidity and low winter temperatures, including snow on the hills because of the north westerly winds. As one move southwards to the interior, the semi-desert and Sahara climatic conditions prevail, with hot temperatures (measuring up to 136°F (58°C) in Aziziyah) and large diurnal temperature variations between night and day and between summer and winter. Temperature can be as low as -3.6^{0}C degrees centigrade in the month of January and up to 47^{0}C in the month of August in cities like Ghadames. The north westerly winds are considered the most desirable winds for summer nights and their lower velocity also makes them less damaging during the winter months.

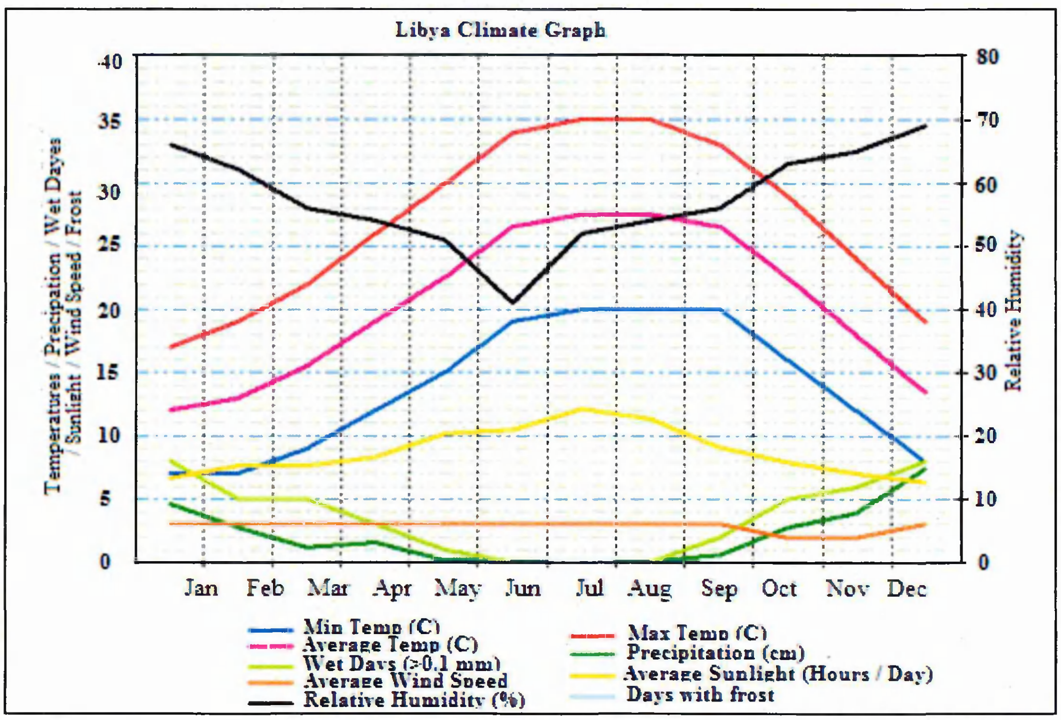

Figure 2.2: Climatic conditions in Libya, 1960-2012. Source: Climatemps (2013)

The spatial pattern of precipitation is one of very fast decline from north to south (ARC-ICARDA, 2008; Hamad, 2012). The average annual rainfall for Libya is 26 mm (Figure 2.2) and only coastal areas have sufficient rainfall to allow agricultural use of the land. In the Sahara, rainfall is almost non-existent, with about 93% of the land receiving below 2.5 cm (25 mm) per year and progressively towards zero. The relative humidity is low throughout the year in this part of Libya. While there is severe rainfall shortage in the Sahara, the rainfall in the northern Tripoli (e.g. Jabal Nafusa and Jeffara Plain) and northern Benghazi (Jabal al Akhdar) exceeds the minimum precipitation (250-300 mm) required for rain-fed agricultural production. In this instance, McCalley and Sparks (2009) have cautioned that high temperature increases and irregular rainfall patterns may lead to nitrogen losses in the semi-desert regions and make the soils infertile and unable to support plant life.

The above brief climatic conditions clearly show that Al-Kufrah region in Libya is one of the ten driest regions worldwide with low annual rainfall, high temperature and evaporation (Al-Ghariani, 1996). As a result of the low precipitation and limited surface water; groundwater has been used in the development of agriculture in Libya. As indicated in Figure 2.3, expanding economy and growing population along the coastal strip is associated with escalating demand on groundwater resources for domestic and industrial usages and for agriculture. The increase in water demand and intensive use with very little recharge is restraining groundwater resources, resulting in serious declines in water levels and saline intrusion into the coastal aquifer (Lawgali, 2008). El Asswad (1995) had earlier stated that groundwater on the coastal regions is over-exploited and non-sustainable. The dwindling water supply and increasing population compelled for creating ways of increasing agricultural productivity through methods such as those carried out in this research.

2.2.2 Population

Figure 2.3 shows how rapidly the Libyan population has changed markedly since the discovery of oil in late 1950s. The total population is steadily growing, from just over four million in the 1990s to more than six million by 2010 (FAOSTAT, 2013). The population has increased from 4.4 million in 1995 to 5.3 million in 2006, with an estimated 6.5 million people by the end of 2015. There are currently 1.1 million non-Libyan migrants from mainly neighbouring countries and the rest of Africa. It is projected that the population of Libyans and migrants may reach up to nine million by 2050. As a result of improvements in the standard of living, per capita income growth, increased health awareness and the availability of medical treatment and urbanisation, the death rate has declined while birth rate has increased respectively (UNICEF, 2011).

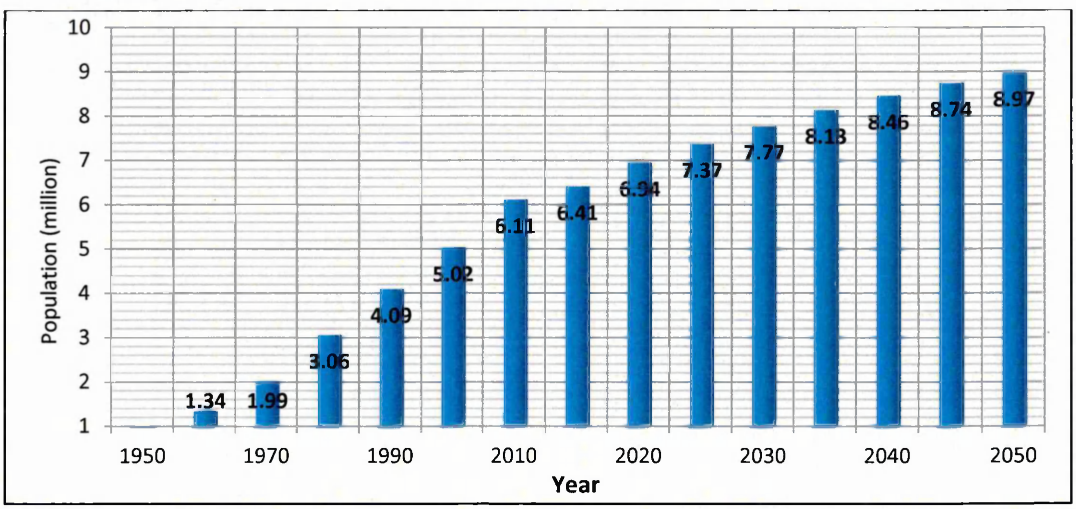

Figure 2.3: Libyan population 1950-2050. Source: FAOSTAT (2013).

The Libyan population inhabit the coastal region of Jeffara and Benghazi Plains. The coastal areas of Tripoli, Benghazi, Misrata, Az -Zawiya, Al Bayda, Zliten and Darnah are have to about 90% of the population of Libya. The urban population is about 78% of the total (UNICEF, 2011), out of which about 44% are in Tripoli and Benghazi because of their significant resources such as soil, water, vegetation and climate. Other important factors attracting population growth is trade legacy and national development plans. In 1995, 54% of the Libyan population lived in the western coastal area. The eastern coastal area has 21% of the population. This means that 75% of the population are dwelling in an area that is just over 1.5 % of the total land area of the country. The expanding economy and population coupled with the absence of control and planning policies, have resulted in increasing pressure and competition between urban and agricultural lands (*Libyan Statistics Book*, 2007). As a result, increased supplies of food are needed to match this growth. According to Wheidah (2012; 146), the needs and demand of the population have been the driving force in the allocation of water resources for food production. Therefore, it is vital to examine prevailing climatic conditions, soil and water resources effects on agriculture and to develop land suitability models that would boost food production policy.

2.3 Soil Resources

Extensive soil studies have been conducted in Libya over the last four decades (e.g. Ben Mahmoud and Suliman, 1989). However, emphasis has been placed mainly on the distribution of morphological characteristics of northern part of Libya and on small scattered areas in the southern desert. The present soil survey reports and maps differ in their content, types of maps, scale of mapping, classification systems used, methods of soil analysis, and the criteria on which the interpretation of data is based. The major soil classification systems used in these reports are the USDA Soil Taxonomy, the modern soil classification of Russia, the French soil classification, and the FAO/UNESCO system. Based on the US Soil Taxonomy, the main soil orders are Entisols, Aridisols, Mollisols, Alfisols, Vertisols, and Inceptisols (FAO and UNESCO, 1998; Selkhozpromexport, 1980; Mahmoud, 1995). Libyan soils are generally Entisols and Aridisols.

The taxonomy of the Soviet soil pedology system was adopted for elaboration of the soil classification, and the soil nomenclature generally applied to characterize the soil mantle of the Mediterranean countries was also partially used. Classes and subclasses have been singled out on the basis of the classification structure for the tropics and sub-tropics. The Russian terminology system used in this study is summarised below: Appendix A.1 contains the definitions of the Soviet terminology for class, subclass, type, subtype and genera

Based on the taxonomy of the Soviet classifications system the soil in the study area are divided into: 2 soil classes, 5 soil subclasses, and 10 soil types, including 30 subtypes and the soils are also subdivided into genera. Besides, non-soil formation represented by Martine and continental sands, rock outcrops and coarse-textured stony alluvial and proluvial deposits are also delineated on the soil map. Most of the soils in Libya have a transition between aridic and xeric moisture regimes and thermic and hyperthermic temperature regime (Selkhozpromexport, 1980; Mahmoud, 1995).

2.3.1 Soil Erosion

Soil erosion in Libya is a major problem occurring mainly in the semi-arid and sub-humid areas. Both water and wind work together, as redeposited silts from surfaces stripped by water erosion are particularly vulnerable to wind transport. Wind erosion starts with the movement of coarse soil particles in one part of a field, then progresses downwind with increasing severity as bouncing soil particles knock other particles into the air in a kind of progressive, increasing effect. Finer materials are lifted as dust into the air and carried away over long distances; coarser sandy materials drift over the surface until they are trapped by plants in accumulations of low, rounded hills and small dunes. A study conducted in 1980 showed that there are two types of soil erosion in Libya: water erosion and wind erosion (Selkhozpromexport, 1980). Wind erosion is a big problem in the Jeffara Plain leading to soil degradation and affects agricultural production and pasture. Over grazing, which involves deflation of the uppermost soil is the major cause of wind erosion. Ben-Mahmoud et al. (2000) added that several centimetres of soils that have sandy texture, such as Camborthids and Orthents, can be easily removed by wind. Erosion is widespread within the Jebel Nafusa upland and the Benghazi region, occurs in the form of sheet washing and rill forms because the vegetation cover has been degraded by over-cultivation. Also, the intensity of soil erosion in this area depends on the amount of precipitation, vegetation density, slope stability and soil moisture. Some of the human causes of soil degradation and consequently erosion in Libya are by: 1) deforestation and the removal of natural vegetation, 2) misuse or poor management and over exploitation, 3) overexploitation of water resources, 4) rangeland conversion to cropland, 5) overgrazing in marginal areas, and 6) urbanisation and increasing population (Saad et. al., 2011).

2.4 Water Resources and Management

Libya like other North African countries bordering the Sahara has always been challenged by the need to use available water to meet human needs for consumption, agriculture and industrialisation (Alghariani, 2004). The situation has been compounded by increasing population, rising standard of living and food demand. Major efforts were designed to mitigate the water shortage in Libya through the construction of dams, seawater desalination, treatment plants; and the so-called Great Man-Made River – one of the world's largest irrigation projects that supplies water from the Sahara to the coast. Despite these efforts, Libya still suffers from an unenviable water shortage (Ramali, 2012).

Table 2.1: Major water basins of Libya in million cubic meters per year

Water basin	Groundwater	Surface water	Unconventional water	Total
Jeffara Plain	200	52	27.5	279.5
Jabal Alakhdar	200	92	45.5	337.5
AL Hamada Alhamra	230	48	50.5	328.5
Kufrah and Sarir	563	-	-	563
Murzuk	771	-	-	771
Total	1964	192	123.5	2279.5

Source: General Water Authority (2006) and Alghariani (2004)

Table 2.1 is an indication of the various water sources in Libya from five major water basins. The Libyan General Water Authority (2006) indicated that the combination of 279.5 m^3 water from the Jeffara Plain basin region is deficit and less significantly so in the Jabal Alakhdar basin region. The deficit is due to population, industrialisation and demand for arable land along the north-western and north-eastern regions of Libya. There is, however, no water deficit in the Murzuk and Kufrah-Sarir basins due to low population and land availability.

Surface water is limited - estimated at less than 200 million m^3 per year and contributes above 5% of the current water resources (GWA, 2000). According to Al-Ghariani (1996), Libya's total mean annual runoff calculated or measured at the entrance of the wadis in the plains (or spreading zones) was at 200 million m^3 per year. However, a high proportion of the runoff either evaporates or recharges the underlying aquifers. Attempts were made to increase water reservoirs from the current 16 dams, whose maximum capacity is around 30-40 * 10^6 m^3/yr., to ones that could take the annual storage capacity of about 61* 10^6 m^3. As indicated in table 2.1, groundwater accounts for about 90% of the water resources in use. The coastal aquifers are being recharged by rainfall but uncontrolled groundwater extraction from these aquifers tends to exceed the annual replenishment rate. This process, leading to seawater encroachment, has caused high salinity. Unconventional water resources in Libya include sea water desalination plants and wastewater treatment facilities. While desalination plants are purpose built for domestic and industrial uses (put presently at 40 million m^3 per year), treated wastewater is for agricultural purposes.

2.4.1 Water Demand and Supply

As indicated in figure 2.4, agriculture represents the largest demand for available water resources in the country, and will continue to be the major water consumer for the next two decades (Algharìani, 2004; Hamad, 2012). According to an estimated work Lawgali (2008), water demand for agriculture is approximately 82%, while the domestic sector consumes about 15%. Industrial consumption, on the other hand, amounts to about 3% of the total water demand by 2020. This result is similar to the current estimates given by the Libyan General Water Authority (2006). The combined future estimates indicate an increase from 6293.89 m^3 in 2006 to 12473.20 m^3 in 2020: an average annual rate of around 5%. By 2020, the increase would be 98% of 2006 consumption rate.

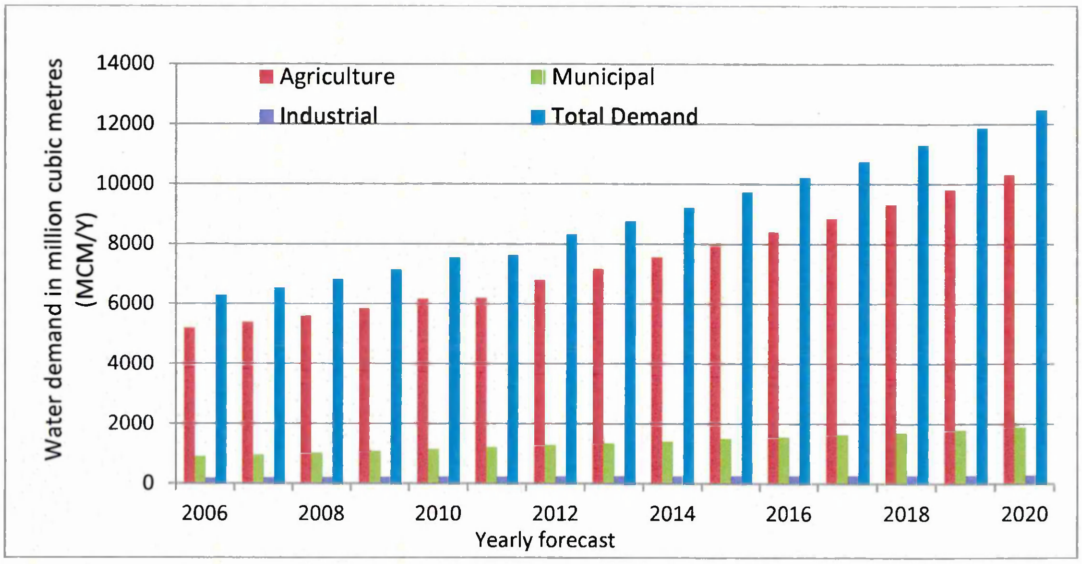

Figure 2.4: Agriculture and municipal water demand in Libya. Source: Author. Data obtained from Lawgali (2008)

Figure 2.4 shows water demand in blue bars against supply for agriculture and municipal use from 2006-2020. The increase in water consumption for agricultural use affects current and planned water reserves. It therefore becomes important to find land suitable to crop production using minimal water supply. As the figure indicates, agriculture has taken the larger proportion of water use because it has been transformed from traditional rain-fed crop production into an extensive mechanised irrigation cultivation which requires intensive water usage. However, available water resources are insufficient to meet the present consumption rate. This prompted huge water transfer and redistribution system otherwise known as The Great Manmade River Project (GMRP) (Figure 2.5). The GMRP is planned in five phases. The three phases have been completed.

The first phase, the largest, and consists of a system that extracted and carries two million cubic metres of water daily to the coastal region. However, the system is designed to be expanded to carry 3.68 million m^3 of water daily in the future (GMRP, 1990).

The second phase consists of a system that delivers one million m^3 of water daily from well fields in Fezzan region to the western coastal belt and in particular to Jeffara Plain. It is designed to accommodate a further one million m^3 a day in the future (GMRP, 1990).

The third phase is an anticipated expansion of the first phase. The water flow will be increased by 1.68 million m^3 daily. The water flow was increased by 1.68 million m3 daily.

The fourth phase is under construction and will carry 200,000 m^3 to Tubruq from Ajdabiya.

The fifth phase consists of two stages. The first stage connects phases one and two by linking a conveyance line between Sirt and the Jeffara Plain to deliver one million m^3. The second stage of phase five expands the second phase system by incorporating two additional well fields to supply one million m^3 of water a day (GMRP, 2008).

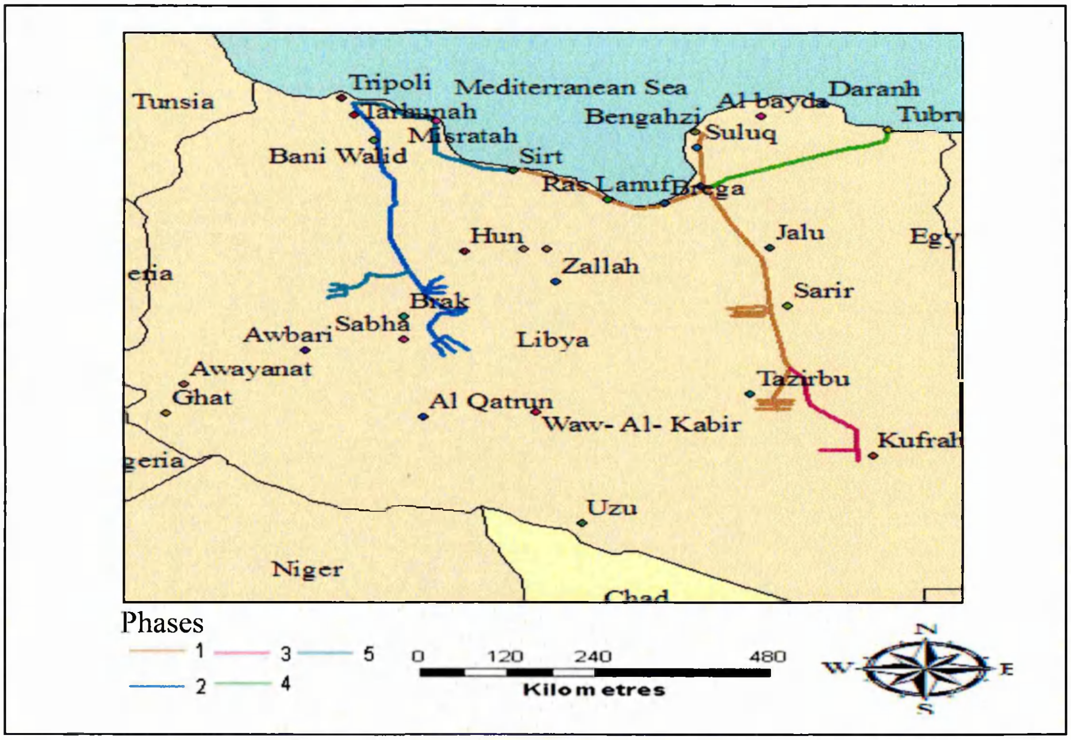

Figure 2.5: The five phases of the Great Man-Made River Project. Source: GMRP (2008)

Similar to Figure 2.4, Table 2.2 clearly indicates that GMRP is only a partial solution to medium term water solution. Estimates by the General Water Authority (2000) has shown deficits of more than 1.2 m^3 in 2010 further increasing to more than 3.5 m^3 by 2025. This calls for a rethink on the use of GMRP for agriculture – it has to be progressively but drastically reduced through contemplating expanding seawater desalination technology and waste water treatment that currently represent only 3% of water sources. Other ways are to reduce agricultural water demand by producing more crops with less water demand, and selecting suitable land for increased productivity are areas that can be explored. The latter is the major area to be discussed in chapter seven of this thesis.

Table 2.2: Water Demands forecasts in Libya, 2006-2020

Year	Water demand	Water supply		Balance
		Without GMRP	With GMRP	With GMRP
1995	3885	2279.5	2360.5	-1524.5
2000	4493	2279.5	3912.5	-581.0
2010	5794	2279.5	4506.0	-1288.0
2020	7236	2279.5	4506.0	-2730.0
2025	8022	2279.5	4506.0	-3516

Source: General Water Authority (2000) and Algharlani (2007)

2.5 Libyan Economy

According to Abubrig (2012:123), the economic transformation of Libya can be broadly categorised into three phases. The first phase is before the discovery of oil in 1958 which started after the abolition of the Trans-Sahara slave trade. Libya was characterised by poverty and the economy depended on foreign aid due to limited wealth. The majority of the population was dependent upon traditional agriculture, which, in turn depends on rainfall and productivity has suffered from soil erosion, water scarcity and harsh climate. The industrial sector was limited, due to shortage of skilled and educated manpower and the lack of raw materials. The second phase began from 1961 when Libya began to enjoy the revenues from oil export and was transferring into a modern society through infrastructure and self-sufficiency in food supply. Within this period, Libya experienced social and political change, such as the aggressive nationalisation programme and the socialist principles movement of 1978. Agriculture's contribution of 20% to GDP prior to 1958 sharply declined to 2% in 1978, due to limited water and migration of local farmers to the coastal areas for oil sector jobs.

The third phase covered consolidation of the economy and the dissolution of private ownership and the public sector development programmes from 1980s up to 2000. While agriculture remained abysmally low (2% of GDP), Libya began food imports from Italy, Germany and the neighbouring countries for the increasing population. For example, the import of cereals, sugar and oil in 2000 represented 68% of the national calorie budget. In 2010, food security at the national level was achieved, but food self-sufficiency is not feasible because of the volatility of imports and the government's over-reliance on oil revenue to subsidise the importation of food. Also, the 2011-2012 Libyan revolution has had an impact on the national economy and agriculture. This I do not intend to expand on here.

2.6 Agricultural Production

According to estimates, agriculture is 9% of GDP and employs 5% of the economically active population. Crop production accounts for 5% of the GDP and occupies about 13% of the total labour force. As a result of climatic and land constraints, Libya's main agricultural products are vegetables, cereals –mainly wheat and barley - fruits, meat, legumes and dairy products (Table 2.3). Olive trees and orchard farms are prevalent in the western part of the country and are intercropped with barley and vegetables. The usual market for most of the products is the local one, where these products are transferred from the farmers to the consumers (Libyan Statistics Book 2007). Libya's agriculture depends mainly on the private sector since the late 1970s. There is large proportion of privately-owned farms in Libya. The private farms, range from one hectare small family holders - purely for subsistence farming - to large-scale irrigation of more than 10 hectares (GMPR, 2008). The rest are government-owned under the irrigation scheme, but mainly for the production of cereals and forage. Mechanised farming system using overhead sprinkler and drip irrigation systems are common in government-owned arable lands.

Table 2.3: Total agricultural production in Libya in 2007

Products	**Productions (1000 tonnes)**
Vegetables	420.000
Cereals	650.000
Fruits	350,000
Meat	16.000
Legumes	22.000
Dairy products	90.061

Source: Libyan Statistics Book (2007)

As a result of climatic factors and land constraints, irrigation has always been of crucial importance to the country's agriculture. According to FAO (2005), Libya dedicated about 470 000 hectares of land for irrigation, of which about 22% has been cultivated. For example, local production of cereals from irrigated land is about 50% and that of fruit and vegetable is almost 90%. In the coastal plains, marginal lands, Jabal Al Akhdar and wadi beds annual, perennial and biennial crops are cultivated depending on the rainfall pattern.

2.7 Summary

This chapter has shown that Libya depends on the importing for most of its agricultural products owing to climatic conditions and poor soils that limit domestic output. The increase in income and population growth has increased food consumption over the years, but food security is becoming a serious challenge in the oil rich country. Because of low rainfall, agriculture relies on limited rainfall on underground water sources. As a sign of commitment, the GMRP remains the primary agricultural water source but also significant resources are being invested in desalinisation of the Mediterranean Sea to meet increasing demand. This means that that agricultural water management must be coordinated with, and integrated into, the overall water and agriculture policies. However, land evaluation research must be integrated to attain best suitability and maximal yield using the limited amount of water and land. As indicated in sections 2.2-2.4, the potential physical and climatic conditions exist to support increased local food production through scientific use of land resources. For example, as there is a large reserve of shallow underground water along the coast, yield can be improved by irrigation due to the short precipitation period during the winter. In order to increase productivity a thorough land evaluation needs to be undertaken as described in the following chapter.

Chapter Three
An Overview of Land Evaluation

3.1 Introduction

This chapter describe a variety of definitions and explanations regarding land evaluation, as well as different approaches to the process of land evaluation. The following section focus on specific instances of the land evaluation and its applications. Section 3.3 discusses the need for land evaluation and section 3.4 identifies the difference between land use and land evaluation. Section 3.5 explains the terms and logic used in land evaluation including types of evaluation. The traditional systems in land evaluation, from the qualitative systems to the single-factor models are contained in this section. Section 3.6 reviews the logic used in land evaluation including Boolean and fuzzy and is further extended in section 5.4. Section 3.7 of this chapter concludes with a description of the role of the land information system in land evaluation and how these systems can contribute to the exercise. The chapter that follows contains a critical overview of the various methods used in land evaluation studies and put into context the specific methods adopted in this study. It also contains the reasons why FAO approach was considered the most suitable approach for this research.

3.2 Land Evaluation: Definition and Explanation

Dent and Young (1981) define land evaluation as the process of estimating the potential for alternative kinds of land use and to predict the consequences of change. It can distinguish between a numbers of forces behind land evaluation emerging as a distinct subject. Firstly, there is an increasing availability of biophysical data, and these data can be processed and presented in a variety of ways. Secondly, countries are committing to the challenges of land use planning. South Africa and Libya for instance, have linked their sustainable development goals and land use planning. In this manner, the function of land use planning is to guide decisions on land use so that they are put to the most beneficial use for present, whilst conserving the same land for future population and their needs.

Land evaluation process may be done qualitatively or quantitatively for the purpose of determining its suitability (for a specific use, as in production of maize or potatoes) or its capability (for a wider utilisation such as agriculture or grazing). In the past, land evaluation was used as part of soil survey studies. However, since 1970, land development has shifted focus to crop growth and crop production, which includes aspects pertaining to climate conditions, soil and land management. There are two approaches being used: 1) parametric systems incorporate land characteristics that influence agricultural production by using mathematical equations. Many parametric approaches have been used for land evaluation. These approaches vary in the specific parameters they include and in their mathematical manipulation (McRae and Burnham, 1980), and 2) categorical systems, focused on the classification of the property into production units according to the units' varying potentials and limitations affecting crop growth (McRae and Burnham, 1980; Rossiter, 1994). Land evaluation involves assessing the production capability of the land using a systematic analysis of both the land's physical conditions and their impact on the current and future land use. Land evaluation offers a technique for comparing the different ways that the land can be used as well as the benefits that may be derived from these uses, considering the present and future economic and social environments (FAO, 2007).

The process of land evaluation will not define the land use or any proposed changes in it. Instead, it provides data that can serve as a basis for deciding which land use option is suitable. In short, land evaluation helps land owners, regional land development agencies and nations to arrive at logical land use decisions. But there are certain requirements for land evaluation to be successfully utilised (Verheye, 2008). Many of these requirements are specific to the type of land use, and they include both the ecological requirements of the crop or other biological product, and the requirements of the management system used to produce it. Evaluation of land resources is essentially a combination of the properties of the land with the requirements of proposed land use. The principles of land evaluation are presented in the Framework for Land Evaluation (FAO, 1976) as follows and illustrated in Figure 3.1.

- Initial consultation, concerned with the objective of the evaluation, data (including land, land use and economics) and defining assumptions;
- Description of the kinds of land use to be considered, and establishment of their requirements that can support particular land use;
- Description of resource base units or "land units";
- Comparison of kinds of land use, such as coffee cultivation, wheat production, irrigation projector poultry farms, with the types of land present ("matching");
- Economic and social analysis e.g. size of land holdings and mechanisation;
- Land suitability classification (qualitative or quantitative);
- Presentation of the results of the evaluation into a form usable by land users.

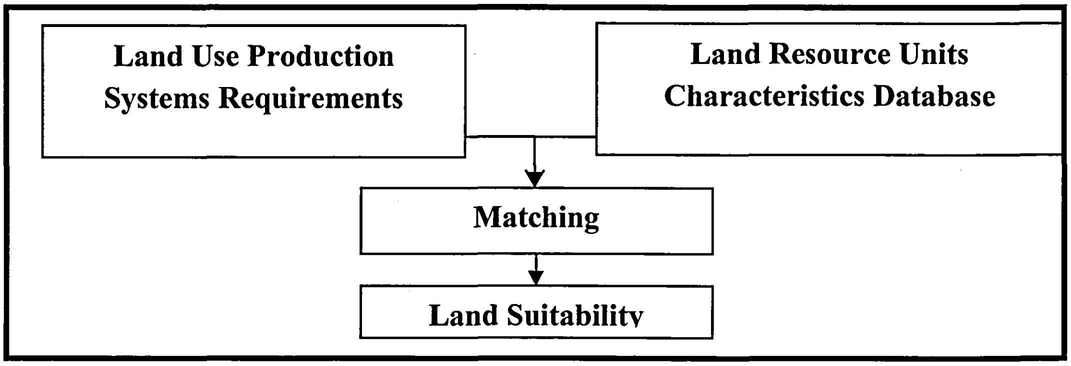

Figure 3.1: Process of land evaluation

3.3 The Need for Land Evaluation

The FAO (1976) argues that in the past, land use changes often came about by gradual evolution as a result of many separate decisions taken by individuals. The increased demand for physical space and food from expanding population, the availability of suitable land for production making land a scarce resource, and even the less suitable or marginal lands had been subjected to cultivation (FAO, 1983; Purnell, 1986; Son and Shrestha, 2008). This calls for a systematic and comprehensive assessment of land. In emerging countries, the growing need for more productive land types, the reservation and preservation of land for agriculture, plus the expanding concern to protect the environment, has created a demand for a total review of land space and its rationality. To achieve this, what is needed is a total inventory of natural resources for a proper assessment of land's suitability for production purposes.

Scientists have been interested in the study of land resources and modifications of the methods of land evaluation (Beek, 1978). Purnell (1986) stated that land evaluation provides a systematic way of looking at various options and predicting the results of alternative courses of action. The inventory and survey of natural resources are essential parts of land evaluation. These helps land use planners to avoid costly mistakes and to improve investment efficiency (Camp, 1999; Young, 1998). Valid techniques of resource survey and land evaluation have helped to translate environmental data into land use potential (Young, 1998). Land evaluation is an essential perspective for all-rational land use planning (Purnell, 1986). It forms the link between basic resource surveys and land use planning (FAO, 1983) and enables land use planners to make decisions on land use.

3.4 Land Evaluation and Land Use Planning

Land use planning is the systematic assessment of land and water potential, providing alternatives for land use and economic and social conditions in order to select and adopt the best land use options. Authors like Beek (1978) have seen no difference between land evaluation and land use planning because whoever is involved in land suitability is also involved in land use planning. Furthermore, FAO (1993) indicated that land use planners rely on land evaluation to choose optimum land for each purpose. Land evaluation, thus, presents itself as a suitable technique for identifying the different land use options for purposes of decision-making at all levels of governance (FAO, 1993). Land evaluation provides essential information on land resources. Land evaluation studies are required to provide information needed to address some problem associated with the use of land such as land degradation and land use conflicts confronting the world today. Presently, the growing scarcity and non-renewability of land as a natural resource underscore the importance and critical need for land valuation and planning. It is desirable for land to be renewable as a resource towards which competition has grown to assume some exchange value.

Moreover, the exchange has to do with social attitudes as these have great influence on decisions involving changes in land use.

Land use planning decisions require not only the political will but also the ability (instrument, budget, manpower) to support and implement the plan. It is also essential that the planned changes are acceptable to the economy, society, environment and land users involved (FAO, 1993). The situation makes it more imperative to look at some truly objective and scientific techniques for land evaluation to be developed as public concern with land planning becomes more critical. Its purpose is to select and put into practice those land uses that will best meet the needs of the people while safeguarding resources for the future. The driving force in planning is the need for change, the need for improved management or the need for a quite different pattern of land use dictated by changing circumstances. There are many land evaluation systems with various conceptual sources that use different techniques. An exhaustive discussion can be found in Van Diepen et al. (1991) and Rossiter (1996). Rossiter`s (1996) article for the first time puts forward an attempt at a theoretical, unifying and systematic framework: for example, if a land evaluation model takes into account variations of a land characteristic, such as salinity or rainfall, with time within a particular time period being studied such as a year or growing season and at a particular place then it is a "dynamic" model. If it is assumed to be constant or if an average value over the time period is used, then it is a "static" model. If a land characteristic varies from one place to another, such as soil depth, then this is considered to be a "spatial" characteristic and if not, then it is "non-spatial", for example a governmental policy applied over a whole region. A land evaluation model may concern both spatial and non-spatial elements, but will only be a dynamic if it contains dynamic land characteristics.

Before Section 3.5, it is important to differentiate between land characteristics and land qualities. On one hand, land characteristics are those features that can be measured – e.g. soil drainage class, slope angle, mean annual rainfall, soil effective depth and topsoil texture – and used to estimate land qualities or assess land suitability through direct comparison between the observed characteristics and suitability rating (Dent and Young, 1981; FAO, 1983). However, relying on the extensive land characteristics data tend to ignore how environmental factors affect land use (Dent and Young, 1981; FAO, 1983). On the other hand, land qualities are comprehensive attributes of land obtained by synthesising the measurable land characteristics (Beek, 1978). According to FAO *Guidelines for Land Evaluation* (1976), land quality is an element of land, which has an enormous influence on the suitability of the land for any specific purpose. These elements include temperature management, moisture availability, drainage, nutrients supply and rooting conditions (FAO, 1976).

3.5 Terminology, Types and Logic of Land Evaluation

There is much confusion over the use of terminologies in land evaluation studies. One of the oldest confusion is the recognition of land evaluation procedures as an inherent part of soil survey and soil classification (Rossiter, 1996; Van Ranst, 1996). It was in 1950 that land evaluation was introduced as an official term at the International Congress of Soil Science, Amsterdam. The term was later adopted in Australia by Christian and Stewart (1968), who pioneered the 'land system approach' as a viable method of classification of lands, such as soils, landforms and vegetation into a coherent pattern. Christian and Stewart (1968) define a land system as 'an area or group of areas throughout which there is a recurring pattern of topography, soils and vegetation'(Verheye, 2009:5). This land system approach is easily adaptable in land evaluation of medium scale areas such as regions and districts where land resources are typically associated with land use thereby creating a matching pair. However, due to the absence of a widely accepted terminology and working methodology, the terms 'land classification', 'soil survey interpretation' and 'land evaluation' are intermixed.

Various attempts were initiated in the 1960s to have clearer terms and definitions for use. Vink (1963 cited in Verheye, 2009:5) is one of the first to use the term 'land classification' to refer to "those groupings of soils that are made from the point of the people that are using the soils in a practical sense". This definition involved the classification of lands according to their land-use orientation as a group of soils. It was Kellogg (1962 cited in Verheye, 2009:5) who first attempted to define the distinction on soil survey interpretations and land classification. Then, Stewart (1968), considered land evaluation as "the assessment of the suitability of land for man's use in agriculture, forestry, engineering, hydrology, regional planning and recreation". In its modern sense, land evaluation includes all of these and much more

Land evaluation is thus defined generally as "the assessment of land performance when used for a specific purpose" (FAO, 1976:1). Evaluation of land may be done directly, as in the collection and analysis of crop-yield results, or indirectly, by assuming that certain diagnostic criteria would influence the performance of the land predictably and that such a performance may be derived from an observation of those parameters. In such a context, the activities involved in land evaluation would include the execution and the interpretation of studies and surveys of landforms, soil types, climate, vegetation, and other land aspects for the purpose of identifying and comparing the promising uses of the land relative to the evaluation objectives (FAO, 1976). Values are assigned to those uses or properties, were to be organised and integrated into a parametric or a categorical system.

The release of the publication, the Framework for Land Evaluation (FAO, 1976), marked the turning point conceptually in the search for the proper definition and distinctions on land use. In this publication, the narrow understanding of soil was disengaged from the deeper and much broader concept of land, which then embraced all the aspects related to land use as well as all the activities connected to it. It was also at this instance that land suitability was distinguished from capability; thus, land evaluation was transformed into a technique and useful tool for land-use planning. It is therefore important for a clear terminology to be established to distinguish the meanings attributed to both land valuation and evaluation, which are general terms and also between land suitability, land capability and land value which are specific. Land assessment and land appraisal can be treated as common vocabulary connotations without any particular technical reference. As can be seen throughout this thesis (e.g. Chapters 5-7), the FAO definition of land evaluation was put into context in evaluating land suitability for crop production in Libya. In the meantime, the next section demystifies the different land capability and suitability classes.

3.5.1 Land Capability and Land Suitability Classification

Land capability and suitability have often been confused or regarded as synonymous. Land capability classification is one the terms introduced by USDA in relation to land evaluation. Using ranking system, this land evaluation approach is graded according to land limitations for agricultural use only (Davidson, 1992; Nwer, 2005). It pertains to the land's ability to produce sufficient crops and pasture without diminution for a considerable length of time. Since land suitability is specific in its usage, land suitability classification refers to land's ability to support specific use or function, whether for agriculture or municipal uses. If it is for agriculture, land suitability varies according to climatic conditions, crop type and duration of yield or land management practices (Clayton and Dent, 2001). Chapter Six contains a land suitability classification for the study area.

3.5.2 Physical and Integral Land Evaluation

Land evaluation can be conducted based on biophysical factors and/or in combination with socio-economic factors. Physical land evaluation deals with the physical aspects of land (Masahreh et al., 2000). Physical land evaluation starts with the basic survey of soil, water, climate and other biophysical resources characteristics. For example, the boundaries between suitability classes for a specific land quality such as rootable depth classes are defined in terms of land characteristics (e.g. of soil, climate, water), using quantitative values wherever possible (Costantini, 2009). For example, high nitrogen availability may be defined as total N content greater than 0.2 percent in the soil to 20 cm depth; a high level of remoteness (a land quality appropriate for determining boundaries of nature reserves) may mean more than 20 km from the nearest road. According to the methodology proposed by FAO (1976), the physical attributes of land govern whether it is classified as Suitable (S) and Not Suitable (N). However, the land that is Not Suitable can be subdivided into two subclasses based on an economic evaluation. According to the FAO (1976) methodology land assessed as N2 (Permanently Not Suitable) is so unsuited that the specified land use is never likely to be economic; N1 (Temporarily Not Suitable) means that the use is physically possible, but at present costs, prices, etc., is not economically viable, although it might become so in the future. It follows that N, Not Suitable; land can only be separated into N1 and N2 on the basis of economic evaluation.

While biophysical factors tend to remain stable, socio-economic conditions are dynamic and highly fluid and susceptible to change due to changing social, economic and political settings. In this case, land suitability selection based on physical factors can be a prerequisite for land use planning especially in a politically unstable environment. In this instance, Masahreh et al. (2000) argued that relying on biophysical factors alone is insufficient to provide adequate information to establish land use policies and guidelines. Maleki et al. (2010:21) emphasised that the accuracy of land evaluation largely depends on the chosen land qualities and their effects on crop production. It therefore appears that, integral land evaluation is a comprehensive approach to land suitability studies (Beek, 1978; Masahreh et al., 2000; Maleki, 2010): it judges land suitability in terms of land use and for land management.

3.5.3 Direct and Indirect Land Evaluation

Land evaluation may be accomplished directly by evaluating the crop yield obtained over a particular area, or indirectly by analysing soil characteristics, interpreting them in either a positive or a negative way on consideration of proposed use. In the first case, evaluation will be based on field experiments, farm economic analyses or agricultural statistics, depending on the scale of evaluation. Since these data are not always available or are discontinuous in time and space and difficult to extrapolate out of the context in which they were surveyed, indirect systems are often used, based on soil and land characteristics, presupposing a correlation between these and the crops yields, for the same level of energetic and technological inputs of the management. This division into indirect and indirect methods is not a strict one, as indirect evaluation considers the economic nature of crops such as costs for agronomic intervention (Constantine, 2009).

Some systems refer to agricultural or forestry land uses, while others relate to engineering uses or to uses aimed at land protection from pollution or erosion (De la and Van Diepen, 2002). Within land evaluation system for agriculture, those with a general intent are distinguished from those from specific ends; in the former, the environmental characteristics are interpreted only to indicate the potential and limits of agricultural land use and forestry (De la and Van Diepen, 2002). In the latter, the evaluation takes into consideration a particular land use type or a particular agro-technique, such as the production of winter wheat or irrigated maize, or the application of animal slurries. In the agricultural context, another distinction may be between types of land evaluation that considers the current or potential use, i.e. the possibility of introducing new crops after reclamation (e.g., irrigation and drainage) (Constantine, 2009).

3.5.4 Qualitative and Quantitative Land Evaluations

Land evaluation and land performance assessment can be associated with qualitative and quantitative evaluation. In between quantification is a transitional phase known as semi quantitative terms (de la Rosa and van Diepen, 2002). A qualitative approach simply consists of description of the land suitability for different land use type, or may group the land into subdivision of suitability classes or levels (hierarchical structure) (Clayton and Dent, 2001). As this is a subjective practice, a thorough expert knowledge (based on experience and intuition) of the land conditions is essential. However, some methods use qualitative data weighted separately and combined with quantitative to obtain a result expressed numerically. This is the case in this research. In the quantitative approach, reference is made to quantities, for example of achievable biomass production, or at any rate to measurable data. It is often the practice to have field-surveyed data collected in the area of study (Clayton and Dent, 2001; Constantine, 2009). As quantitative methods are much more demanding, models can be adopted that can simulate the environmental processes when supported by a sufficient amount of reliable data. However, the amount of data available is the determining factor in the construction of a model, for example, the soil response to the different land uses. Similarly, a considerable amount of continuous data in space is a requirement. This limitation is remedied by employing a complex survey system in the form of remote sensing, to capture and store data continuously (see chapter four for details).

Semi-quantitative evaluation is more frequent, for which a reference crop is considered and evaluation classes for land qualities or/and characteristics are established and expressed in percentages fractions of the target production. An example of this evaluation system is the single-factor system, which adopts a mathematical expression to identify the influence of individual land characteristics on the general performance of land use. Such systems quantitatively represent the influence of a single land feature, for example, on crop yield by means of the yield curve response to single-factor variations (De la Rosa and van Diepen, 2002).

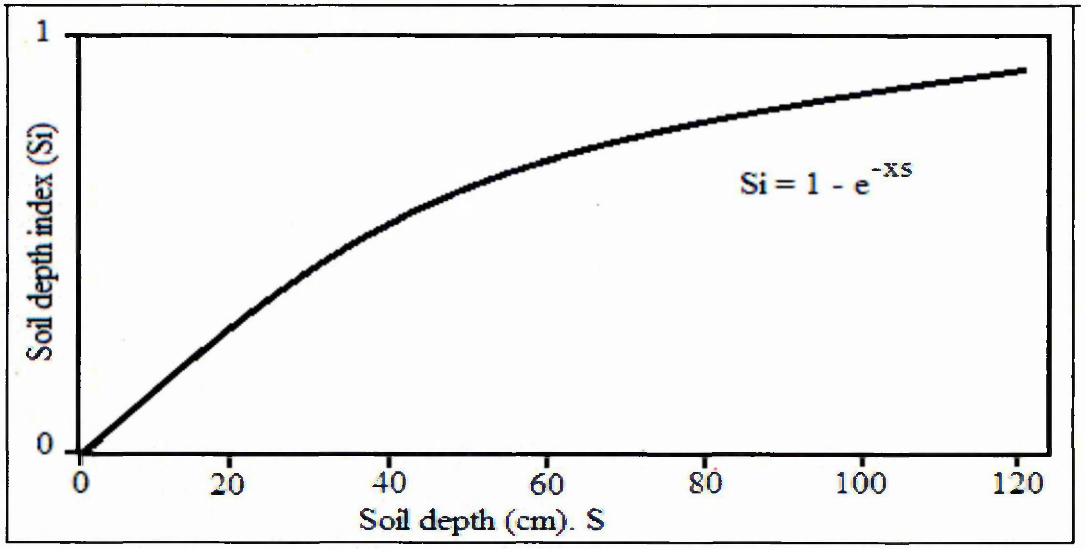

Figure 3.2: Response curve of single-factor systems. Source: De la Rosa (2002).

Figure 3.2 is an example of the response curve to express the sufficiency of an individual factor soil depth to crop productivity. This approach is well adapted to a case where a single land characteristic has a clear positive or negative effect on a proposed land use, such as, for example, soil depth on crop productivity. Details of the mathematical expression can be found in de la Rosa (2002). The single-factor systems do not take into account the combined interaction of many factors of land characteristics, but the calculated values for single response curves can combine a few significant single land characteristics to generate a suitability index (De La Rose, 2002). In addition, De la Rosa et al. (2002) believe that the so-called arithmetic or parametric methods can be regarded as semi-quantitative so long as they are based only on expert opinion, whose results are expressed numerically as the solution to mathematical formula. The combination of all these data makes possible the modelling of land suitability for the potential production of a crop system. However, in some cases, models are used for indirect estimation of the land qualities to be used in the evaluation process.

3.6 Calculation Logic for Land Evaluation

There are many kinds of calculation logic on which mathematical models are based for land evaluation. The main ones are Boolean logic, Fuzzy logic and artificial neural networks. The following sections are summaries, detailed discussion about Fuzzy and Boolean are contained in Chapter 5 and 6.

3.6.1 Boolean Logic

Boolean logic follows a ruled-based approach, where the limits of sets are clearly defined, so that an element does or does not belong to a determinate set. It is the logic of true or false, traditionally used in the applicative science, the logic that permeates the FAO method (1976). According to that approach, a soil may be very suitable, moderately suitable, marginally suitable or not suitable. There is no possibility of describing the slight distinctions between the classes, as intermediate classes are not considered. As this method fails to incorporate the inexact nature of land data, there is growing awareness for a quantification trend that captures fuzziness, as seen in the following section.

3.6.2 Fuzzy Logic

The term fuzziness was defined by Lotfi Zadeh in 1968. He famously wrote, "*as complexity rises, precise statements lose meaning and meaningful statements lose precision*". From this statement, Zadeh (1965) introduced the concept of fuzzy logic where the truth of any statement becomes a matter of degree. This theory is an extension of conventional Boolean logic that was introduced to resolve the term of partial truth between completely true and false (Malczewski and Rinner 2005; Lodwick, 2007; Zadeh, 2008). Zadeh has used this term as a means to model the ambiguity of natural language, but the approach has been applied to modelling many processes that are complex and ill-defined. A fuzzy logic is a mathematical way to represent and deal with ambiguity in everyday life. Zadeh (1965) indicated that one of the reasons humans are better at control than machines is that they are capable of making successful decisions because of imprecise linguistic information. It generalizes classical sets theory in which the membership degree of any object to a set is limited to the integers 0 and 1 only, by allowing the membership to take any real number between 0 and 1. By this definition, a fuzzy set is a set with imprecise boundaries in which the transition from one set to another is gradual rather than abrupt (Eastman, 2006; Zadeh, 2008).

Fuzzy logic was applied to evaluation of soil erodibility (Wischmeier's K factor) in the Fusle programme (Borselli, 1995). It was used at Cochabamba in Bolivia for an urban development land evaluation procedure (IAO, 1999) as well as in Iran (Maleki et al., 2010) and several others too numerous to mention. With the notable exceptions of Nwer (2005) and Elaalem (2011), this method has not being widely applied in Libya. Therefore, this study in an effort to expand on Nwer (2005) and Elaalem (2011) used fuzzy logic to model land suitability for cereal production (barley, wheat and maize) in Libya - a developing country lying between semi-desert and coastal climates.

3.7 Summary

Land varies in its physical and human-geographic properties and this variation (physical, political, economic and social) can be mapped, i.e., the total area can be divided into regions with less variability than the entire area. However, to evaluate or map any form of land for any specific uses, a high sense of understanding of the context of land evaluation is required i.e. by understanding the logic and methods to apply. The behaviour of the land when subjected to a given use can be predicted with some degree of certainty, depending on the quality of data on the land resource and the depth of knowledge of the relationship of land, to land use. Decision makers can then use these predictions to guide their decisions. The next chapter specifically charts the evolution of methods used in land evaluation.

Chapter Four

Approaches to Land Evaluation Methods

4.1 Introduction

As already highlighted in Section 3.2, land evaluation identifies the most appropriate land to be used for a defined purpose. To achieve this, methodologies have been developed to evaluate land for various purposes. Before the FAO Framework for Land Evaluation (1976) was developed, the American Land Capability method (Klingebiel and Montgomery, 1966), the USBR Land Suitability for Irrigation (U.S. Department of the Interior, 1951) and several others existed. The differences among different evaluation methods however, depend on the land use, the factors that affect that use, and the analytical rigour required. This chapter focuses on reviewing methods commonly applied in land evaluation studies.

The chapter is organised in the following manner. Sections 4.2 and 4.3 present mathematical and parametric approaches in land evaluation. Regional methods developed are outlined in Section 4.4. Country based land evaluation systems such as by the USDA, the Canada inventory, land capacity assessment in Britain and land capability for agriculture land in Scotland are contained in Section 4.4. The emergence of and adoption of computerised evaluation methods and their limitations can be seen in Section 4.5. Apart from regional methods that have wider acceptance and implementation outside the country of origin, other special purpose systems are developed (Section 4.6). Since this research relied on the FAO framework for evaluation, Section 4.6 reviews the method. Table 4.1 presents a comparison of the various land evaluation methods. A discussion of the robustness and applicability of the system in Libya can be found in Chapter Seven.

4.2 Mathematical Yield Correlations

By the second half of the 1900s, improvements in soil interpretations were observed as these evaluations adopted better structure and the anecdotal and observational approaches were replaced gradually with correlations between yield data and the soil parameters (Verheye, 2008; 2009: 11). The correlations are assessed by desired protocols and combined to provide an index that may subsequently be ranked. This approach was adopted in view of its objectivity and acceptability as a scientific procedure, despite the need to have it modified locally by introducing site-specific factors such as slope, climate, stone contents and soil moisture limits. Many rural assessments quickly embraced these systems, especially when the socio-economic factors such as distance-to-markets were added. In this instance, simple numerical correlations often involving one parameter are distinguishable from the complicated correlations and parametric systems, which involve several factors with more universal applications (Verheye, 2008; 2009: 11)

4.2.1 Simple Mathematical Correlations

Mathematical formulas for regional land assessment, also known as crop-yield models, are unavoidable. The model usually takes the form of yield-prediction equation using simple analysis or even multiple regressions. Examples of equations in their simplest formulations may be found in the formulas developed by Tachinov et al. (1971 cited in Verheye, 2009) who projected direct relationships between crop yields and one or several key factors. Taichinov et al.'s (1971) spring wheat production index for the southern Urals uses the formula, $y = 8.25x + 945$, Equation 4.1 where x represents the thickness (in cm) of the humus rich topsoil, to estimate the yield y in kg/ha. Yield in this equation is expressed directly in kg/ha.

Similarly, Finck and Ochtman (1981 cited in Verheye, 2009) derive the percentage cotton yield y for the Gezira soils in Sudan from their formula $y = 2.57x - 49.3$ Equation 4.2 where x is the average clay percentage over the upper 40 cm of soil. Compared to the Taichinov's formula, Finck and Ochtman's cotton yield can be transformed into effective cotton yields. Where there are less available data, rapid evaluations may be made by using simple mathematical correlations. These are however applicable only for a particular crop and falling within a limited area. Despite their characteristic approximation of results, they are accepted as rapid assessment tools.

4.2.2 Complex Formulae

One example of a very complex mathematical formula involving a more-than-one-factor combination is the 'potential biomass production index' derived by Steely et al. (1983) for the Mediterranean and steppe regions. The formula combines soil and climatic factors as follows:

$Y = 2.33 \times AM1.09$ Equation 4.3

where Y = potential dry matter yield

$AM = K1 \times K2 \times K3 \times R$

$K1$ = slope gradient

$K2$ = soil depth

$K3$ = salinity level of the soil

R = annual rainfall in mm.

4.3 Parametric Approaches

Parametric systems proceed from the basic relationship that exists among several factors affecting the land's productivity. Most of these parametric systems are simple and empirical, where the number of elements involved does not go beyond 10. Parametric systems are sometimes described as productivity indices or ratings because they lead to an index related to productivity. In employing parametric systems, all factors that bear an impact on the land's potential use are given numerical values 0 to 1 (van Diepen et al., 1991; Rossiter, 1994). The best rating is assigned to optimal conditions and those conditions that are found to be marginal or unsuitable will be assigned decreasing values (McBratney et al, 2000). Situation with 'no constraints' should be given a 1.00, while slight constraints would command a rating of 0.8 and moderate constraints 0.5. The land index is derived by adding or multiplying individual ratings.

The FAO Soils Bulletin (1974) provides a complete summary detailing the parametric methods and principles of soil as well as land evaluation. The type and number of factors being included in the mathematical manipulations of parametric systems are varied. Two types can be identified: additive parametric (index = A+B+C+....) or multiplicative (index= A*B*C*.....). In an additive approach, what is being inferred is that the characteristics are independent of each other, i.e. a low score for one variable does not unduly affect the overall results. However for evaluation of land for the suitability of crops, this does not necessarily hold true: if the soil depth is very small, it does not matter how good the rating of the other characteristics are e.g. excellent organic matter as the land will still not be very suitable for growing crops. Therefore a multiplicative or geometric mean type of approach where the characteristic are not independent is more suitable. A multiplicative approach will result in a smaller absolute value for the index and it may appear lower than that of the measured factors (De la Rose, 2002), but this number is subsequently adjusted when a meaningful score is assigned to it (e.g. FAO, 1976). Alternatively a geometric mean could just be calculated.

The most well-known multiplicative system to rate land quality is the Storie Index which was originally designed for soil and agricultural rating in California for taxation purposes. In addition, Sys and Verheye (1975) introduced another parametric system that established a Soil Capability Index for application to all semi-arid lands. This soil-related system works on the assumption that constraints in climate have been solved and are not affecting or limiting production.

4.3.1 Categoric Land Capability Classifications

Categoric systems group land into a number of categories as a function of production constraints from particular soil or location properties. These put limitations on the range of suitable land uses. The concept behind this is that the capability of agricultural land is determined by broad agricultural systems and not by specific crops or management practices (Verheye, 2009).

The best-known land capability classification (LCC) is the USDA system, developed by Klingebiel and Montgomery (1961). This system has also resulted in a wide range of derived systems adapted to local knowledge or specific purposes e.g. the Canada Land Inventory and the Land Use Capability Classification (Davidson, 1992).

4.4 Country Based Land Evaluation Systems

This section provides a catalogue of country based land evaluation systems that have had wider acceptance and implementation outside the country of origin.

4.4.1 The USDA Land Capability System

The USDA Land Capability Classification (LCC) was developed as result of the Dust Bowl of the 1930s to the 1960s to provide assistance to agricultural planners and farmers in interpreting data from soil maps for maximum productive land use. There are eight classes designated using Roman numerals. Thus, the best lands are Class I, soils that have little or no limitations restricting their use for crop production, to Class VIII, where the soils cannot be used for commercial crop production. Four letters are used as subclasses to represent the major hazard or limitation that contributes to the soil occurring within the capability class: (e) erosion, (w) excess wetness, (s) problems in the rooting zone, and (c) climatic limitations. Inputs for the classification system are based on properties that cannot be altered due to technical or economic constraints and include landscape location, slope of the field, depth, texture, reaction of the soil, climate, erosion and risk of flooding. Criteria for classification are subjective as they depend on the cropping systems and climate (Davidson 2002). Classes I to IV are reserved for agricultural uses while classes V to VIII are for non-agricultural uses such as forestry, natural parks, grazing, wildlife, and grazing.

There are three levels used in the USDA classification structure:

1. **Capability class** – Eight classes labelled I-VIII arranged in diminishing production potential and expressed in projected yield and types of crops to be grown.
2. **Capability subclasses** – The limitations exhibited in the class are indicated by letter subscripts for such limitations as erosion hazard, climate, rooting

restrictions, low fertility, wetness, salinity or stoniness. For instance, a subclass of V descriptive of main limitations coming from excessive water and unstable climate.

3. **Capability units** – Putting land under a capability unit may indicate various different soils present but there is little variation in in degree and type of limitation to land use, but in addition is suitable for similar crops under similar farm and soil management practices (Davidson1992). Essentially, capability units are not generally used; when a more detailed method of evaluation is needed, the system shifts to suitability classification.

The USDA Land Capability System has introduced a range of variations on the system by adapting these to the local knowledge for specific reasons. These adaptations pertain to amendments in the variety of classes or the limiting factors, new subdivisions outside of the main limitations, efforts to put value on the limiting factors and changes resulting from the rejection of some basic assumptions.

4.4.2 The Canada Land Inventory (CLI)

In Canada, assessment for land capability began in 1963 following the approval of the Agricultural Rehabilitation and Development Act (ARDA) of 1961. The assessment involved a comprehensive land capability survey mainly to provide support to the various land-based activities around the country, with the particular aim of targeting rural areas. The survey is much like a general reconnaissance inventory of all settled and adjacent areas in Canada. The Canada Land Inventory (CLI, 1970) was a very successful adaptation of the USDA Land capability System. It is different in approach; instead of an eight-class system, it has seven classes, only focusing on the Class and the Subclass levels. This CLI planted the seeds of the Canada Geographic Information System (CGIS) - the originator of computerised mapping that became the base for geographic information systems worldwide. The

CLI programme provides assessments for agriculture, wildlife, forestry and recreation. The Soil Capability Classification for Agriculture, groups mineral soils into seven various classes based on their capacity to grow common crops (i.e. no fertilisers). The classes represent the estimated productivity potentials of the land relative to soil, climate and landform. The limitations are identified and recognised the subclass level: moisture (A), topography (t), heat (h), stoniness (p), soil moisture (m), inundation (i), salinity (n), structure (d), fertility (f), erosion (e), excess wetness (w) and shallowness at rock base. See 6.6 for details about classes.

4.4.3 Land Capability Assessments in Britain

In Britain, the initial National Land Utilization Survey began in the 1940s. The main objective of that survey was to zero in on the top priorities for the production of food and of timber. This initiative was upgraded in 1950 and in 1960 to provide protection for prime agricultural land against being developed for non-agricultural purposes, and to make sure that food would be sufficient after the Second World War. The ALC that was published sometime in the 1960s and referenced the USDA classification system but it consisted only of five classes, which were based on the limitations derived from the conditions of the soil and the climate affecting agriculture. The level of limitations was represented by the range and type of crops to be grown, consistency and level of yields and the overhead needed to harvest the yield. This classification's main objective was to assist in planning decisions pertaining to the conversion of agricultural lands for urban development.

The problem with ALC was the earlier classification of about half of the land in Wales and England devoted to agriculture as Grade 3, and together with that, all the upland and hilly areas were graded at 4 and 5. Sometime between 1970 and 1980, the system received some revisions as greater attention was focused towards better climate assessment and improved criteria quantification. In Wales and England, these changes caused the introduction of new guidelines for establishing the quality grades of agricultural lands under the (MAFO) Ministry of Agriculture, Fisheries and Food (1988). Bibby et al. (1982) reports the publication of a system seeking to classify land capability for agriculture (LCA) in Scotland. The main elements of these systems can be found in Davidson (1982).

4.4.4 The Land Capability for Agriculture in Scotland (LCAS)

The LCAS uses the same assumptions and principles as the USDA system, where the primary purpose is agriculture. It assumes the need for a stricter and more high-level management. The grading is based only on limitations that are not removable or reducible. More particularly, the classification is based on the degree by which the land's physical features may affect cropping and its potential for production consistency. Factors such as distance-to-markets, road types and land structure are not considered in the procedure. The key difference between the two systems is the degree of quantitativeness in the assessment of the criteria. LCAS guidelines for the criteria include the following:

1. Climate includes the maximum potential soil moisture deficit, accumulated temperature, and modifications due to exposure (wind speed).
2. Gradient, soil properties includes soil structure, shallowness, stoniness and drought. Wetness: characteristics and their implications on workability, traffic ability and poaching risks.
3. Erosion, Pattern and Vegetation including the rating of plant species and calculation of relative grazing values.

The system uses seven classes, with classes 1 up to 4 appropriated to arable lands and classes 5 up to 7 to grassland and grazing land. The previous land scheme has been critiqued as being too diversified in the individual classes, a problem that was resolved by subdividing the classes into new subdivisions.

4.4.5 The Land Classification for England and Wales (LCEW)

The LCEW is a revised version of an earlier classification made during the 1960s. This version focuses on the analysis of limitations brought about by climate, drought and soil wetness. This system has adopted the following as its limiting factors: 1) climate, to include annual average rainfall, local climate and accumulated temperature, 2) site characteristics, to include gradient, flooding hazard and micro-relief, 3) soil properties, to include structure and texture, depth, chemical status and stoniness, and 4) interactive limitations, to include wetness, soil erosion and drought. The quality grades and the quality subgrades under the system are:

Grade 1	:	Excellent
Grade 2	:	Very good
Grade 3	:	Good-to-moderate
Grade 4	:	Poor
Grade 5	:	Very Poor

4.5 Computerised Land Evaluation Systems

In recent past, computerised systems of land evaluation were developed to use quantified spatial information on land resources, e.g. pedometrics (an expression that means measurement of soil and is derived from Greek roots; pedos means soil and metron means measurement) to meet the requirements for quantitative spatial soil information (Webster, 1994). While some of these systems used statistically derived and analytically applied land use models, others are based on qualitative assessment of experts. The recent geo-information technology that has greatly improved spatial data handling and enabled spatial modelling of terrain attributes is the GIS (Bailey and Gatrell 1995; Burrough and McDonnell 1998). The advent of GIS has enabled the use of methods that were not available at the time when the 1976 FAO Framework was developed. Other systems, developed before the popularity of GIS have been integrated with GIS (Hoobler et al., 2003).

The Automated Land Evaluation System (ALES; Rossiter, 1990) is a computer program enabled land evaluators to build their own expert systems to evaluate land (FAO 1976). In the ALES framework, evaluators can express their own knowledge for use in projects or regional scale land evaluation, taking into account local conditions and objectives. Since each expert system is built by an evaluator to satisfy local needs, lists are determined by the evaluator to suit local conditions and objectives of the study. The framework also allows estimation of land qualities by pedotransfer function or simulation model (Bouma et al., 1993). Process-based models have been used to evaluate some determinants of land qualities such as soil moisture (and solute leaching (Bouma, 1989)

Micro LEIS is an integrated system for land data transfer and agro-ecological land evaluation (De la Rosa et al., 1992). This system orderly arranges land resources and agricultural management data and generates the output in a format readily accepted by GIS. An extensive catalogue on the major components of Micro LEIS can be found in De la Rosa (2001). De la Rosa et al. (2001) reported that components have been added in predicting global change impacts and sustainability concept in land use including potentiality, risks, impacts and responses. Intelligent System for Land Evaluation (ISLE) models are based on the SYS model for land evaluation (Sys et al., 1991a and b, 1993). Land evaluation is automated to graphically demonstrate the results on digital maps (Tsoumakas and Vlahavas, 1999). Its main features are the support of GIS capabilities on the digital map of an area and the support of expert analysis of regions of this area, through a single sophisticated user interface (FAO 2007).

4.6 Special Purpose Evaluation Systems

4.6.1 The US Bureau of Reclamation (USBR) System

A widely used system for selecting lands for irrigation is the Land Classification for Irrigated Land Use of the US Bureau of Reclamation (USBR, 1953). In this classification, there are five classes defined according to the land's suitability for irrigation: three for arable, one for special use and another one for non-arable. The main parameter for differentiating suitability classes is the land's payment capacity which refers to the amount of money that remains with the farmers after all expenses (excluding water) have been paid and an allowance for the farmer's livelihood has been allocated. This parameter serves as an indicator of the overall productivity of the land. Inversely, the land's payment capacity may also be used to settle water charges in accordance with the land's productive value. This quantification would require data on development costs, maintenance and operating costs and budget.

Furthermore, estimate of the land's payment capacity is usually based upon drainage, selected soil and topography. For some projects with identified farm types and patterns of cropping, there is need to draw estimates of the impact of effects of soil deficiencies and the characteristics of drainage on construction activities, the requirements for soil improvements and farm water, salt leaching, needs for special irrigation, land levelling, yield risk and yield levels. The estimates are drawn from the experiences with other irrigated projects and even from data on local experiments. For purposes of classification, these estimates can be utilised to define or establish relevant class limits in relation to the conditions of the soil, drainage factors and topography. There are six classes and the subclasses are usually represented by small letters to define the specified limitations, such as (s) for soil, (t) for topography and (d) for drainage.

4.6.2 The Fertility Capability Classification of Sanchez

The Fertility Capability Soil Classification System (FCC) is a technical approach for grouping soils that was initiated to provide a bridge to connect soil classification to soil fertility (Sanchez et al., 1982). The system's approach is based on the problems the soil poses for the agronomic handling of the soil's physical and chemical properties. As a system for classifying soils, it is focused on what the classifications interpret, such as the FAO-UNESCO Soil Map of the World or Soil Taxonomy. The FCC system has three categorical levels:

1) Type (texture of topsoil),

2) Substrata type (texture of subsoil) and;

3) Modifiers, which provide description to the physicochemical in soil profile.

Soils are grouped by analysing the characteristics that are present or absent. Then the list is drawn with the type and substrata type in capitals and the modifiers in small letters. The FCC is a very useful instrument for relating limitations of fertility to yield responses from a selection of soils and of crops. The system focuses mainly, on management but not for the purpose of producing yield responses since these responses are also affected by other factors. Along this line, the FCC could easily be included in other evaluation systems. Most of the land qualities present in the FAO Framework for Land Evaluation (FAO, 1976; 1983) can easily be adopted using modifier and type combinations.

4.6.3 Agro–ecological Zonation: FAO Agro –ecological zone (AEZ)

For small-scale application (national or continental), the reference evaluation system of natural resources for land evaluation is the FAO`s agro-ecological zonation AEZ (1978-1981). This approach was widely used by FAO in studies of a general nature in developing countries, such as Africa, Southeast and Southwest Asia and central and South America (FAO 1978-1981). This system envisages the representation of land in distinct layers of spatial information, with their consequent integration using GIS (Fischer et al., 2002 and FAO, 2007). A key concept is the length of growing period as determined by rainfall and temperature regimes, which forms the basis for quantitative classification of each crop with climate and soil resources. An AEZ is created with additional information on topography, management, demographic and land use. Models can be derived for crop's growing period, soil suitability and for other land use planning.

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4.7 The FAO System of Land Evaluation

As already indicated in Section 3.2-3.4, sustainability is the main focus of the FAO method of land evaluation even before the concept became popularised in the last two decades. Table 4.1 is a compilation of pre and post FAO land evaluation systems including their similarities and differences. The FAO Framework for Land Evaluation defines land suitability evaluation as the assessment of land performance when used for a specified purpose, involving the execution and interpretation of surveys and studies of land forms, soils, vegetation, climate and other aspects of land in order to identify and make a comparison of promising kinds of land use in terms applicable to objectives of the evaluation" (FAO, 1976). After this definition, McRae and Burnham (1981) describe FAO's suitability evaluation as an attempt to evaluate land for homogeneous purpose. In this case it is expected that both the physical and socio-economic aspects of land are taking into account with the requirements of specific land use and differences in degrees of suitability are determined by the relationships actual or anticipated between benefits and required inputs associated with the use of land in question. Sustainability is the focus of the FAO method of the land evaluation. For example, the FAO Framework Land Evaluation (FAO, 1976) noted that any land use with short-term profitability, but with negative consequences such as degradation and depletion of resources, erosion, deforestation, environmental pollution and pasture degradation, is not sustainable and therefore, classified as unsuitable.

The FAO Framework (1976) further warned that the probable environmental impact on land should be assessed and the results examined when evaluating a land for any use. This means that land evaluation for any suitability assessment must be sustainable and the benefits now and in the future justify the inputs.

The FAO land suitability evaluation system is based on six principles:

1. Land suitability is assessed and classified with respect to specified kinds of land use.
2. Evaluation requires comparison of inputs and outputs.
3. Requires a multidisciplinary approach.
4. The evaluation is made with careful reference to the physical, economic and social context of the study area.
5. Suitability refers to the use on a sustainable basis.
6. Different kinds of land use are compared.

Suitability is classified into suitability order, classes, subclasses and units. *Suitability order* distinguishes between lands, which are suitable with an upper case S and N denotes unsuitable. *Suitability classes* specify degrees of suitability and include three classes: highly suitable (S1), moderately suitable (S2) and marginally suitable (S3). There are two classes within the unsuitable order: N1 indicating currently unsuitable and N2 is indicating permanently unsuitable areas. *Suitability subclasses* point towards certain limitations of the land such as moisture, erosion risks and drainage. The symbol S2d indicates drainage limitations, which can be overcome using tile drains or open ditches. *Suitability units* represent sub-classes on the basis of differences in land management requirements or practices. Depending on land management practices, the land suitability unit is either S2d-1 or S2d-2, where d = drainage limitation; 1 or 2 indicates the management method to be applied. It should be noted that the criteria given for defining land suitability classes are not fixed and there is choice in the number and type of criteria to be used (Davidson, 1992).

Land suitability evaluation procedure based on the FAO involves a sequence of activities summarised below and as undertaken throughout the research:

- Initial consultations between planning authorities and the organization that will carry out the evaluation.
- Planning the evaluation.
- Identification of land utilisation types.
- Selection of relevant land qualities for evaluation.
- Description of land mapping units.
- Assessment of land use requirements.
- Comparisons of land qualities with land use requirements.
- Presentation of results.

The FAO Framework is not a formal classification system, but rather a collection of concepts, principles and procedures based on which local, regional and national evaluation systems can be developed. The concepts and principles are universal and scale neutral, and they can be used to construct systems at all levels of intensity and for all kinds of rural land uses. Recommended procedures for a suitability classification are provided, but these are optional.

Each type of land use requires different conditions for the proper function of crops, which includes water, nutrients, soil and topographic requirements (FAO, 1976). It was argued that determining crop requirements for a specific crop is the most difficult and critical aspect of land evaluation, because land use requirements in especially the developing countries, is difficult to obtain (Beek, 1978; McRae and Burham, 1981). According to the FAO (1983), the three major groups of crop requirements are:

a) Physiological crop requirements: requirements of a crop for its proper physiological functioning e.g. climatic and ecological factors.

b) Management requirements: requirements related to technology of management systems.

c) Conservation requirements: requirements for avoidance of soil erosion and degradation.

In summary, the FAO framework evaluating land suitability for crops has been selected as the most suitable and simple method with which to design land suitability model for the study area in question based on the following rationale. In the first instance, FAO framework uses a large array of natural resource databases and integrates them to obtain comprehensive land classes. This is very important because it represents the integration and compilation of a wide variety of different types of data. Second, data obtained can be analysed either quantitatively or qualitatively. As some regional data may be limited in terms of their quantifiability, the FAO framework is useful in that the user has the option to choose the method of analysis. It should, however, be recalled that the FAO Framework allows for the rating method to be selected; since land quality rating largely depends on individual judgment based on an understanding of the study area. This process also allows for the validation of results in the field. Third, FAO framework for land evaluation allow the matching of land characteristics against crop needs and the assessment of a suitability rating for each selected land characteristic. This is particularly the key concept of land evaluation, because, as Nwer (2005:52) concludes, "the matching is very much a requirement in Libya, where the land suitability for certain crops is required to meet the national policy." Fourth, as mentioned above, the FAO system has also been previously applied in Libya by Nwer (2005) and Elaalem (2010) to derive land suitability maps for cash crops. Lastly, the existing land suitability evaluation model for selected cash crops for study area was based on the FAO framework.

Table 4.1: Comparison of various land evaluation systems

Land evaluation system		Purpose	Land Uses	Information Required	Procedure	Results
Pre-FAO	USDA	Capability	General agricultural use	Physical	Qualitative	8 capability classes
	CLI	Capability	General agricultural use	Physical	Qualitative	7 capability classes
	LCEW	Capability	General agricultural use	Physical	Qualitative	5 capability classes
	LCAS	Capability	General agricultural use	Physical	Qualitative	7 capability classes
	USBR	Capability	Irrigation projects	Physical Economic	Qualitative	6 capability classes
	Parametric Indices	Capability	General agricultural use	Physical	Quantitative	Continuous classification
	Storie-index	Capability	General agricultural use	Physical	Quantitative	Continuous classification
	Riquier, Bramao and Cornet System	Capability	irrigation agricultural use	Physical	Quantitative	Continuous classification
	The Sys and Verheye System	Capability	Irrigated and rain-fed crops for semi-arid land	Physical	Quantitative	Continuous classification
	Mathematical Yield Correlations	Suitability	Specific Uses	Physical	Quantitative	Crop yield predictions
FAO framework		Suitability	Specific Uses	Physical Socioeconomic	Quantitative/Qualitative	5 suitability classes
Post-FAO	LESA	Capability	General agricultural use	Physical Socioeconomic	Quantitative	Continuous classification
	LECS	Suitability	Specific Uses	Physical Economic	Quantitative/Qualitative	5 suitability classes
	ALES	Suitability	Specific Uses	Physical Economic	Quantitative/Qualitative	5 suitability classes
	Micro LEIS	Suitability	Agro-forestry land use	Physical	Quantitative/Qualitative	5 suitability classes
	Soil Potential Ratings	Suitability	Specific Uses	Physical Economic	Quantitative	Continuous classification
	FCC	Capability	General agricultural use	Physical	Qualitative	Several capability classes
	AEZ	Suitability	Specific crops	Physical	Quantitative/Qualitative	5 suitability classes
	Fuzzy-based systems	Suitability	Specific Uses	Physical	Quantitative	Continuous classification
	Expert systems	Variable	Variable	Variable	Qualitative	Several suitability classes

Source: modified from Riveira and Maseda, (2006)

4.8 Summary

This chapter presents an overview of the methods that are currently employed in land evaluation studies. The FAO model, which is one of the approaches adopted in this research, was explained in the previous section. The three major approaches – parametric, categoric or special purpose – with their sub-classes were presented and discussed. Parametric system is based on numerical expressions and correlations between land and yields. Under this method, Storie Index, Riquier et al. method and the Sys and Verheye methods are common but with different application purposes. For example, while Sys and Verheye methods are for application in semi-arid environment, the Storie Index was constructed for tax purposes. Categoric systems group land into different user categories but are often related to land capability assessment. Within these categories country specific land evaluation approaches such as The USDA Land Capability System and Canada Land Inventory have gained popularity outside their country and are good examples of land classification approaches.

The rationale and principles of land evaluation and land-use planning as well as key steps in the FAO approaches are outlined in Section 4.7. The chapter has also demonstrated that the FAO approaches to land-evaluation and land-use planning have been successfully applied in various parts of the world including Libya. However, these approaches are not rigid and can be modified to suit local conditions Using the Multi Criteria Decision Making (MCDM) analytical tool as well as increasing awareness for the integration of institutional, social and environmental factors into land evaluation studies, it is possible to consider complex alternate scenarios of land use for improved productivity as well as the sustainable use of land and the livelihood of land users.

Chapter Five

Land Suitability Analysis Using GIS and Multi-Criteria Evaluation

5.1 Introduction

Multiple criteria land suitability evaluation involves a set of quantifiable spatial criteria, their standardization functions, techniques for expressing preferences regarding the relative importance of the criteria, and aggregation procedures combining the quantitative representations of the preferences with standardized criterion values into an overall suitability score. The score is then assigned to each land unit and may be used as the bases for land use allocation. There has been quantitative and qualitative progress over the last 20 years in methods of multiple criteria land suitability evaluation, especially involving the integration of GIS and Multi-Criteria Evaluation MCE (Chakhar and Mousseau, 2008; Pereira and Duckstein, 1993).

5.2 Multi-Criteria Decision Making (MCDM) for Land Suitability Evaluation

The Multi-Criteria Decision Making methods (MCDM) were first introduced in the 1960s to help decision makers incorporate a multitude of options, with the opinions of those involved able to be included within a framework that can be either retrospective or potential (Malczewski, 1999). This framework is ''primarily concerned with how to combine the information from several criteria to form a single index of evaluation'' (Feizizadeh and Blaschke, 2013; Feizizadeh et al., 2012; Yu et al., 2011). The MCDM process requires a researcher to define their objectives, (e.g. maximise crop yield or minimise water requirements) to choose the criteria to measure the objectives, and can evaluate alternatives (e.g. which crop is most suitable for a particular piece of land). It transforms the criterion scales into measurable units, assigns weights to the criteria that reflect their comparative importance, selects and applies an empirical algorithm for ranking alternatives, and selects an alternative as well. It also includes integration of expert knowledge at different levels of decision-making process (Elaalem, 2010; Prakash, 2003). In the FAO framework (1976), decisions are taken into consideration at different levels, from choosing the land utilisation types relevant to the area under consideration, to the selection of the land qualities and land characteristics for each selected land utilisation type. Determination of optimum land use type for an area involves integration of data from various domains and sources like soil science to social science, meteorology to management science. All these major streams can be considered as separate groups; further each group can have various parameters (criteria) in itself and can contribute towards the suitability at different degrees (Gundimeda, 2007). The relative degree of contribution of various criteria can be addressed well when they are grouped into various groups and organized at various hierarchies. Agricultural land suitability evaluation, for example, involves major decisions at various levels starting from choosing major land use types, selection of criteria, organization of the criteria, deciding suitability limits for each class of the criteria, deciding the preferences (qualitative and quantitative). Relative importance of these criteria or parameters can be well evaluated to determine the suitability by multi-criteria evaluation techniques (Perveen et al., 2007).

MCDM in general includes a set of alternatives, which are assessed based on conflicting and incommensurable factors, which are quantitative and/or qualitative in nature (Elaalem, 2010, 2013). Multi-criteria decision analysis is a field of theory that analyses problems based on a number of criteria or attributes and can be used with both vector and raster data. The main techniques of multi criteria evaluation methods are Boolean and Fuzzy logic and are detailed in Sections 5.3 and 5.4 respectively. Moreover, every criterion is assigned a weight representing relative importance in the final assessment as to overall suitability (Chow and Sadler, 2010). The choice of weights assigned to criteria represents a critical and important stage, which may be affected by an expert`s judgment, knowledge of the place, experimental data and other factors (De la Rosa, 2002; Costantini, 2009). There are many multi-criteria evaluation methods frequently used to generate the weights assigned to the criteria: ranking, rating, trade-off and the Analytic Hierarchy Process methods (see Section 5.6). Frequently they can be integrated into GIS to perform land suitability analyses (Banai, 1993; Riveira and Maseda, 2006). The following section shows how MCDM is integrated into GIS.

5.2.1 Integration of Multi-Criteria Evaluation (MCE) Techniques with GIS

Multi-criteria evaluation methods may appear in the literature as multi-criteria analysis (MCA), multiple criteria decision making (MCDM) or multi-criteria evaluation (MCE) and all refer to the same process. MCDM is a systematized framework for analysing decision related challenges with complex multiple objectives (Nijkamp et al., 1990). Voogd (1983) presented the application of several multi-criteria evaluation techniques to land planning, where the number of spatial units evaluated was limited. The integration of multi-criteria methods and GIS overcomes this limitation and provides a tool with great potential for obtaining land suitability maps or selecting sites for a particular activity (Eastman et al., 1995; Jun, 2000; Mendoza, 1997). The use of GIS with MCE allows multi criteria decision making to be applied spatially, allowing trade-offs between conflicting objectives to be evaluated by taking into account multiple criteria and the knowledge of the decision maker (Carver, 1991).

The integration of multi-criteria evaluation (MCE) techniques in a GIS provides a powerful spatial decision support system that offers the opportunity to produce land suitability maps efficiently (Elsheikh, et al., 2013; Mendas and Delali, 2012). In addition, the integration provides the user with the means to evaluate various alternatives based on multiple and conflicting criteria and objectives.

MCDM provides a rich collection of techniques and procedures for structuring decision problems, and designing, evaluating and prioritising alternative decisions. At the most rudimentary level, GIS-MCDM can be thought of as a process that transforms and combines geographical data and value judgments and represent them in terms of weights assigned to different criteria to obtain information for decision-making. It is in the context of the synergistic capabilities of GIS and MCDM that one can see the benefit for advancing theoretical and applied research on GIS-MCDA. Consequently, the terms, GIS-based multi-criteria decision analysis and spatial multi criteria analysis, will be used interchangeably. Spatial multi criteria analysis can be thought of as a process that combine and transform geographical data into a resultant decision (Figure 5.1).

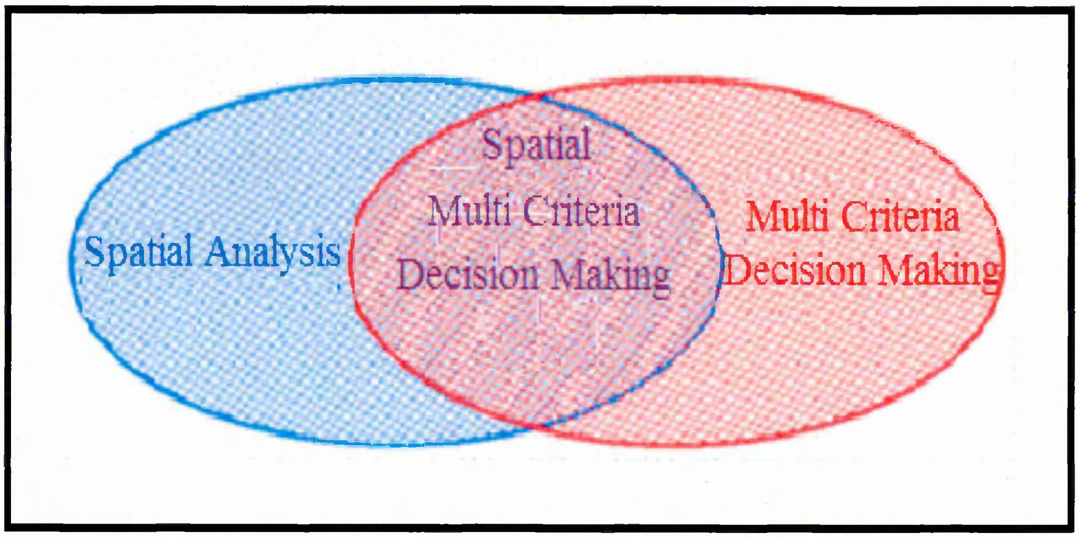


Figure 5.1: Integration of Multi-Criteria Evaluation (MCE) with GIS. Source: modified from (Malczewski, 1999).

Traditional multi-criteria decision analysis approaches such as the Boolean approach, are subject to the hypothesis that the location under consideration is completely homogenous in nature and ranked as non-spatial in nature. This hypothesis has made the traditional approaches impractical as in many cases evaluation factors differ across the space. The main difference between traditional multi-criteria decision analysis which considers information at a single point and spatial multi-criterion decision analysis, where there is a relationship between two or more points under consideration, is the explicit presence of a spatial element and therefore the need for geographical data defining criterion values (Phua and Minowa, 2005). To this end, Costantini (2009:18) summarised the advantages of the integration of multi-criteria evaluation techniques with GIS in this manner: 1) a more detailed specialisation of the evaluation; 2) automating evaluation procedure; 3) modify evaluation parameters and immediately verifying the results; and 4) integrating many information layers.

5.3 Boolean Logic and its Application in Land Evaluation

Within the context of multi-criteria decision analysis, this section details the applications of Boolean and Fuzzy logic in land evaluation. As already indicated in Section 3.6, Boolean and Fuzzy are the main mathematical models built for land evaluation (Constantine, 2009).

Named after George Boole, Boolean logic is based on Boolean algebra where limits of sets are clearly defined, so that an element does or does not belong to a determinate set. It deals with two truth values 'true' and 'false' with nothing in between. The conditions of true and false are often represented by 1 for 'true' and 0 for 'false. It has three basic Boolean operators: Intersection operator (the logic AND), Union (the logic OR) and Complement (the logic NOT). For example, a Boolean rule such as "IF soil texture = loamy AND site = mesic THEN suitability = high" could represent expert knowledge that loamy soil conditions are conducive to tree growth. All these operations, as described in chapter three, can be undertaken within a GIS environment (Baja et al., 2002a; 2002b; Malczewski, 1999). Within this framework, datasets are combined, analysed, and decisions made as to their relative contributions to produce a land suitability map (Hall et al., 1992).

In the context of a GIS, statistical and rule-based (Boolean Logic) methods are most commonly used to assess biophysical land suitability (Malczewski, 2004). Statistical methods tend to be empirical, involving regression-based prediction of suitability (which is often represented by a surrogate variable such as growth or yield) as a function of environmental variables. These methods cannot be employed successfully when quantitative data is either not available, or much of the information is qualitative in nature (Berguson, 1994; Hansen et al., 1995) cited in Joss et al. (2008). Even when sufficient data is available, the sample data utilised may not accurately represent or capture the relationships that exist between variables throughout the entire area being assessed Joss et al. (2008). Consequently, statistical models may be limited from the lack of empirical data, and results generated may be unrealistic, differ from expectations, or vary in accuracy (McBratney and Odeh, 1997).

Boolean logic, rule-based approaches are qualitative and thus, are not limited by the availability of empirical data. That is why the popularity for using Boolean systems to evaluate land suitability is a result of their simplicity, flexibility and capacity to utilise qualitative data such as that derived from expert knowledge (Kalogirou, 2002). The simplicity of Boolean systems result in maps depicting landscape conditions, however, that tend to be overly discrete and homogenous (Zadeh, 1965; Burrough, 1989). Physical suitability by qualitative procedure is presented in a categoric way, which means that a small number discretely ranked suitability classes are allocated to land (McRae and Burnham, 1981). The contents of the suitability classes are qualitatively described using the terms highly suitable, moderately suitable, marginally suitable and not suitable. However, a good classification system should not only aim to reduce information loss to a minimum, which can occur for example if the principle of limiting factor from Liebig`s law of the minimum is used to classify overall land suitability (which states that in agriculture, crop growth is not controlled not by the total amount of resources available to a plant, but by the scarcest resource which can be termed the limiting factor), but also provide a convenient means of information transfer, by identifying natural groups of individuals that have common properties (Burrough, 1989; Hall et al., 1992). In the conventional land evaluation methods, all LCs or LQs are split into discrete classes according to the value of certain important and discriminating criteria (Chang and Burrough, 1987).

During the last 25 years, the concept of Boolean logic has been applied to land suitability evaluation by many researchers, and their attempts have made progress in developing land evaluation methods based on the concept of the Boolean technique (Elaalem, 2010). In fact this approach have been adopted and applied in many studies in accordance to the FAO (1976) framework methodology (refer to Section 4.7). Davidson et al. (1994) stated that the FAO (1976) methodology for land suitability evaluation classifies suitability of land in terms of two suitability orders (suitable and unsuitable). Numerous examples can be identified. Nagowi and Stocking (1989) developed a land suitability assessment for coconuts in Tanzania based on FAO (1976). Yizengaw and Verheye (1995) assessed land suitability number of crops following the guidelines of the FAO (1976). Bydekerke et al. (1998) adapted the guideline of the FAO Framework (1976) to implement land suitability evaluation for Cherimoya in Ecuador. Kalogirou (2002) applied Expert systems and GIS, including physical and economic evaluation for land suitability in Greece based on the FAO land classification for crops. For the physical evaluation of the land, data for seventeen land characteristics were used and a Boolean classification method applied. The implementation includes models for general cultivation and five specific crops (wheat, barley, maize, seed cotton, sugar beet). In China, Messing et al. (2003) developed a land suitability classification within the FAO Framework (1976).

Nwer (2005) utilised GIS techniques in the development of a land suitability framework for irrigation of a number of cash crops in northeast Libya (the study area). He applied a weighted overlay technique to produce a land suitability map for each crop, where four suitability maps were derived in accordance with the FAO framework, and equal weights were given to each thematic layer. The output data (i.e. suitability map for each crop) are a raster (grid) file containing the suitability classes. Each cell in a grid stores a number, which indicates the suitability class for that cell (i.e. 4, 3, 2 and 1 represents, S1, S2, S3 and N respectively). Similar work to Nwer (2005) was done by Pirbalouti et al. (2011), who assessed land suitability for German chamomile, (a medicinal plant), based on GIS (weighted overlay) and the FAO (1976) in Khuzestan province, southwest Iran. Patil et al. (2006) used GIS for the modelling of land use planning and land suitability frameworks for irrigation in Karnataka, India.

Elaalem (2010) argues that there are many studies, including the above, mentioned that used a straightforward process, where no weights have been assigned to land properties. This has a major effect on results. However, only Nwer's (2005) study was not straightforward as different weights were given to different land properties to derive the overall land suitability maps. Environmental variables are often treated with equal weighting in Boolean type operations, whereby decision rules are used to define their range of values for a given suitability class (Malczewski 2002). Boolean modelling methods assume biophysical phenomena are sharply delineated in both attribute and geographic space resulting in homogenous polygons with single attribute values (Burrough, 1989). In addition, variability in properties within mapping units is the norm and thus there is always some uncertainty in stating that mapping units have values for particular properties above or below certain threshold values (Davidson, 2002). Consequently, these methods and any accuracy assessment procedures, do not address the continuous nature of the biophysical data and their inherent variability, uncertainty or ambiguity (Baja et al., 2002a, 2002b, 2011; Davidson et al., 1994; Joss et al., 2008; Kurtener and Badenko, 2000; Kurtener et al., 2008; Liu and Samal 2002; Nisar et al., 2000; Prakash, 2003; Sarmadian et al., 2010). It is increasingly being realised that the methodology fails to incorporate the inexact or fuzzy nature of a multitude of land resource data. The implicit assumption in Boolean approaches is the absence of any uncertainty or vagueness associated with the suitability model, measurement, vagueness in the concepts that are specified. In reality these assumptions may be invalid. Fuzzy set methodologies have been proposed as a method for overcoming problems related to vagueness in definition and other uncertainties. The use of fuzzy set methodologies in land suitability evaluation allows imprecise representations of vague, incomplete and uncertain information. Fuzzy set methodologies have the potential to provide better land evaluations compared to Boolean approaches because they are able to accommodate attributed values and properties which are close to category boundaries. Fuzzy land evaluations define continuous suitability classes rather than 'true' or 'false' categories as in the Boolean model (Elaalem, 2010; Keshavarzi, 2010). Therefore, the general lack of precision in both the data and formulation of queries has led to the need for methods that can handle inexactness such as the fuzzy method. Geo-spatial data consisting of discrete, sharply bounded units is incapable of representing the reality: the continuous nature of variability of environmental factors and their small-scale spatial heterogeneity.

5.4 Fuzzy Set Theory

Fuzzy logic permits logical operations to be carried out without using the rigidity typical of Boolean logic. In fuzzy logic, the set limits are blurred and an object is defined by a certain degree of belonging, the degree being defined by a number between 0 and 1. Whereas in Boolean logic, an object does or does not belong to a determinate set, the limits of which are strictly defined: it takes the value 1 in the first case, in the second 0. A fuzzy set is, therefore, a set in which there is no precise, well-defined border between the objects belonging to it and those that do not (Sicat et al., 2005), but the borders are blurred. Figure 5.2 shows a representation of classical Boolean and Fuzzy sets.

With fuzzy logic in land evaluation, the concept of belonging to a class, represented by the 'Membership Function' (MF) is introduced. Individuals with a value under a defined class are attributed a value of belonging to class that is equivalent to 1 (MF = 1). Individuals with a value outside such a class are assigned a membership value lower than 1 and greater than 0 (0 < MF > 1); the lower it is the more value draws away from that of the class. Therefore rather than as a class, the value of land characteristics or quality is expressed as degree of class of membership. Furthermore, single land characteristics or qualities are attributed with weight representing their relative importance in the final assessment as to overall suitability. Hence, a land unit`s overall suitability is expressed as a degree of joint membership function (JMF), which is the sum of the weight of the function of the various characteristics or qualities considered. So:

$$JMF = (W_a * MF_a) + (W_b * MF_b) + \ldots\ldots + (W_n * MF_n) \qquad \text{Equation 5.1}$$

Where: $W_a + W_b + \cdots \ldots . + W_n = 1$

The choice of weights attributed to the various parameters $(W_a, W_b, \ldots\ldots W_n)$ represents a critical and important stage, which may be affected by an expert`s judgement, knowledge of the place, experimental data and other factors (De La Rosa, 2002).

5.4.1 Fuzzy Logic vs. Boolean Logic

As aforementioned in Section 3.6.2, the membership function values assigned to each object range between 0 and 1; the higher the grade of membership the closer is the class value to 1. Figure 5.2 shows a representation of traditional Boolean sets and fuzzy sets: while with Boolean logic the boundary between sets is clearly defined (***A*** and ***B***), with fuzzy logic there is a transition zone where each set has less membership grade in relation to the other. In fuzzy theory, the map for *(A)* shows membership values closer to 1 when the set falls within *(A)* category, while the values are close to 0 when they are far from the category; the same applies for category *(B)*.

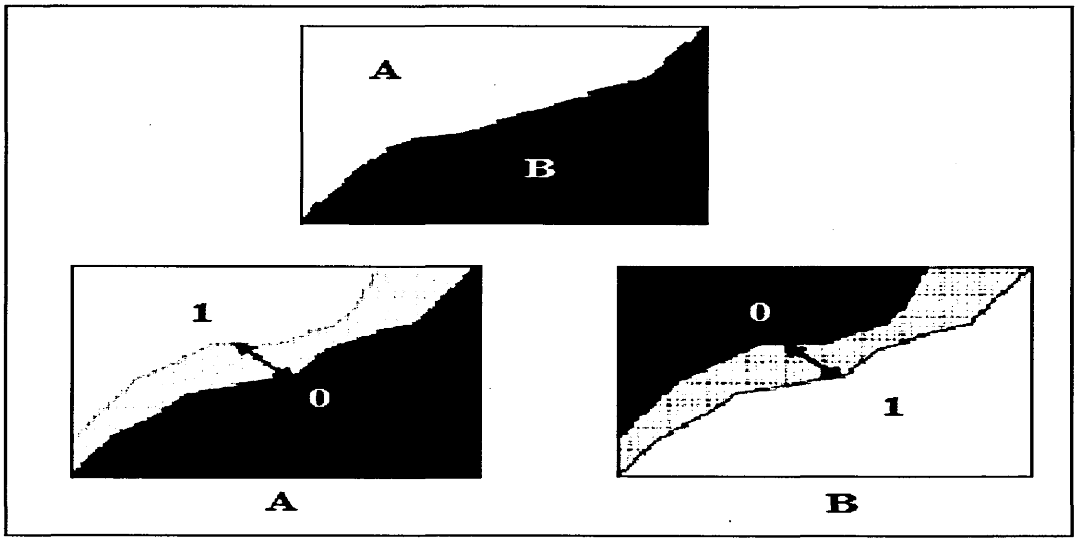


Figure 5.2: Representation of Boolean sets and Fuzzy sets. Source: modified from Moreno, 2007

Using fuzzy logic approach, the strict Boolean logic of suitability as determined by suitable or non-suitable land characteristics, is replaced by fuzzy membership functions. Land characteristics that exactly match the strictly defined suitable situation are assigned a membership value of 1. Land characteristics which do not match the defined class will get membership values between 0 and 1 corresponding to their closeness to defined class, the closer the membership values to 1, the higher is the land suitability (Joss et al., 2007). The membership function of fuzzy logic illustrates how the grade of membership of a land characteristic in the different land units is determined.

For instance, the FAO framework for land suitability classifies land into the following classes: Highly suitable-S1, Moderately suitable-S2, Marginally suitable-S3 and Non suitable-N. Let us assume that when a land-mapping unit with a value of organic matter 1.5 is considered a 'S1', and with organic matter between 1.5-1 is considered as 'S2'. If the value of organic matter between 1-0.5 is considered as 'S3' and the value of organic matter less than 0.5 *is* considered N. In this case, problems can arise, if the land with a value of organic matter 1.499 or 0.49 is considered S2 or N respectively according to Boolean logic. In contrast to this traditional set, a fuzzy set has fuzzy boundaries. A membership function of a fuzzy set therefore allows for values between 0 and 1, with the membership function also considering to what extent an attribute belongs to a fuzzy set as typified in Figure 5.3 above. The following figure is a diagrammatic expression of suitability classes under a normal distribution curve.

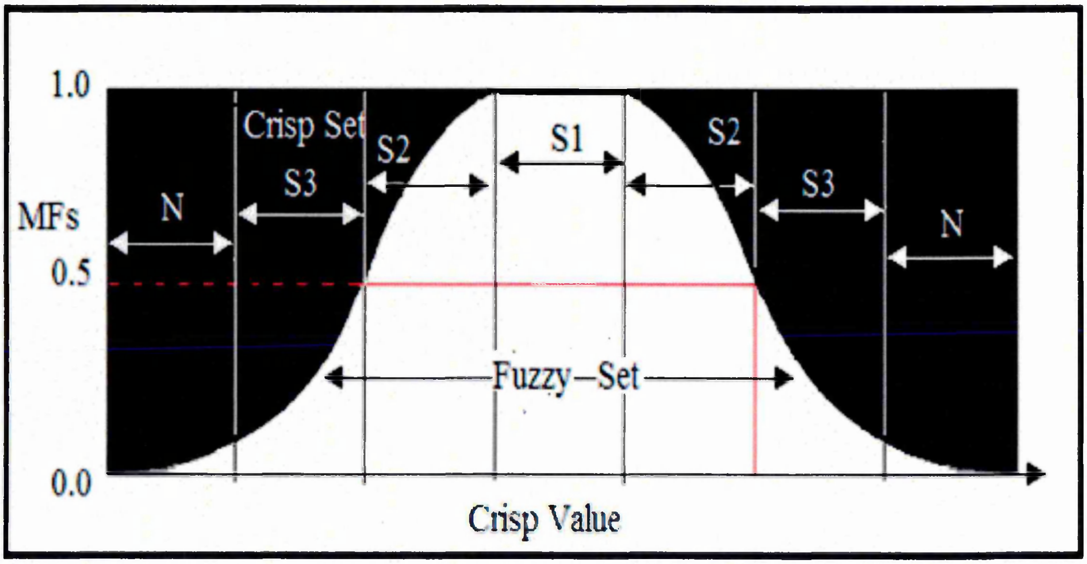


Figure 5.3: Typical presentation of crisp sets and fuzzy sets.

The fuzzy set theory offers a useful alternative in this respect; it permits the gradual assessment of the membership of elements in a set with the aid of a continuous scale of membership (Burrough and McDonnell, 1998), the so-called *membership function,* valued in the real unit interval [0,1] on the Boolean scale and [0, 255] on the byte scale. The fuzzy set classification allows transition from one class to another to be described by means of a membership function. This can be expressed as a gradual transition (soft classification), rather than as abrupt shifts from one class to another (hard classification). Such a gradual transition can be quantified according to fuzzy membership functions valued in the interval [0, 1] or [0, 255], where 1 or 255 means a complete suitability (the environmental factor matches the ecological requirements of the target species: the so-called *optimum* of the species) and 0 means no suitability (Corona et al., 2008).

5.4.2 Fuzzy Sets Membership Functions

The appropriate fuzzy membership function is dependent on the best available knowledge of the target species' ecological requirements, as drawn from literature and field knowledge (Eastman, 2006). Although the fuzzy logic approach to land-use suitability modelling has fewer limitations than conventional techniques, the approach is not without problems. The main difficulty associated with applying the fuzzy logic approach to land suitability modelling is the lack of a definite method for determining the membership function (Malczewski, 2004). Again, the selection of membership functions is a critical issue since the degree of land suitability will be defined according to the membership value.

A number of fuzzy set models can be used to derive membership function values. According to Van Rast and Tang (1999), many geometrical shapes of membership functions can be used in land evaluation studies, out of which two basic geometrical shapes (bell-shaped or Gaussian and triangular membership functions) are most common (see Figure 5.4-5.5 and their Equations). For both shapes, functions may be chosen with regard to the central concept and degree of dispersions of the boundaries for a considered land characteristics. The most popular are those used to model land evaluation for agricultural crops, including asymmetric left models, asymmetric right models and symmetric models (Burrough et al., 1992; Davidson, 1994; Burrough and McDonnell, 1998; Baja, 2011). Fuzzy set models have been chosen in this research to convert "standardised" measured data "land characteristics" to common membership grades (i.e. from 0 to 1).

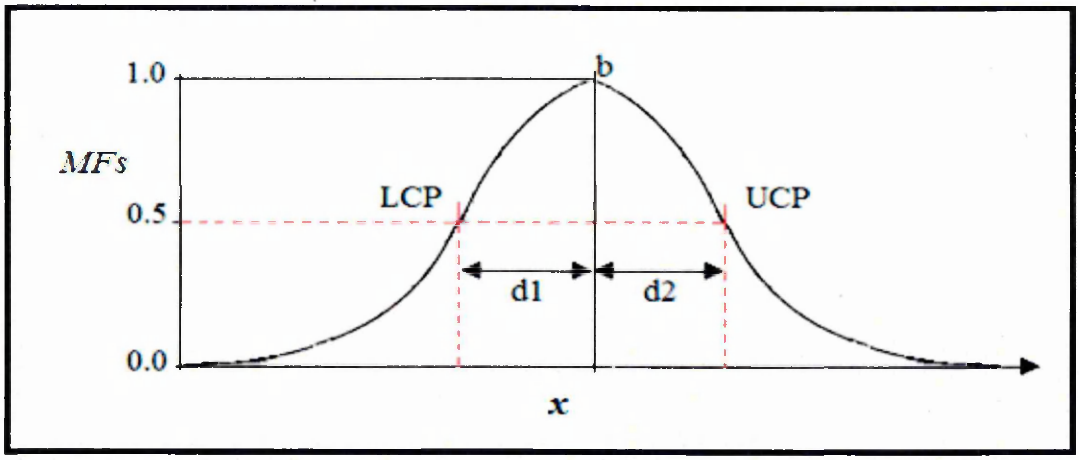


Figure: 5.4: Bell-shaped or Gaussian membership functions.

MFs = $1/[1 + a\,(x - b)^2]$ Equation 5.2

Where $a\ = (d1 + d2)$

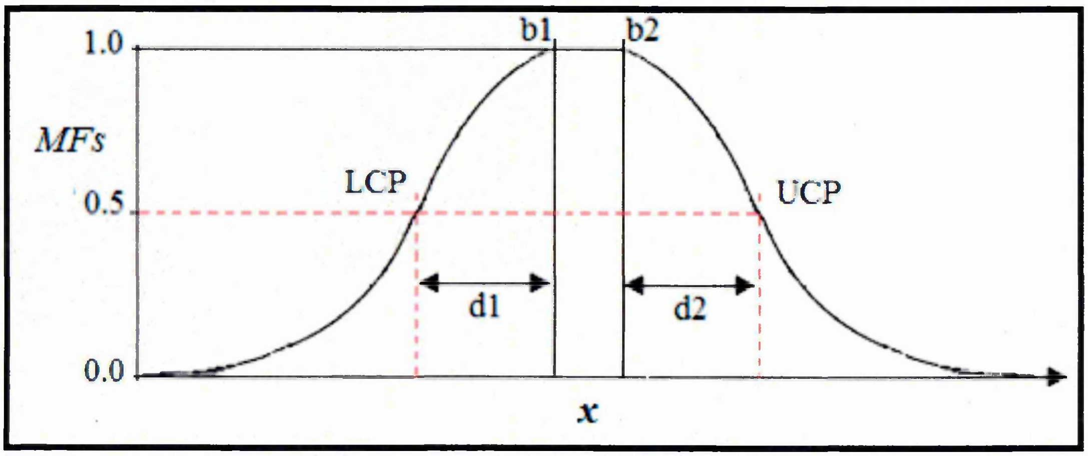


Figure: 5.4a: Symmetrical fuzzy membership functions.

The Symmetrical fuzzy membership functions is calculated using

$$\mathcal{MF}_{(x_i)} = \begin{cases} 1/\left[1 + \left(\frac{x-b_1}{d_1}\right)^2\right] & x < b_1 \\ & b_1 \le x \le b_2 \\ 1/\left[1 + \left(\frac{x-b_2}{d_2}\right)^2\right] & x > b_2 \end{cases}$$ Equation 5.3

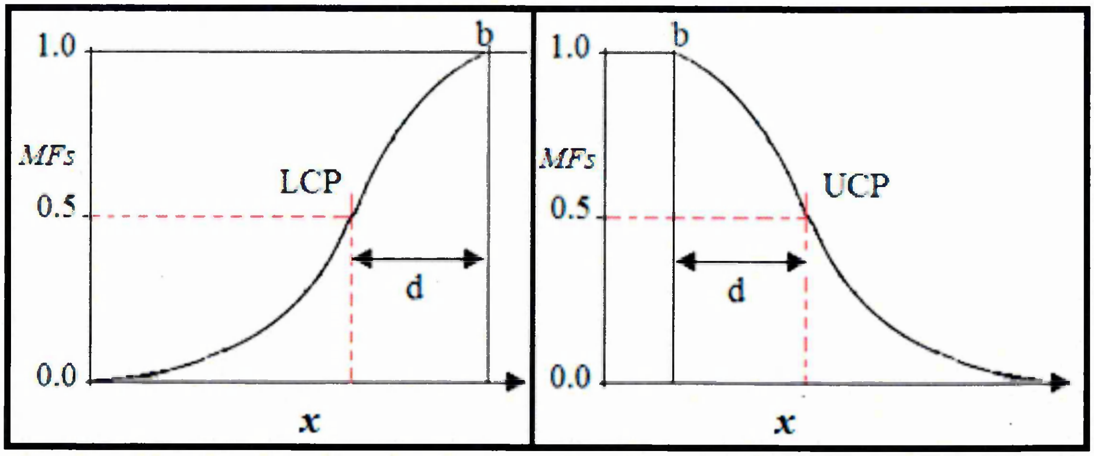


Figure: 5.4b: Asymmetrical left and right fuzzy membership functions.

The asymmetrical left model is calculated using:

$$\mathcal{MF}_{(xi)} = 1/\left[1 + \left(\frac{x-b_1}{d_1}\right)^2\right] x < b_1 \qquad \text{Equation 5.4}$$

The asymmetrical right model is calculated using:

$$\mathcal{MF}_{(xi)} = 1/\left[1 + \left(\frac{x-b_2}{d_2}\right)^2\right] x > b_2 \qquad \text{Equation 5.5}$$

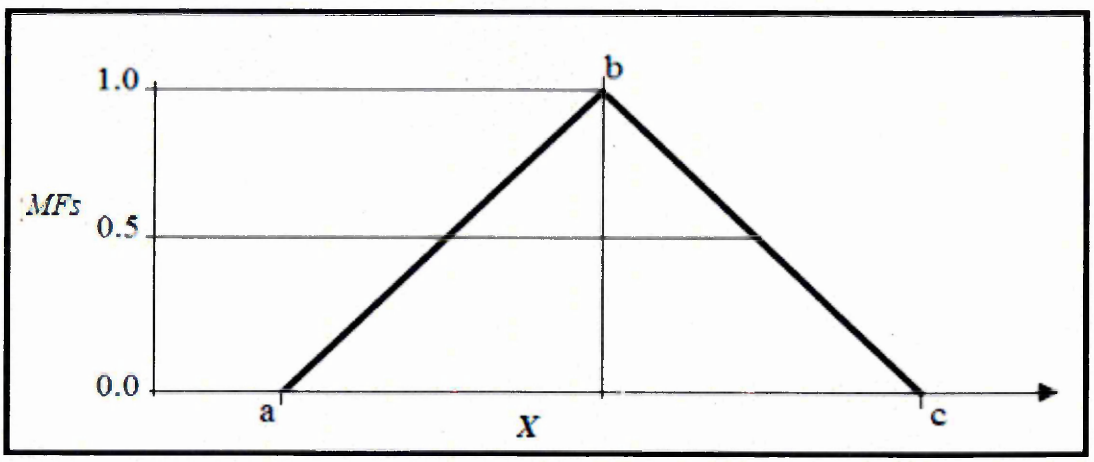


Figure 5.5: Triangular fuzzy membership function and the definitions to calculate membership values.

$$\mathcal{MF}_{(xi)} = \begin{cases} 0 & x \leq a \\ (x-a)/(b-a) & a < x \leq b \\ 1-(x-b)/(c-b) & b < x < c \\ 0 & x \geq c \end{cases} \qquad \text{Equation 5.6}$$

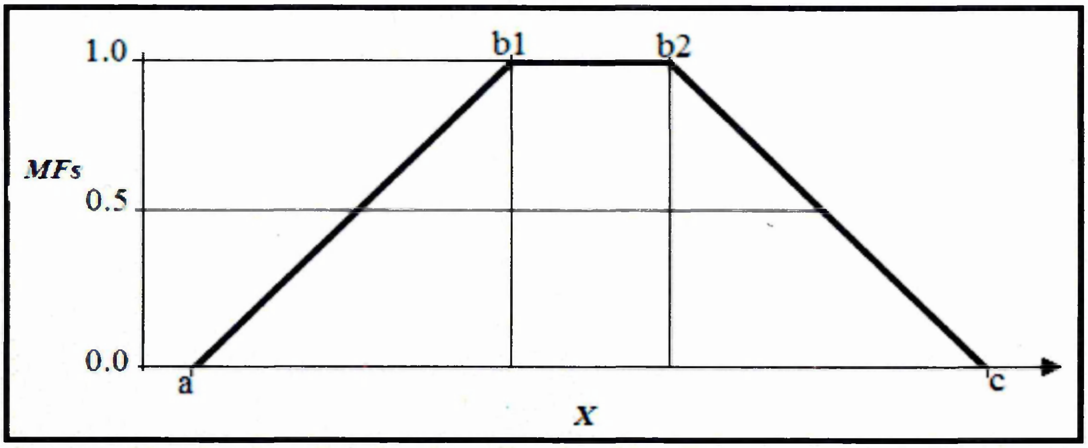


Figure: 5.5a: Trapezoidal (Symmetrical) fuzzy membership function and the definitions to calculate membership values.

$$\mathcal{MF}_{(xi)} = \begin{cases} 0 & x \le a \\ (x-a)/(b_1-a) & a < x < b_1 \\ 1 & b_1 \le x \le b_2 \\ 1-(x-b)/(c-b) & b_2 < x < c \\ 0 & x \ge c \end{cases} \qquad \text{Equation 5.7}$$

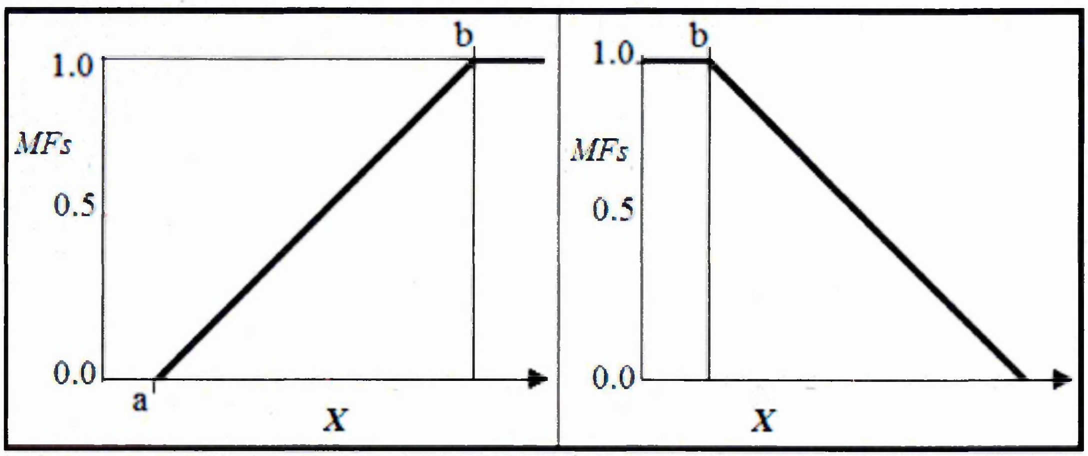


Figure: 5.5b: Trapezoidal (asymmetrical left and right) fuzzy membership function and the definitions to calculate membership values.

The asymmetrical left model is calculated using:

$$\mathcal{MF}_{(xi)} = \begin{cases} 0 & x \le a \\ (x-a)/(b_1-a) & a < x < b_1 \\ 1 & b_1 \le x \le b_2 \end{cases} \qquad \text{Equation 5.8}$$

The asymmetrical right model is calculated using:

$$\mathcal{MF}(x_i) = \begin{cases} 1 & b_1 \le x \le b_2 \\ 1-(x-b)/(c-b) & b_2 < x < c \\ 0 & x \ge c \end{cases}$$ Equation 5.9

The symmetric model is applied where the attribute of land has two ideal points of optimum ranges such as in soil pH. The asymmetric model - left and right -applies to land characteristics with either a lower or upper boundary of a class based on 'more is better and less is better' principles (Baja et al., 2001; Burrough and McDonnell, 1998). A number of scholars have used fuzzy in determining membership grades for different land characteristics (e.g. Baja et al., 2011). Braimoh et al. (2005) Burrough et al. (1992), Davidson et al. (1994), Elaalem et al. (2011), Moreno (2007), McBratney and Odeh (1997), Sicat et al. (2005), Stoms et al. (2002), Sui (1992) and Van Ranst and Tang (1999)). Groenemans et al. (1997) posited that selecting membership functions is a challenging task in fuzzy set theory because all decisions are based on membership values depending on the extent of their suitability. The above studies confirmed that the main issue in the application of fuzzy logic to land evaluation lies in the selection of the values of the membership functions (MFs).

5.5 Methods for Deriving Weights

A weight can be defined as a value assigned to an evaluation criterion, which indicates its importance relative to other criteria under consideration. Weights are usually normalised to sum up to 1 in a set of weights ($\sum_{i=1}^{n} w_i = 1$) (Malczewski, 1999). Assigning weights is of importance to evaluation criteria because it accounts for the changes in the range of variation for each evaluation criterion and the different degrees of importance being attached to these ranges of variation (Kirkwood, 1997). The critical issue relating to how the weight value affects the result, according to Davidson (1994) Van Ranst and Tang (1999) and Baja (2002a) lies on the choice of weighting factors. They further suggested that relying on experts' judgement and literature could provide vital information to land properties and crop production. However, these data gathered on crop requirements may not conform to those obtained in the field or laboratory. Therefore, it is important to find an appropriate way to assign weight values to land characteristics. There are four different techniques when assigning the weights: Ranking, Rating, Trade-off Analysis Methods and the AHP Method.

5.5.1 Ranking Methods

In ranking, every criterion under consideration is ranked in the order of decision maker's preferences. Either straight ranking; the most important = 1, second important = 2 or inverse ranking; the least important = 1, next least important = 2 can be used. Several procedures for generating weights from rank-order are available, but the most popular approaches are rank sum, rank reciprocal, and the rank exponent method (see details in Malczewski (1999) and Stillwell et al. (1981)). Due to its simplicity, the method is very attractive. However, the practical application of these methods is limited by the number of criteria to be ranked. Generally, the larger the number of criteria used, the less appropriate is the method (Voogd, 1983).

5.5.2 Rating Methods

The method requires the decision maker to estimate weights based on a predetermined scale. One of the simplest rating methods is the point allocation approach. It is based on allocating points ranging from 0 to 100, where 0 indicates that the criterion can be ignored, and 100 represents the situation where only one criterion need to be considered. Another method is the ratio estimation procedure, which is a modification of the point allocation method. A score of 100 is assigned to the most important criterion and proportionally smaller weights are given to criteria lower in the order. The score assigned for the least important attribute is used to calculate the ratios. The disadvantage of this method is like the ranking, method, is the lack of theoretical foundation - hence the assigned weights might be difficult to justify (Kolat, 2004; Malczewski, 1999).

5.5.3 Trade-off Analysis Method

In this method, the decision maker is required to compare two alternatives with respect to two criteria at a time and assess which alternative is preferred. Trade-offs define unique set of weights that will allow all of the equally preferred alternatives in the trade-offs to get the same overall value/utility. The main assumption in this method is that the trade-offs the decision maker is willing to make between any two criteria do not depend on the levels of other criteria (Malczewski, 1999). The weakness of this method is that the decision maker is presumed to obey the axioms and make judgement (Kirkwood, 1997).

5.6 Analytical Hierarchy Process (AHP)

The AHP method, developed by Thomas Saaty in 1977, is used to assist in making appropriate decisions for problems (Boroushaki and Malczewski, 2008; Duc, 2006; Malczewski, 1999; Saaty, 2008). AHP is widely employed in criteria weighting since it can incorporate numerous data types involved in land suitability applications (Abdi et al., 2009; Coulter, 2004; Malczewski, 1999). The decision-making process in AHP is a continuous procedure, which begins with an analysis of the decision environment, so that the parameters can be arranged into different groups and levels (Vogel, 2008). AHP consists of three principles: decomposition, comparative judgment and synthesis of priorities (Eldrandaly et al., 2005; Malczewski, 1999; Jaskowski et al. 2010). Under the principle of decomposition, complex problems are understood by decomposing them into a hierarchy, with comparative judgment then being used to evaluate parameters by comparing them at each level of this hierarchy. This principle takes each of the ratio-scale local priorities within the hierarchy and builds a group of priorities for each parameter in the lowest level of the hierarchy.

The analytical hierarchy process has three stages as follows (Boroushaki and Malczewski, 2008; Malczewski, 1999):

Stage 1: Hierarchy Development

During this stage, the elements of the decision-making problem are sorted into levels of importance. Each level in the hierarchy is linked to the next higher level. At the top-level of the hierarchy is the overall goal of the problem; the goal is then broken down into the important decision criteria. These criteria can then be broken down further into sub-criteria. It is possible to represent these sub criteria in a GIS database, with the map layers being made up of the element values assigned to the sub criteria, which are then linked to the criteria in the higher level of the hierarchy. Figure 5.6 show a hierarchy structure where the overall goal is broken down into three criteria. In turn, each of these criteria is broken down into sub-criteria; criterion 1 and 3 have one sub criteria for each and criterion 2 has 12 sub-criteria.

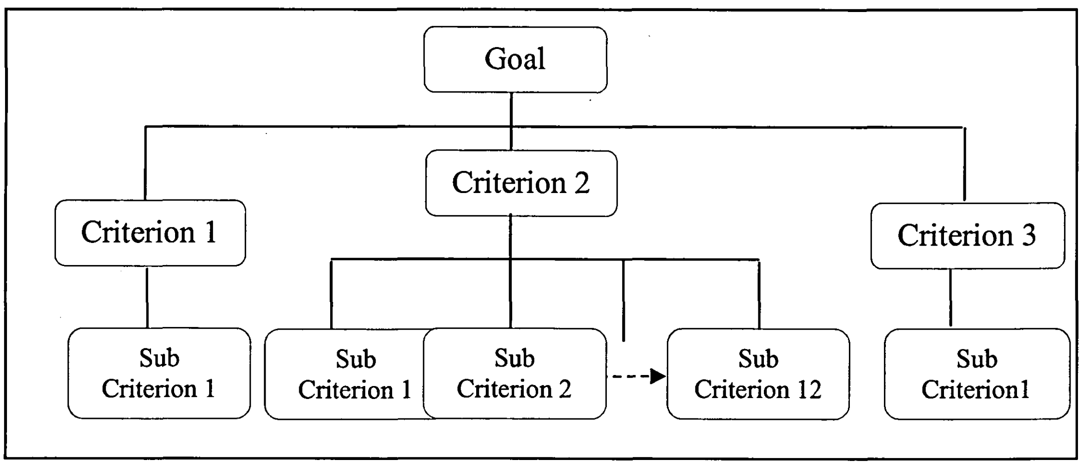


Figure 5.6: An AHP hierarchy structure.

Stage 2: Pairwise Comparisons (PCM)

The primary way in which the importance of criteria and sub-criteria is assessed within AHP is through pairwise comparisons. Within the context of the AHP procedure, the pairwise comparison matrix (PCM) method was introduced by Thomas Saaty in 1980. Its purpose here is to assess the importance of criteria, sub-criteria, and to determine the weight of each criterion and as such is able to compare two variables simultaneously. The comparison process usually begins at the top of the hierarchy and moves down. For the general case depicted in Figure 5.6, Criterion 1 is compared against Criterion 2 and 3 and Criterion 2 is compared against Criterion 3, with respect to their impact on the overall goal. Each PCM generates a numerical value of a scale of relative importance range from 1 to 9, or a reciprocal thereof Saaty (1980). It is important to note that these values represent absolute magnitudes and are not mere ordinal numbers. As Table 5.1 indicates, if a decision maker believes criterion one is three times as important as criterion two, a value of 3 would be assigned to this comparison and an attribute compared with itself is assigned the value 1, so the main diagonal entries of PCM are all 1. The numbers 3, 5, 7, and 9 correspond to the experts judgements (with 2, 4, 6, and 8 for compromise between these values).

Table 5.1: Scale for pairwise comparison

Intensity of importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values between adjacent scale values

Source: Saaty (1980)

The values created in a set of pairwise comparisons are stored in a PCM, denoted by A. The comparison of n factors will require an $n \times n$ comparison matrix, where factor k is assigned to row k and column k. Each entry in A, denoted by a_{ij}, represents the comparison of factor i to factor j, and a_{ij}=1 for i =1,2,...,n. Correspondingly, the comparison of factor j to factor i is the reciprocal of the entry for factor i compared to factor j. Thus $a_{ji}={}^{1}/_{a_{ij}}$ for all i, j, and can be observed that PCM is a positive reciprocal matrix. A general PCM is of the form:

$$A = \begin{bmatrix} 1 & {}^{1}/_{a_{12}} & \cdots & a_{1n} \\ a_{12} & 1 & \cdots & {}^{1}/_{a_{2n}} \\ \vdots & \vdots & 1 & \vdots \\ {}^{1}/_{a_{1n}} & a_{2n} & \cdots & 1 \end{bmatrix}$$

Stage 3: Determining Priority Vectors (weight) with the Eigenvector Method

This can be achieved using the following steps:

1. Sum the elements of each column j;

$$\sum_{i=1}^{n} a_{ij} \qquad \forall\, i,j \qquad \text{Equation 5.11}$$

2. Divide each value by its column sum;

$$\grave{a_{ij}} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \qquad \forall\, i,j \qquad \text{Equation 5.12}$$

3. Calculate the average of the elements in each row k to obtain weights;

$$w = \frac{\sum_{j=1}^{n} a_{ij}}{k} \qquad \forall\, i,j \qquad \text{Equation 5.13}$$

4. Determining the input consistency ratio CR:

$$CR = \frac{CI}{RI} \qquad \text{Equation 5.14}$$

Where CI is the consistency index, and

$$CI = \frac{\lambda\max - n}{n-1} \qquad \text{Equation 5.1}$$

$\lambda\max$, is the maximum Eigen value of the pair-wise comparison matrix and n is the number of elements (n) (criteria) being compared and;

RI is the random index, which depends on the number of elements (n) (criteria) being compared (Table 5.2).

Table 5.2: Random Consistency Index (RI)

n	1	2	3	4	5	6	7	
RI	0.00	0.00	0.58	0.9	1.12	1.24	1.32	
n	8	9	10	11	12	13	14	15
RI	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Source: Saaty (1999)

The consistency ratio of the pairwise comparison matrix must be less than or equal to 0.1. If it is greater than 0.1, the matrix has to be re-evaluated or ignored.

5. Solving for the Weights by Successive Squaring and Checking Differences;

In this step squaring the original PCM and continue the process from 1 - 3 (Eigenvector solution) until the difference in weights does not change from the previous iteration.

The five aforementioned operations can be implemented either manually or automatically by employing an Excel spreadsheet model (Kirkwood, 1997), or using IDRISI software (Eastman et al., 1993; Jaskowski, 1995). Table 5.3 summarises the steps towards achieving pairwise comparison.

Table 1 Table 5.3: Steps for the pairwise comparison method

	Step1 *(sum columns)*			Step 2 (*normalize*)	Step 3 (*average*)			Weights
	1	2	5	1.7	0.5882	0.6154	0.5	0.5679
A	1/2	1	4	3.25	0.2941	0.3077	0.4	0.3339
	1/5	1/4	1	10	0.1176	0.0974	0.1	0.0982
∑=	1.7	3.25	10					∑= 1

The consistency-ratio is calculated using equations:

$$CI = (\lambda\max - n)/(n-1)$$

To compute *CI*, λmax be determined as follows:

λmax = (1.7× 0.5679) + (3.25 × 0.3339) + (10 × 0.09819) = 3.0326

CI = (3.0326 – 3)/ 2= 0.01629

From Table 5.4 *RI* is; where, *n*=3, *RI* = 0.58

Where consistency ratio CR= CR= CI/RI = 0.01629/0.58 = 0.028, and so the consistency is acceptable.

Table 5.4: Step 5(a) of the pairwise comparison method

	Step1 *(sum columns)*			Step 2 (*normalize*)	Step3 (*average*)			Weights
A	3	5.25	18	5.325	0.5634	0.5738	0.5714	0.5695
	1.8	3	10.5	9.15	0.3380	0.3279	0.3333	0.3331
	0.525	0.9	3	31.5	0.0986	0.0984	0.0952	0.0974
∑=	5.325	9.15	31.5					∑= 1

Table 5.5: Step 5(b) of the pairwise comparison method

	Sep1 *(sum columns)*			Step 2 (*normalize*)	Step3 (*average*)			Weights
A	27.9	47.7	163.13	48.9825	0.5696	0.5695	0.5695	0.5695
	16.313	27.9	95.4	83.7563	0.333	0.3331	0.3331	0.3331
	4.77	8.156	27.9	286.425	0.0974	0.0974	0.0974	0.0974
∑=	48.983	83.76	286.43					∑= 1

There is no deference between eigenvector (weights) in step 5 (a) and eigenvector (weights) in step 5 (b), so weights derived from PCM are: 0.5695, 0.3331and 0.0974.

Stage 4: Construction of an overall priority rating

In this stage, composite weights are created by multiplying the relative weights matrix for each level in the hierarchy.

Table 5.6 summarises the major features of the four methods for assessing criterion weight. The methods differ in several important ways. Although some of the summary statements are oversimplifications of complex issues, it is suggested that they provide a guideline for choosing a method for weight assessment. Which method to use would depend on the trade-off one is willing to make between ease of use, accuracy, the degree of understanding on the part of decision maker, and the theoretical foundation underlying a given method; the availability of computer software; and the way the method can be incorporated into GIS-based multicriteria decision analysis.

Table 5.6: Comparison of the methods used for estimating weights

Feature	Methods			
	Ranking	Rating	AHP(PCM)	Trade-off
Number of judgements	n	n	n(n-1)/2	<n
Response scale	Ordinal	Interval	Ratio	Interval
Hierarchical	Possible	Possible	Yes	Yes
Underlying theory	None	None	Statistical /heuristic	Axiomatic/ deductive
Ease of use	V. easy	V. easy	Easy	Difficult
Trustworthiness	Low	Low	High	Medium
Precision	Approximations	Not precise	Quite precise	Quit precise
Software availability	Spreadsheets	Spreadsheets	Expert choice	Logical decision
Use in GIS	Import from a Spreadsheet	Import from Spreadsheet	Component of Idrisi	Import from Logical decision

Source: Kolat, 2004; Malczewski, 1999

5.6.1 Applications of the AHP Method in Land Evaluation

As has been pointed out in the preceding section, AHP procedure consists of three principles: decomposition, comparative judgment and synthesis of priorities (Eldrandaly et al., 2005). Under the principle of decomposition, complex problems are understood by decomposing them into a hierarchy, with comparative judgment then being used to evaluate parameters by comparing them at each level of this hierarchy. Land suitability analysis using the AHP method is a very common technique (Boroushaki and Malczewski, 2008; Malczewski, 1999, 2004) in the context of this study three steps were taken in a GIS environment. Step 1 is the development of the analytical hierarchy structure. During this stage, the elements of the decision-making problem are sorted into levels of importance. Each level in the hierarchy is linked to the next higher level. The PCM using a scale range 1-9 was applied in Step 2. This allows an independent assessment of the contribution and importance of each factor for assigning weights (Rezaei-Moghaddam and Karami, 2008; Sener et al., 2010). In Step 3, composite weights were created by multiplying the relative weights matrix for each level in the hierarchy.

The AHP method can be used as a set of tools for deriving weights of criteria and as a whole method for decision-making. The AHP has the ability to deal with inconsistent judgments and offers a measure of the inconsistency of the judgment of the respondents. The AHP method can cope with the real world problems that are multi-dimensional (Malczewski 1999; Saaty, 1980; Voogd 1983). This method capitalises on the fact that humans are very good at comparing two things at a time, but have increasing difficulty making reliable judgements, as more items need to be compared simultaneously. In the pair-wise comparison technique, the user compares all land factors against each other two at a time. This results in a robust and reliable method for capturing preferences. When all comparisons are made, mathematical techniques are used to generate relative weights for each criterion (Itami et al., 2000)

One of the main principles of the AHP is to decompose the problem into a hierarchy of elements; thus, each part or level of the hierarchy becomes important in determining the weight assigned to each element within that hierarchy (Prakash, 2003). In the AHP, the whole decision problem is organised in a hierarchic structure of objectives, criteria, and sub-criteria (Bernasconi et al., 2013). The process of measurement occurs at each level of the hierarchy generating specific comparison matrix relevant for that level. Broadly speaking, many studies (such as Elaalem et al., 2010; 2011) used the AHP through PCM to derive weight for criteria only, and did not take into account the basic requirement of hierarchical structure of criteria. When Elaalem et al. (2010; 2011) used PCM for land suitability evaluation for the growing of wheat in western Libya, the criteria were organised into a hierarchical structure comprising goal, criteria and sub-criteria, but applied the PCMs only at the sub-criteria level. By doing this, Elaalem et al. (2010; 2011) neglected the hierarchy of criteria, and yet derived weight for all land characteristics using sub-criteria.

Xiang et al. (1992) first introduced the integration of the AHP with a group of fuzzy set models. Xiang et al. (1992) applied the AHP with a group of fuzzy set models for land use planning. It is important now to clarify the confusion or misunderstanding on the use of the term 'Fuzzy AHP' and 'Fuzzy with AHP'. While the former (Fuzzy AHP) means fuzzifying AHP (i.e. using Fuzzy method to set the Scale for pairwise comparison), the latter uses Fuzzy method for standardising criteria and AHP method for deriving weights for these criteria (i.e. Using Fuzzy and AHP). For example, Ceballos-Silva and Lopez-Blanco (2003) applied AHP technique as a set of tools for deriving weights of criteria that affect maize and potato crops. Duc (2006) used the AHP method in combination with GIS to identify land use suitability in Vietnam, where twelve different criteria are organised into a hierarchical structure. It begins with the overall goal (Suitability) and decomposes into a number of criteria and sub-criteria. Similar studies carried by Moreno (2007) employed different fuzzy membership functions for standardising factors related to land suitability for upland rice and rubber in Lao PDR, and weights for these factors were calculated according to AHP that relied on pairwise comparison. Similar studies from different geographical zones that have applied AHP method for deriving weights and fuzzy set for standardising criteria can be seen in Kontos et al. (2005), Keshavarzi (2010), Elaalem, (2010, 2011, 2013), Anane et al. (2012) among others.

Moreover, the AHP approach is often criticised, due to its scale of judgments (crisp judgments) and its inability to adequately deal with the inherent uncertainty associated with pairwise comparison judgments (e.g. Ahamed et al., 2000; Deng, 1999; Erensal et al., 2006; Ertuğrul and Karakaşoğlu, 2009; Prakash, 2003; Vahidnia et al., 2008; Xiang et al., 1992). These studies argue that the Fuzzy set theory can be used for solving vagueness or ambiguity associated with pairwise comparison judgments. According to Erensal et al. (2006), the conventional AHP approach may not fully reflect a style of human thinking because the decision makers or experts usually feel more confident to give interval judgments rather than expressing their judgments in the form of single numeric values. Chen et al. (2011) argue that the assessment of experts judgements or opinions have always involved certain ambiguity and uncertainty; consequently the evaluation results may not be adequate for assigning weights for criteria in the process of decision making and so FAHP is capable of capturing a human's appraisal of ambiguity when complex multi-attribute decision analysis problems are considered. This ability comes to exist when the crisp judgments transform into fuzzy judgments. However, Saaty and Tran (2007) believe that intermediate values are themselves fuzzy enough to capture decision makers' opinions even in the state of doubt. They further contest that fuzziness AHP assessment can lead to wrong judgement, but can also improve consistency. In their words: "making poor judgments leads to poor outcomes and fuzzifying poor judgments still leads to poor outcomes" (Saaty and Tran, 2007).

5.6.2 AHP _ Group Method and Member Weights

It has been argued that integrating local knowledge into land evaluation methodologies can enhance the output of the process (FAO, 2007; Itami et al., 2000). Thus, land suitability evaluation decisions should incorporate inputs from group of experts with varying knowledge and experience in different field of agronomy. However, many studies such as Elaalem (2010, 2011, 2013), Keshavarzi (2010) and Prakash (2003) have applied AHP individual decision (i.e. only one person or expert) to determine the weights of considered criteria. Such studies are recognised as subjective and limited in generalisation (Chen et al., 2010; Dinh and Duc, 2012; Thapa and Murayama, 2008). Ishizaka and Labib (2011) state that as a decision affects several persons, the standard AHP has been adapted to capture group decisions. Consulting several experts also avoids bias that may be present when judgement is considered from one expert. To facilitate the involvement of experts from different backgrounds and reducing individual's subjectivity, the AHP-group method is utilised to involve several local experts' opinions.

A number of authors (e.g. Dyer and Forman, 1992; Malczewski, 1999; Ramanathan and Ganesh, 1995; Saaty, 2003; Ishizaka, 2013) have suggested ways of using AHP as a consensus builder through information derived from decisions made by a number of experts. Forman and Peniwati (1998), and Ishizaka and Labib (2011), went further to develop two different AHP mathematical approaches (within AHP) for group decision making, if a consensus cannot be reached. These are (1) Aggregate Individual Priority (AIP) which weights geometric or arithmetic means based on the pairwise comparison matrix of each expert; and (2) Aggregate Individual Judgment (AIJ), which aggregates individual judgements by weighted geometric means to create a new pairwise comparison matrix for the group in order to derive weight for each factor and then applying eigenvector (EV) methods (see Ramanathan and Ganesh, 1995; Saaty,1980; Zadnik-Stirn and Groselj, 2010; Tan and Li, 2012; Warren, 2004; and Wen-Hsiang et al., 2008). In both AIP and AIJ, the geometric mean and athematic mean can be used. However, many studies (such as Bahurmoz, 2006; Zadnik-Stirn and Groselj, 2010; Tan and Li, 2012; Warren, 2004; Wen-Hsiang et al., 2008), maintain that a weighted geometric mean can be used with AIJ. On the contrary, Jaskowski (2010) and Topcu, (2004) argue that the arithmetic mean cannot be used to aggregate the AIJ; it can only be applied to the final priority AIP.

In a situation where the group was unable to arrive at a unanimous final weight taking into account differences in opinions, the Group Analytic Hierarchy Process (GAHP) would allow the group to resolve the differences. Assuming there is a group of three individuals (experts) completing a PCM using AHP, though they may agree on many of the comparisons, it is unrealistic to expect them to agree on every entry in the PCM. In the GAHP, each member completes his or her own comparisons and records these in their individual PCM. By following the steps indicated in Section 6.6.4. It should be noted that the consistency ratio of the PCM, must be less than or equal to 0.1 for each individual PCM. If it is greater than 0.1, the matrix has to be recalculated or ignored. Each entry in the group pairwise comparison matrix is then determined as the geometric mean of the respective entries in the individual pairwise comparison matrices. The method for expressing GAHP is mathematically derived thus:

$$A = (a_{ij}), \qquad k = 1,2,3 \qquad\qquad \text{Equation 5.16}$$

represent the (3 x 3) PCM generated by individual k when considering the three criteria of the second level, let;

$$A = (a_{ij}),$$

be the group pairwise comparison matrix with entries given by using the geometric mean to compute each entry of A;

$$a_{ij} = \left(a_{ij}^1 \cdot a_{ij}^2 \cdot a_{ij}^3\right)^{1/3} \quad i,j = 1,2,3.$$

The geometric mean preserves the reciprocal nature that is required of pairwise comparison matrices, that is:

$$a_{ij} = \left(a_{ij}^1 \cdot a_{ij}^2 \cdot a_{ij}^3\right)^{1/3} = \left(\frac{1}{a_{ij}^1} \cdot \frac{1}{a_{ij}^2} \cdot \frac{1}{a_{ij}^3}\right)^{1/3} = \frac{1}{a_{ij}}$$

and, $A = (a_{ij})$ is a positive reciprocal matrix. The group priority vectors (i.e. weight of each element in that level of hierarchy) are then determined using the Eigenvector method described in Section 5.6.

5.7 GIS and Overlay Techniques

One multi-attribute technique incorporated into the GIS-based, land use suitability procedure is the AHP (Saaty, 1980, Malczewski, 2004). This is a twofold approach realised within a GIS environment. First, it can be employed to help derive the weights associated with suitability (attribute) map layers. The weights can then be combined with the attribute map layers in a manner similar to that used in the linear additive combination methods (Malczewski, 2004). MCDM methods such as the AHP method have been successfully applied to land evaluation techniques (Bakhtiar and Thomas, 2012). The potential of the integrated approach in GIS for quantitative land evaluation has been demonstrated earlier by several researchers (Beek et al., 1997). One of the most widely used tools in land suitability is the map overlay approach typically applied to land-use suitability in the form of weighed linear combination (WLC).

The overlay procedures play a central role in many GIS applications including techniques that are in the forefront of the advances in the land-use suitability analysis such as MCDM (Carver, 1991; Diamond and Wright, 1988; Malczewski, 1999; Thill, 2000). The main overlay approaches available are Weighted Overlay and Weighted Sum. Each approach has different basic premises and assumptions. The most appropriate approach is dependent on the overlay problem being solved. The Weighted Overlay is a technique for applying a common scale of values to diverse and dissimilar input to create an integrated analysis. Geographic problems such as land use suitability require that multiple factors are analysed. This information exists in different rasters with different value scales, for example, a raster of depth in cm (a quantitative value) cannot be added to a raster of texture (a qualitative value) to obtain a meaningful result. Additionally, the factors in the analysis may not be of equal importance. It may be that the depth of the soil is more important than the texture. Although the concept of the weighted overlay method is simple, there are many steps required to ensure model validity (Carr and Zwick, 2007). The following is a summarisation of these steps (Carr and Zwick, 2007):

1. A numeric evaluation scale is chosen. This may be 1 to 5, 1 to 9, or any other scale. Values at one end of the scale represent one extreme of suitability; values at the other end represent the other extreme.
2. The cell values for each input raster in the analysis are assigned values from the evaluation scale and reclassified to these values. This makes it possible to perform arithmetic operations on the raster that originally held dissimilar types of values.
3. Each input raster is weighted, or assigned a % influence, based on its importance to the model. The total influence for all raster equals 100%.
4. The cell values of each input raster are multiplied by the rasters' weights.
5. The resulting cell values are added together to produce the output raster.

5.7.1 Weighted Overlay Analysis for Land Suitability Evaluation

Two forms of analysis are used: Weighted Overlay Sum (WOS) and Weighted Overlay Technique (WOT). Many authors (such as Nwer, 2005) applied Weighted Overlay Technique to produce land suitability maps for barley, wheat, maize and sorghum in the Benghazi region in Libya. Similar to Nwer's study Al-Mashreki et al. (2011) applied WOT for modelling land suitability evaluation for Sorghum in Yemen. Perveen et al. (2013) used Weighted Overlay function for classification of suitable areas identification for cotton crop cultivation in the Sindh province of Pakistan. Elsheikh et al. (2013) used the GIS Model Builder to organize and integrate spatial processes to model land suitability. In all these studies, spatial geo-environmental factors (such as soil, climate, slope, erosion and flood hazard) were integrated into the GIS as information layers and overlaid to produce overall land suitability assessment for a particular land utilisation type. Figure 5.7 below illustrates how to calculate overall suitability in the context of this research. Three input rasters were used (Soil, Slope and Erosion) which have been reclassified to an evaluation scale of suitability between 1 and 4; where 1 represents the lowest suitability and 4 the highest. For example, in the soil raster, if soil has a high depth then it is highly suitable, and if the soil has high salinity, it is not suitable. In the slope raster, suitability values are low for land that has high steepness and high for low-steepness.

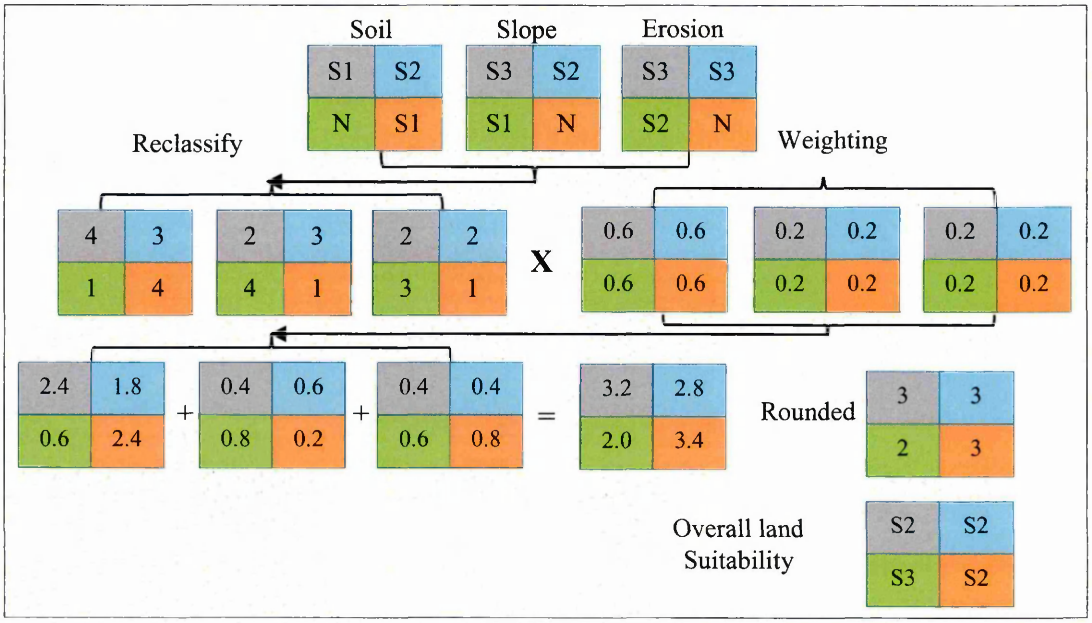


Figure 5.7: Overall land suitability overlay.

In the erosion raster, suitability increases with lower soil erosion. Each raster is then assigned a weighting influence expressed as a percentage. The influence of soil, slope and erosion rasters is 60, 20 and 20 percent respectively. The weighting influence percentage for each factor is then multiplied by the respective value, the results are then added together to derive the output raster. In Figure 5.7 for the top left hand cell (4 * 0.6) = 2.4, (2 * 0.2) = 0.4 and (2 * 0.2) = 0.4, the sum total is 3.2 (2.8, 2 and 3.4). Because the output raster should be discrete, it is common practice for a coarse discrete scale to be used to define the output raster i.e. the output raster will be rounded to 3, 3, 2 and 3. This is because the original scenarios for which the WOT was developed used a coarse scale to define characteristics and in addition, a coarse output was all that was required. This is a limitation especially were a finer resolution of the output would help decision makers take the most suitable choice, and also where more detailed description of the magnitude of characteristics is available.; however, this is a limitation because much of the information is lost: a value of 3.4 is considered the same as 3 and likewise 2.8 is considered to be 3. This approximation is thus an inaccurate reflection of reality.

In addition, the weighted overlay tool is applied to solve multi-criteria problems such as location selection and suitability models, and allows for the consideration of geographic problems, which may often require the analysis of different factors. Such is the case with land suitability analysis where determination of overall land suitability of an area for a particular agricultural crop (e.g. wheat and barley) will require consideration of many criteria e.g. soil pH, depth and texture, (Van Diepen et al., 1991). Each criterion can be represented by a separate map (a single thematic layer), in terms of the degree of suitability for each land unit. But in the existing land evaluation model for the study area, the land characteristics that are related to soil are grouped and represented as one thematic layer. Arguably, this may result in the loss of interaction between factors, particularly when weights are being assigned to each land characteristic.

To overcome this problem, the weighted overlay sum can be used where the output raster is a floating-point and/or integer. However, there is a problem in interpreting the results where there are no guidelines or clear reference to follow. This highlights the need to fine-tune the approach for specific purposes, something this study has achieved. Based on the above, therefore, this study develops a continuous scale for the output of the WOS whereby important information is not discarded. The solution applies a concept similar to linear-scale transformation methods that are used to convert raw data into a standardised creation score (Malczewski, 1999). One of the most widely used methods is the maximum score procedure (Massam, 1988; Voogd, 1983). In this study, this approach is applied by standardising the output raster (values of the total suitability) according to the relative distance between the origin and the maximum rank value, i.e. 4. This is because the factors (land characteristics) are classified as a value between 1 and 4 using the following formula:

$$X = {x_i}/{x_{max}} \qquad \text{Equation 5.17}$$

where X is the overall land suitability, Xi is output raster and Xmax is the maximum rank value. For instance, dividing the total suitability value of 3.4 by 4 equals 0.85; by doing this, the results it will be on a continuous scale (0 to 1) instead of four classes as it was in the original weighted overlay and none of the information is discarded and the result is a more accurate reflection of reality. This step can be implemented in ArcGIS for both raster and vector: for raster format; by using raster calculators then divide operator under spatial analysis tool while, for vector format can be done in excel spreadsheet.

5.8 Summary

The review of multiple criteria land suitability evaluation techniques has shown that evaluating land suitability using fuzzy set models achieves better results when compared to traditional techniques. Fuzzy logic is able to resolve problems associated with crisps nature of Boolean algebra theory as well as integrate different types of land attributes that are peculiar to the environment in question. Some of the cited empirical studies have shown that the fuzzy set technique has the ability to handle uncertainty in land suitability, while GAHP is used to determine weights for land characteristics. The GAHP enables involvement of several experts coming from different backgrounds while reducing subjectivity. As a consequence, the fuzzy set model and AHP techniques have been selected to develop a land suitability map for agricultural crops in the study area outlined in this research, a region in which these methods have not yet been fully applied by previous studies. How these methods worked out together to develop land suitability models in the research is contained in the next chapter.

Chapter Six
Research Methodology

6.1 Introduction

The previous chapters provided an extensive review of some empirical studies applying GIS technique to the modelling of land evaluation systems, an overview of different land evaluation models, and a review of existing land evaluation model for the study area. How results change when different approaches are applied and when compared with the results derived from an existing land evaluation model of the study are also contained in the chapter.

This chapter explains the methods used in the research by highlighting data requirement, land suitability assessment, building the GIS database, creating the models and reporting the findings. Figure 6.1 illustrates the research methodology employed in this study. The next section identifies the various sources of data used for the research.

6.2 Data Requirement and Data Collection

The limitations associated with the existing land suitability evaluation model in study area by Nwer (2005) were addressed in chapter one. This research explores the potential of using advanced GIS functions and methods, such as the Analytical Hierarchy Process (AHP), to handle this problem. A number of authors (Burrough et al., 1992; Davidson et al., 1994; Malczewski, 1999; Baja et al., 2006) also suggest the use of fuzzy membership function. As mentioned earlier, to resolve the problems derived from the use of the Boolean method in producing the model of land evaluation for the study area, this research aims to develop a model of land evaluation using the AHP and Fuzzy AHP method. In addition, a comparison was made between the new model (using AHP and Fuzzy AHP) and the existing model (Boolean method), but first the data requirement and collection process.

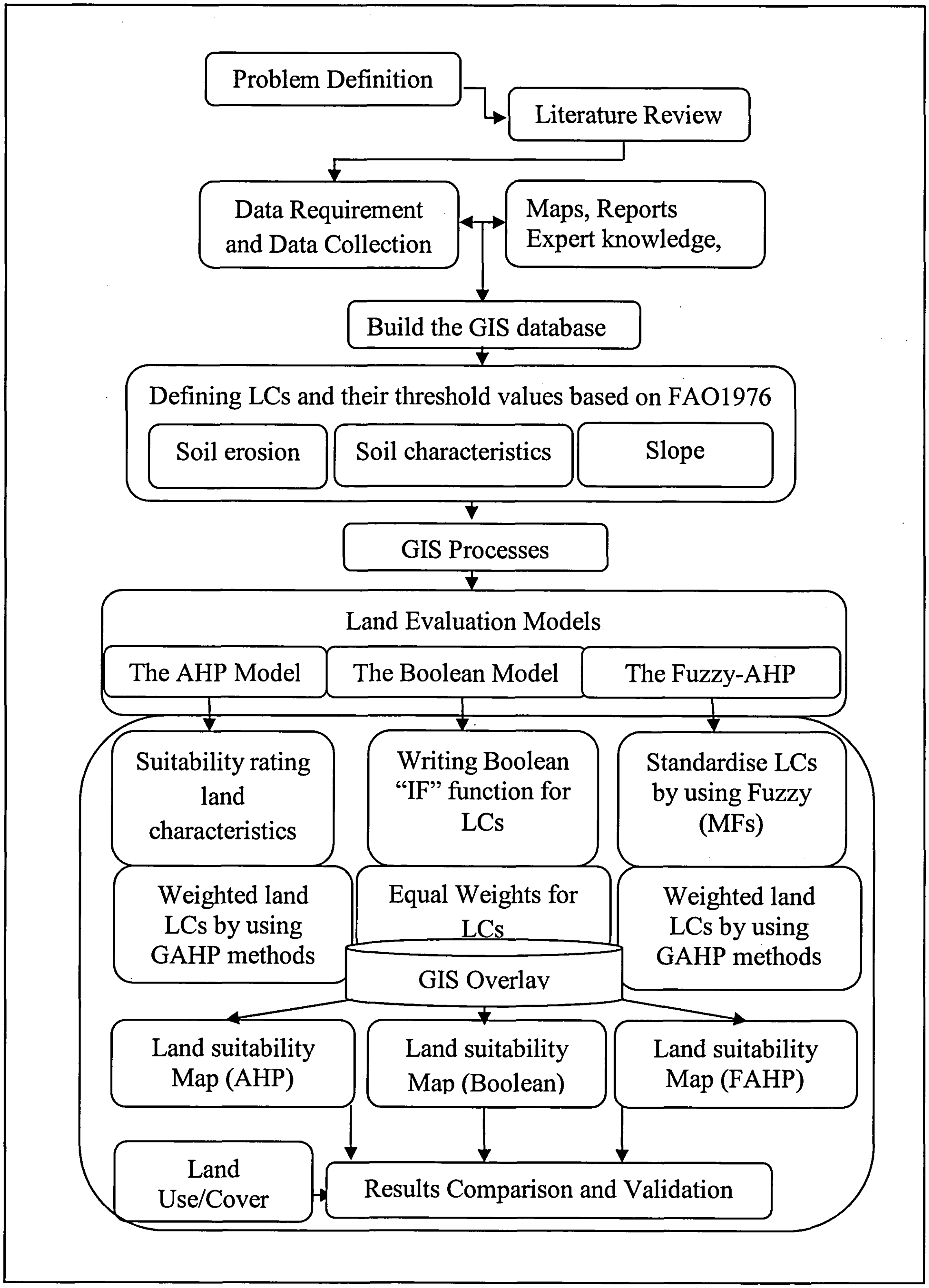


Figure 6.1: The research process.

Various data are required to produce a land evaluation model were gathered from a number of sources – both primary and secondary. Secondary sources include:

- Land use and land cover map for study area at a scale of 1:50,000
- Soil maps: 1:50,000 scale
- Soil erosion maps also available at a scale of 1:50,000
- Topographic maps also available at a scale of 1:50,000
- Soil database report comprising both physical and chemical soil properties.
- Climate data including rainfall, temperature and relative humidity.

All these data were collected during a visit to the following sources: Library of Agricultural Research and library of Tripoli University, Project of database for the Libyan Natural Resources, Meteorological and Climate Department, Department of the Great Man-Made River Project (GMPR) and the Department of Information and Documentation of the Ministry of Agriculture.

Primary data were collected from three field surveys:

- There are two aims of the first field visit: The initial aim was to collect secondary data about the above mentioned sources that are only available in Libya, The second aim was to contact and conduct interviews with two local experts (Prof Ben Mahmoud and Nwer) review and reflect on the existing data (Nwer 2005) for land utilisation types, qualities, characteristics and their threshold values. Two experts were selected in an attempt avoid bias.
- The second field visit was used to establish the relative weights of the land characteristics for selected crops. This was achieved by identifying and assembling a team of local experts and researchers of the Libyan Agricultural Research Centre (ARC) who are interested in the field of land evaluation. Whilst it is simple to state that local experts are required, it is a different matter to locate them. A database of experts who have the experience and knowledge on the assessment of land and land resources is lacking. In order to resolve this problem, a non-probability technique of snowball sampling was relied upon to identify future subjects through acquaintances (see

Morgan, 2008). The first two experts identified were the Head of the Soil and Water, Faculty of Agriculture, Tripoli University and the Director of Department of Natural Resources Research. These two experts identified 15 other experts from various backgrounds but access to them was difficult for a number of reasons: 1) no personal established contacts, 2) work outside Libya, and 3) may have left the country due to the civil uprising. A total of 10 experts were finally accessed, but it turned out that only six were able to make contributions on the selected land characteristics. These six experts had background comprises soil and water conservation management, soil physics, inventory and classification of land, soil chemistry and fertility, irrigation science and land management. Appendix B contains the local experts' background. Establishing consistent weighting of land characteristics according to their importance will be achieved by pair wise comparison.

- The aim of the third visit was to collect sufficient crop yield data to allow validation of the results of the theoretical models. The methodology for this is described later in this Chapter.

6.3 Selection of the study area

The strip of the coastal territory and Jabal Akhdar Upland, Benghazi region were selected to develop a land suitability classification because it is the first area planned to be irrigated with the GMRP (Figure 4.1). This area of the country is known as North East and includes the Benghazi region and the Jabal Akhdar highlands (Figure 2.1). Upon the completion of the GMRP, the first stage aims to irrigate about 155,000 ha. The reclamation and development of some 38,000 ha in the Benghazi region served by the Ajdabiya- Benghazi line from the GMRP will also be undertaken. In addition, it is the area with the most data available compared to other regions of Libya.

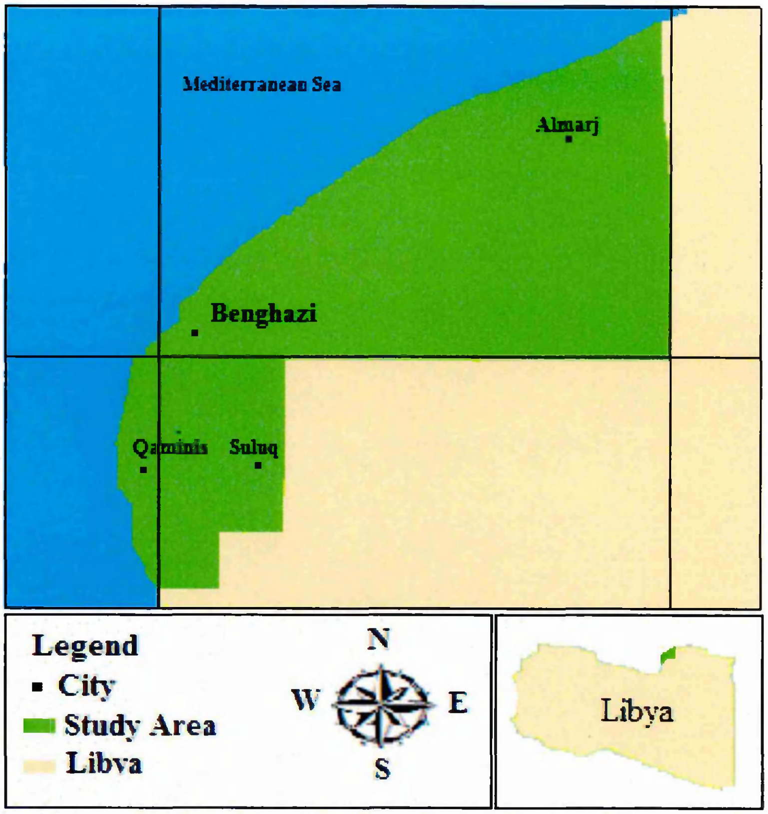


Figure 6.2: Selected study area.

6.3.1 Climate and Soil Information for the Study Area

The study area is located in a Mediterranean type climate, in the belt of subtropical alternate atmospheric circulation. An extensive distribution of Libyan climatic factors was presented in Chapter Two. According to Binnina Meteorological Report (2010) the mean annual temperature is 18.9°C in Benghazi, 17.45°C in the Almarj while in Slouq is 19.7°C (Figure 6.3). Based on a threshold value for each selected crop the suitability classification for mean temperature in the growing season is considered highly suitable for selected crops therefore, this factor was not included in the models because it is not influence barley, and wheat production for the study area.

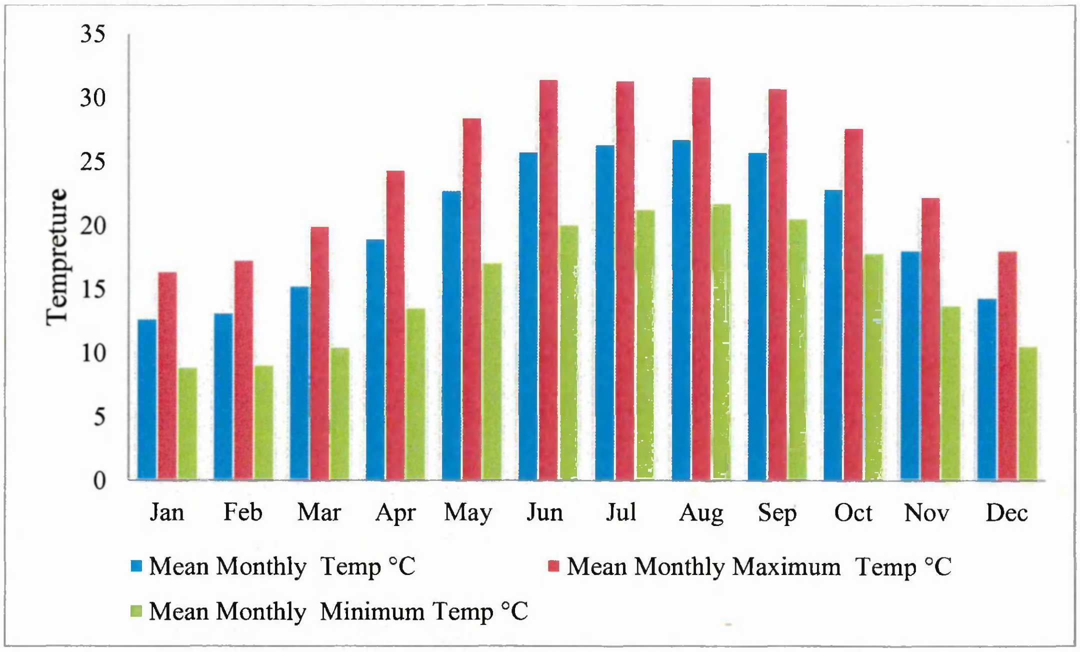


Figure 6.3: Benghazi Mean Monthly Temperature from 1973-2010. Source: Benina Meteorological Report (2012)

The soils in the northeast and northwest of Libya have been investigated by Selkhozpromexport, Agriculture Research Centre (ARC), Tripoli University and the Ministry of Agriculture. While the geography of soil in Libya is explained in Section 2.3, the spatial soil information available to this research is the 1: 50,000 soil maps on soil subtypes level. The physical and chemical soil properties which are available in the study area are: soil texture, rootable depth, infiltration rate, soil drainage, percentage stones at surface, available water holding capacity (AWHC), soil reaction (pH), organic matter (OM), electric conductivity (EC), exchangeable sodium percentage (ESP), percentage of soil calcium carbonate ($CaCo_3$), and cation exchange capacity (CEC). Soil classification in study area distinguishes 9 soil types, 26 soil subtypes and 51 soil genera. Appendix A contains the definitions of the Soviet terminology used and a brief description of the soil types, sub types and genera in the study. Table 6.1 contains the classification of soils division into types and sub-types and their codes.

Table 6.1: classification of the soils of the study area

Type	**Subtype**	**Code**
Red Ferrisiallitic	Typical	F-t
	Concretionary	F-c
	Crust	F-cr
	Hydrated	F-hd
	Hydromorphic	F-h
	Of a truncated profile	F-i
Yellow Ferrisiallitic	Typical	Y-t
	Concretionary	Y-c
Siallitic Cinnamon	Typical	CS-t
Rendzina	Dark	RZ
	Red	Rz-r
Reddish Brown Arid	Differentiated	FB-d
	Differentiated Crust	FB-dc
	Slightly Differentiated	FB-sd
	Slightly Differentiated Crust	FB-sdr
	Non-Differentiated	FB-nd
	Hydromorphic Crust	FB-hcr
Brown Arid	Differentiated	B-d
	Slightly Differentiated	B-sd
Lithosols	Reddish Brown	L-fbl
	Brown	L-bl
Crusts	Non-Monolithic	CR-nm
Solonchaks	Automorphic	Sa
	Hydromorphic	Sh
	Hydromorphic crust	Shcr
	Hydromorphic sebkha	Shs

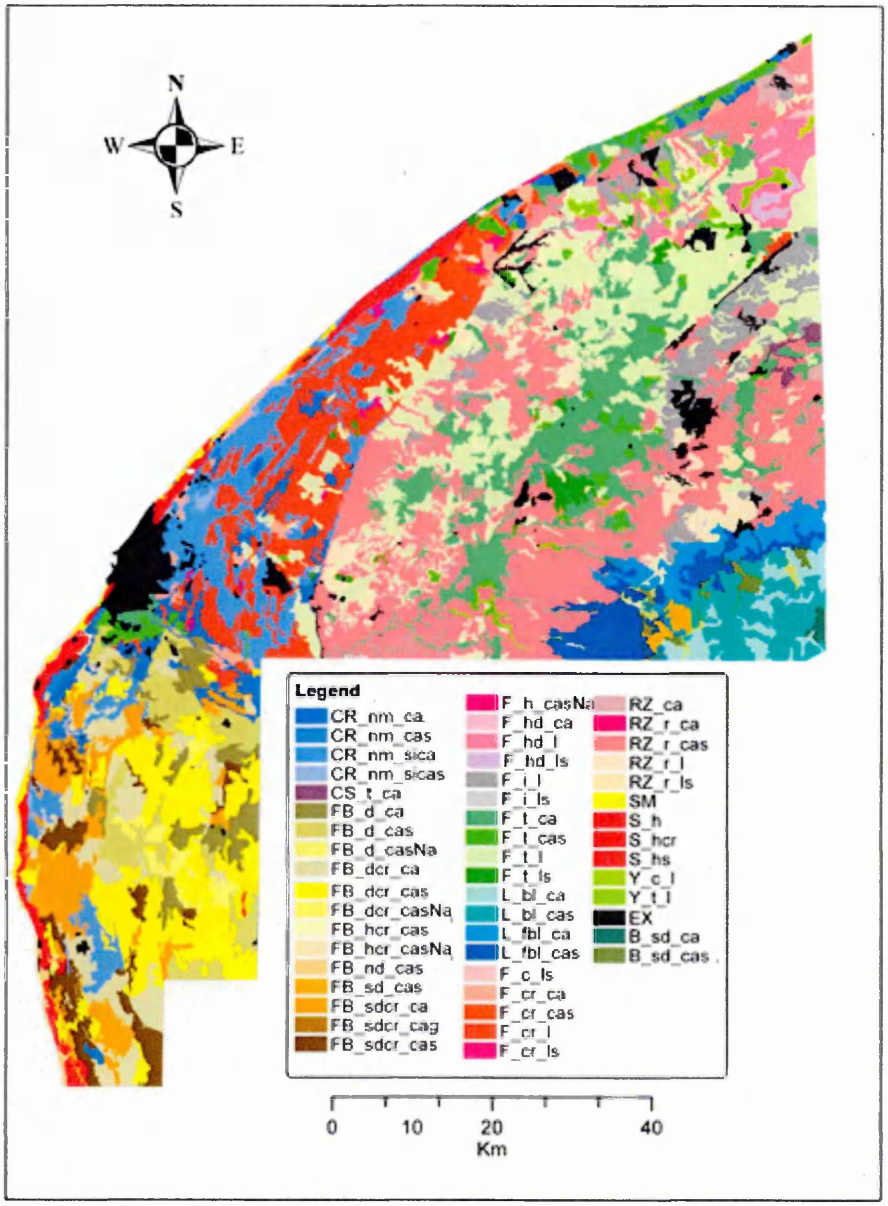


Figure 6.4 Soil Map for study area

6.4 Land Suitability Assessment in the Study area

The FAO Framework for land evaluation (FAO, 1976) was selected as the method for land evaluation within the study area. The rationale for selection of the framework provides a set of methodological guidelines suited for implementation in land evaluation projects and assessment of defined land utilisation (Davidson, 1992). Land suitability can be assessed based on a number of criteria, which includes:

- Specific land uses and the requirements of these land uses;

- A comparative multi-disciplinary analysis of inputs vs. benefits;
- The physical, economic, social and political context of the area concerned;
- Potential environmental impacts and land use sustainability.

The FAO Framework recognises four main kinds of suitability classification: qualitative, quantitative, current or potential suitability (FAO, 1976). However, the two-stage approach and the parallel approach can be adapted to carry out land evaluation. The first approach mainly comprises qualitative land evaluation, followed by analysing economic and social contexts (although not always necessarily). In the second approach, the relationships between land and land productivity can be analysed concurrently with the social and economic context (FAO, 1976). In the case of this study, a qualitative land evaluation of the physical conditions was conducted. It was not possible to carry out social and economic evaluation for two main reasons. First there is the difficulty in accessing and meeting ethical conditions of conducting research on the GMRP. Secondly, there is a volatile commodity market arising from the lifting of United Nations sanctions on Libya. Thirdly, there are security concerns arising from the consequences of the Libyan civil uprising.

To use the FAO Framework it is first necessary to define land utilisation types and then define land use requirements in terms of land qualities and/or land characteristics and their threshold values. Three groups of land use requirements can be identified for selected land utilisation type for barley and wheat production in the study area: crop requirements (physiological requirements) which can be measured by soil characteristics, management requirements (potential for mechanisation) which can be measured by slope steepness, and conservation requirement (erosion hazard) which can be measured by soil erosion (Nwer, 2005).

6.4.1 Land Utilisation Types in the Study Area

The FAO guidelines identify different factors that determine alternative land uses, namely: existing land use, prevailing rainfall and other climatic elements, physical and chemical characteristics of soil, and social and economic conditions necessary for their success (Clayton and Dent, 2001). A variety of factors may be included within the characterisation of land utilisation types according to the purpose of the land evaluation study. Physical, economic and social settings form a background to all the land utilisation types of an area. As a minimum requirement, the nature of production must be specified. A single crop can be regarded as a land utilisation type provided a statement is made as to the socio-economic setting in which it is cultivated, as productivity will vary considerably according to the technology available to the farmer (FAO, 1983). At more detailed levels of evaluation it is normally appropriate to regard the farming system or cropping system as the definition of land utilisation types. FAO (1983) describes three levels of land utilisation types: summary, intermediate and detailed. The degree of detail with which land utilisation types are described varies according to the intensity and purposes of the evaluation.

In reconnaissance studies, the descriptions correspond to major divisions of rural land use, e.g. rain-fed or irrigated agriculture, grassland or forestry. However, for detailed studies, more information on the management conditions is required since, in practice, these strongly influence the attainable levels of production. In these studies, a land use option is described using the following set of management-related attributes and socio-economic settings that together define a land utilisation type (LUT): level of inputs, produce, market orientation, capital intensity, labour intensity, mechanisation, infrastructure, infrastructure, land tenure (FAO, 1983; 1985).

As noted the irrigation scheme is proposed in the case study area to accommodate four main crops (barley, wheat, maize and sorghum) to meet local requirements for these strategic commodities. However, this research focuses on two main crops, wheat and barley, where the data for validation were collected only for these crops during the field study. The irrigation scheme aims to (GMRP, 1990):

- Provide a good opportunity for the coastal aquifers to recover part of the groundwater lost over the previous years;
- Cultivation and development of large areas of land which remain currently idle through lack of sufficient irrigation water;
- Agricultural expansion to encourage people in rural areas to remain on their land, thus relieving the population pressure in big cities such as Benghazi (Nwer, 2005).

The planned large and small farms under irrigation conditions are supervised by the Agricultural Service Centre in each area. These farms aim to produce cereals and to be equipped with modern machinery and overhead sprinklers for irrigation. The irrigation system can be divided into two levels of distribution. The primary network takes water from reservoirs in Benghazi NS Ajdabiya at the end of the main pipeline and distributes it under gravity where possible to agricultural reservoirs. Some pumping stations are required to service higher-level reservoirs (GMRP, 1990). Descriptions of LUTs in the study area are given in Table 6.2a-b.

Table 6.2a: Definition and description of LUT1 (Barley) in the study area

Characteristic	Description of LUT1 (Barley)
Level of inputs	High
Produce & production	Irrigated barley
Market orientation	Commercial production
Capital intensity	High
Labour intensity	Medium
Mechanization	Mechanized farming
Infrastructure	Market accessibility and distribution centre should be improved
Land tenure	State farms owned and operated by government (GMPR and ARC)
Water inputs	Carefully controlled irrigation with water pumped from the agricultural reserves to the area under consideration

Source: Nwer (2005); GMBR (2008)

Table 6.2b: Definition and description of LUT2 (Wheat) in the study area

Characteristic	Description of LUT2 (Wheat)
Level of inputs	High
Produce & production	Irrigated wheat
Market orientation	Commercial production
Capital intensity	High
Labour intensity	Medium
Mechanization	Mechanised farming
Infrastructure	Market accessibility and distribution centre should be improved
Land tenure	State farms owned and operated by government (GMPR and ARC)
Water inputs	Carefully controlled irrigation with water pumped from the agricultural reserves to the area under consideration

Source: Nwer (2005); GMBR (2008)

6.4.2 Land Qualities and Land Characteristics in the Study Area

Land qualities (LQs) are estimated or measured by means of land characteristics (LCs). Land characteristics, as described in Chapter 3, refer to an element of land that can be measured and estimated. According to Nwer (2005), the following land qualities and land characteristics (Table 6.3) have a major effect on land suitability evaluation for wheat and barley in the study area.

Table 6.3: Land use requirement, LQ and LC in the study area

Land Use Requirement	Land Qualities	Land Characteristics
Physiological Requirements (Soil)	Rooting condition	Rootable depth
		Soil texture
	Moisture availability	AWHC
	Nutrient availability	Soil reaction (pH)
	Nutrient retention	Organic matter
		CEC
	Excess of salts	Soil salinity (EC)
		(ESP) (%)
	Calcium carbonate	$CaCO_3$ in root zones
	Condition for germination	Stones at surface (%)
	Oxygen availability	Soil drainage classes
	Infiltration	Infiltration rate
Management Requirements	Potential for mechanisation	Slope steepness
Conservation Requirement	Erosion hazard	Soil erosion

Source: Sys et al. (1993); Nwer (2005); GMBR (2008)

Table 6.4a: Land suitability classes and their threshold values for barley

	Suitability classes*			
Land Characteristics	S1	S2	S3	N1
Rootable depth(cm)	>80	80-50	>50-30	<30
Soil texture class	1	2	3	4
AWHC (mm/m)	>150	110-150	110-75	<75
Soil pH	7-8 ,7-6.5	8-8.2,6.5-5.3	8.2-8.5,5.3-5	<5, >8.5
% organic matter	>1.5	1.5-1	<1-0.5	<0.5
CEC (me/100g soil)	>16	>8-16	5-8	<5
soil salinity (EC)	0-8	>8-10	>10-13	>13
% ESP	0-15	>15-25	>25-50	>50
% $CaCO_3$ in root zones	0-20	>20-30	>30-40	>40
% stones at surface	0-3	>3-9	>9-20	>20
Soil drainage classes (mm/h)	>125	>42-125	17-42	<17
Infiltration rate (mm/h)	>12	>8-12	6-8	<6
% slope steepness	0-2	> 2-4	>4-8	> 8
Soil erosion (classes)	Non	Slightly	Moderately	High

Source: Sys et al. (1993); Nwer (2005); GMBR (2008)

Table 6.4b: The Land suitability classes and their threshold values for wheat

	Suitability classes*			
Land Characteristics	**S1**	**S2**	**S3**	**N1**
Rootable depth(cm)	>120	120-100	>100-50	<50
Soil texture class	1	2	3	4
AWHC (mm/m)	>150	110-150	110-75	<75
Soil pH	8.2-7,7-6.5	8.2-8.3,6.5-5.5	8.3-8.5,5.5-5	<5,>8.5
% organic matter	>1.5	1.5-1	<1-0.5	<0.5
CEC (me/100g soil)	>24	16-<24	8-16	<8
soil salinity (EC)	0-6	>6-7.4	>7.4-9.5	>9.5
% ESP	0-10	>10-25	>25-35	>35
% $CaCO_3$ in root zones	0-20	>20-30	>30-40	>40
% stones at surface	0-3	>3-9	>9-20	>20
Soil drainage classes (mm/h)	>125	>42-125	42-17	<17
Infiltration rate (mm/h)	>12	>8-12	6-8	<6
% slope steepness	0-2	> 2-4	>4-8	> 8
Soil erosion (classes)	Non	Slightly	Moderately	High

Source: Sys et al. (1993); Nwer (2005); GMBR (2008)

6.5 Building GIS Database

One of the benefits of a GIS approach in this instance is the combining of data from a variety of sources and scales to allow land suitability analysis to take place. To construct a database for the study area, the relational database was designed to allow the matching between land use requirements and land resources to take place as follows:

- review and select suitable information technologies;
- relational database design and normalisation including GIS design;
- compile all sources of data from section 6.2;
- construction and classification of thematic layers into maps/models.

A number of procedures were followed in compiling the spatial and attribute data: input - spatial data (digitising where needed) and non-spatial; manipulation; linking the spatial to the non-spatial data; query and analysis and visualisation. The data available to this research were discussed in Section 6.2. Some of the data available for this research were initially obtained in paper format and then digitised.

6.6 Deriving Weights for Land Characteristics for Selected Crops

6.6.1 Multi-criteria decision analysis

As pointed out in Chapter Five, there has been growing interest in integrating GIS capability with Multi-Criteria Decision-making Methods (MCDA) in recent years. The MCDA includes integration of expert knowledge at different levels of decision-making. In this regard, the GIS environment has proven a useful tool in handling both technical and logistical problems through the construction of different thematic layers (in the form of MCDA) to define land suitability map layers (Malczewski, 1999). The most widespread multi-attribute methods are the AHP and Fuzzy Methods. Land suitability analysis using the AHP method is a very common technique; in this context, the AHP method can be used in two ways within the GIS environment. First, using pairwise comparison, it calculates weights associated with land suitability map layers (Malczewski, 2004). Second, it can aggregate the priority for all levels of the hierarchy structure.

6.6.2 Hierarchy Development

The hierarchy structure in the AHP method organises the decision problem into a number of levels. The first step in building the AHP model for this research is the organisation of criteria into a hierarchical structure. In this case, the highest level has the overall goal, which is evaluating the suitability of land in study area for the irrigated crop of barley or wheat. This is followed by second level criteria, which includes three groups, or criteria based on land use requirements for selected land utilisation type identified by existing land evaluation models:

i. Crop requirements (physiological requirements) which can be measured by soil characteristics;

ii. Management requirements (potential for mechanisation) which can be measured by slope steepness;

iii. Conservation requirement (erosion hazard) which can be measured by soil erosion.

In addition, the lowest level sub-criteria containing fourteen land characteristics included twelve for soil characteristics, slope and soil erosion for erosion hazard (Figure 6.5).

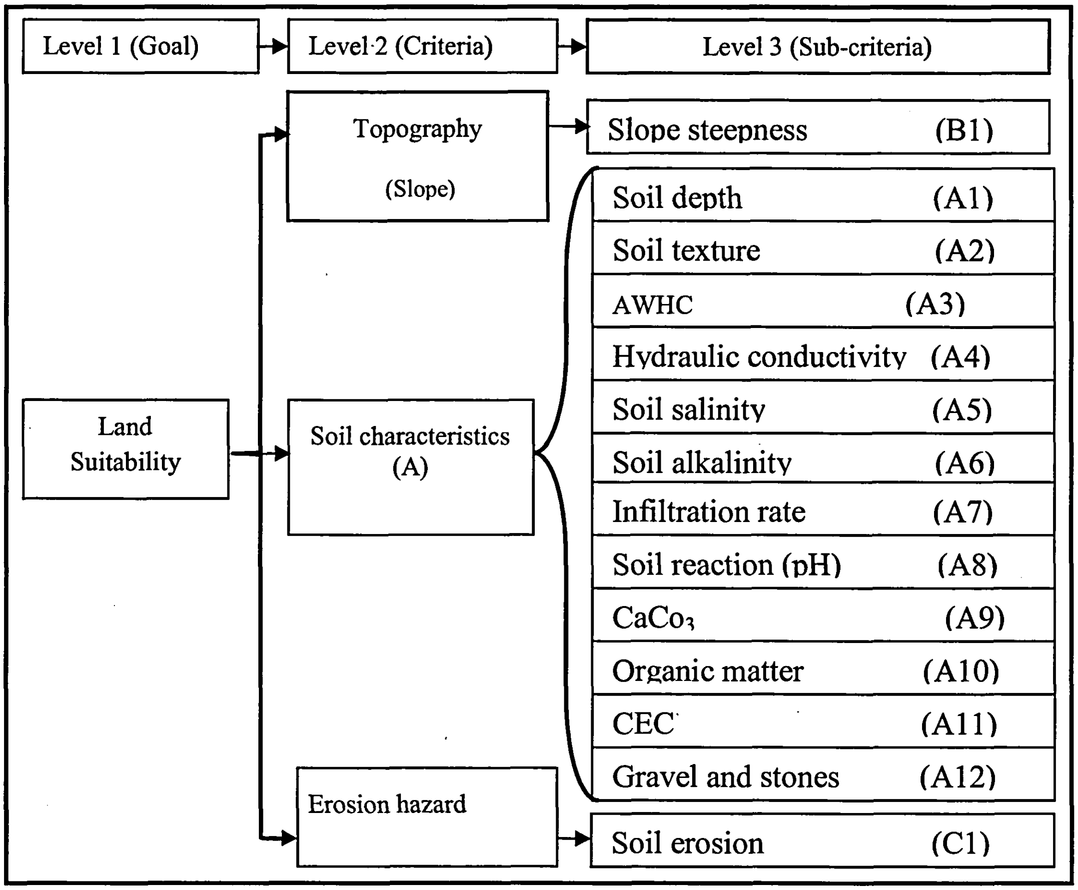


Figure 6.5: Hierarchical structure for agricultural land suitability in study area.

Once the hierarchy structure is defined and the number of criteria and sub-criteria is determined, the next step is the Pairwise Comparison Method (PCM) within the context of the AHP procedure. This allows an independent assessment of the contribution and importance of each factor for assigning weights. This involves the creation of a pairwise comparison matrix using a scale range 1-9. Then, the construction of an overall priority rating; in this stage, composite weights are created by multiplying the relative weights matrix for each level in the hierarchy. In order to obtain the suitability of a given area, a weight for each land characteristics is assigned. The process is achieved through the pairwise comparison between the elements for each level of hierarchy. A pairwise comparison matrix PCM for the three main decision criteria was constructed in level 2. Another pairwise matrix is constructed for sub-criteria in level 3 only for land characteristics related to crop requirement (i.e. soil characteristics) because the other criteria (i.e. management requirements and conservation requirement) have only one land characteristic in this level (i.e., slope steepness, and soil erosion).

According to the FAO (2007), incorporation of local knowledge into land evaluation methodologies is encouraged in suitability evaluation as it can enhance the output of the process. Local experts were consulted in the identification or selection of factors (i.e. land use requirements; crop, management and conservation requirements, land qualities, land characteristics and their threshold values) that affect the production of agricultural crops to create land evaluation suitability model (i.e. existing land evaluation suitability model) and were asked to assign weights to selected factors for barley and wheat.

The AHP has been adapted in order to be applied in group decisions and different weights were assigned to different land properties that need to be considered for the production of barley and wheat. Six local experts were selected to use their experience, and, based on land use requirements, to assign different weights to selected land characteristics for barley and wheat crops. The six local experts were asked to each independently produce weights for each level in the hierarchy applying the PCM. In the process of weighting criteria, each expert made their own assessment. Relying on their field experiences weights were assigned to factors that affect barley and wheat production in the study. In addition, more general indigenous knowledge about crop requirement for each crop under local conditions in the study area was taken into account by the local experts. They compare in a pairwise manner the three criteria at the same level of the AHP hierarchy. Each expert provides a set of $m = n\,(n-1)/\,2$ comparative judgments, and assigns a numerical value of an importance ratio using the Saaty (1980) scale: 1/9, 1/7, 1/5, 1/3, 1, 3, 5, 7, and 9.The scale may be extended by some intermediate values: 1/8, 1/6, 1/4, 1/2, 2, 4, 6, and 8 if necessary.

The local experts played an important role in the process of land suitability and in the iterative adjustment of weights to improve the consistency ratio to ≤ 0.1. The weights that must be used for the pairwise comparison analysis should have a consistency ratio (CR) ≤ 0.1. A CR ≤ 0.1 shows that the comparisons of land characteristics were perfectly consistent, and the relative weights are appropriate for use in land suitability evaluation. The calculation of the CR for the selected land characteristics for barley and wheat was made for each hierarchy level. The pairwise comparison based on the Saaty scale was tested in the matrices on the basis of discussion with local experts to derive the CR for the selected land attributes within the established acceptable limits of 0.1. This step was done with each PCM constructed by each local expert.

It should be noted that all of the experts provided a consistency ratio of the PCM less than or equal to 0.1 as can be seen in Appendix B. However, the question that arose was which weight should be chosen? As pointed out in chapter five, group decision making involves aggregation of diverse individual preferences to obtain a single collective preference. Such aggregation is extremely difficult as opinions may be conflicting even within small group. Therefore, the Group Analytic Hierarchy Process has allowed for robust participation in deriving weights for selected factors. This was done by using AIJ method, where a new pairwise comparison matrix for the group is constructed to aggregate of the weights the individual judgements by calculating a geometric mean.

$$Geometric\ mean = \left(\prod_{i=1}^{n} a_i\right)^{1/n} . \qquad \text{Equation 6.1}$$

Discussion with local experts was carried out during a study visit to the study area in 2010 and 2012. The experts were able to identify the differences in land use requirements for wheat and barley, which had been placed or organized (i.e. Management requirements, crop requirements, conservation requirements) in the second level (criteria) of hierarchy structure of land suitability model. However, the main difference between two crops can be seen in third level of hierarchy form in terms of crop requirements (e.g. soil depth salinity soil alkalinity, soil $CaCO_3$ and soil pH). Based on these criteria, Tables 6.4a and 6.4b show wheat is more sensitive to these factors than barley. The PCM was applied by experts and the derived weights at this level of hierarchy (criteria) were used for both crops. Figure 6.5 is an example of a pairwise comparison matrix for second level criteria in the hierarchy.

6.6.3 Pairwise Comparison Matrices

Each of the six local experts participating in this study completed two sets of pairwise comparisons in order to assign their preferences to criteria and sub criteria. The first set of comparisons determined which of the second-level criteria, where there are three groups of land use requirements. The second set of comparisons considered only the twelve soil properties (crop requirements). There is no set of comparisons considered for slope and erosion because, both of them are represented by only one sub-criterion or factor. To illustrate this process, consider criteria for the second level hierarchy for selected crops depicted in Figure 6.5. An example of a pairwise comparison matrix generated by six local experts through the GAHP is covered in Section 6.6.4.

Second–level Pairwise Comparison Matrices:

As stated earlier, six PCM were generated using the 9-point continuous Saaty scale. The matrices are given in Table 6.5 where 3 x 3 size matrix are completely consistent i.e. CR $\leq$ 0.1. They were constructed based on three criteria at the second level (i.e., crop requirements, management requirements and conservation requirements) thus: A, B and C represent these criteria respectively and LE1, LE2……LE6 for the local experts. All of local experts felt soil was more important than slope and erosion. With respect to comparison between slope and erosion, four local experts felt both criteria were equally important and one felt slope was more important than erosion and the last one felt erosion was more important than slope. Tables 6.5 to 6.7 summarise the rankings by local experts.

Table 6.5: Second-level pairwise comparison matrices and weights

E1					E2				
Criteria	*A*	*B*	*C*	Weight	Criteria	*A*	*B*	*C*	Weight
A	1	5	6	0.7324	*A*	1	7	8	0.7838
B	1/5	1	1	0.1378	*B*	1/7	1	2	0.1349
C	1/6	1	1	0.1297	*C*	1/8	1/2	1	0.0813
CR = 0.001				$\sum = 1$	CR = 0.0194				$\sum = 1$

E3					E4				
Criteria	*A*	*B*	*C*	Weight	Criteria	*A*	*B*	*C*	Weight
A	1	5	7	0.7471	*A*	1	7	7	0.7778
B	1/5	1	1	0.1336	*B*	1/7	1	1	0.1111
C	1/7	1	1	0.1194	*C*	1/7	1	1	0.1111
CR = 0.0014				$\sum = 1$	CR = 0				$\sum = 1$

E5					E6				
Criteria	*A*	*B*	*C*	Weight	Criteria	*A*	*B*	*C*	Weight
A	1	7	7	0.7778	*A*	1	7	6	0.7582
B	1/7	1	1	0.1111	*B*	1/7	1	1/2	0.0905
C	1/7	1	1	0.1111	*C*	1/6	2	1	0.1512
CR = 0				$\sum = 1$	CR = 0.0092				$\sum = 1$

Table 6.6: The result of weighting for Level 2 (criteria) of hierarchical for barley and wheat generated by local experts

Level 2 (Criteria)	Local Experts					
Land Characteristics	E1	E2	E3	E4	E5	E6
Soil Characteristics	0.7324	0.7838	0.7471	0.7778	0.7778	0.7582
Topography (Slope)	0.1378	0.1349	0.1336	0.1111	0.1111	0.0905
Erosion hazard	0.1297	0.0813	0.1194	0.1111	0.1111	0.1512
CR	0.001	0.0194	0.0014	0	0	0.092

Third–level Pairwise Comparison Matrices for barley:

As abovementioned at this level the remaining sets of comparisons considered only for the twelve soil properties (12 x 12 size matrix are completely consistent i.e., CR ≤ 0.1). Six PCMs were generated. The matrix given in Table 6.8 was generated by local expert (E1) for barley. The remaining matrix is in Appendix B.

Table 6.8: Third-level Pairwise Comparison Matrix and weights for barley generated by local expert 1

Local Expert 1 (E 1)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	1	1	1	2	3	1	2	2	3	3	3.0	0.1265
A2	1	1	1	1	2	2	2	2	1	1	3	1.0	0.1090
A3	1	1	1	2	3	3	1	1	1	2	2	2.0	0.1138
A4	1	1	1/2	1	2	2	1	1	2	2	2	3.0	0.1023
A5	1/2	1/2	1/3	1/2	1	2	1/2	1/3	1	2	2	3.0	0.0675
A6	1/3	1/2	1/3	1/2	1/2	1	1/3	1/2	1	2	1/2	0.5	0.0456
A7	1	1/2	1	1	2	3	1	1	1	2	3	2.0	0.1005
A8	1/2	1/2	1	1	3	2	1	1	2	2	2	3.0	0.1028
A9	1/2	1	1	1/2	1	1	1	1/2	1	2	2	3.0	0.0792
A10	1/3	1	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1	3	2.0	0.0581
A11	1/3	1	1/2	1/2	1/2	2	1/3	1/2	1/2	1/3	1	2.0	0.0512
A12	1/3	1	1/2	1/3	1/3	2	1/2	1/3	1/3	1/2	1/2	1.0	0.0434
CR=0.0623													$\sum$=1

Table 6.9: Derived weighting for Level 3 (Sub-criteria) of hierarchical for barley generated by local experts

Level 3 (Sub-criteria)	Local Experts					
Soil Characteristics	E1	E2	E3	E4	E5	E6
Soil depth	0.126	0.137	0.151	0.124	0.113	0.130
Soil texture	0.110	0.102	0.111	0.070	0.067	0.061
AWHC	0.114	0.131	0.137	0.122	0.119	0.110
Infiltration rate	0.102	0.110	0.107	0.109	0.096	0.084
Hydraulic conductivity	0.067	0.069	0.075	0.076	0.101	0.097
Organic matter	0.046	0.052	0.051	0.046	0.064	0.072
CEC	0.100	0.111	0.107	0.111	0.102	0.106
($CaCO_3$)	0.102	0.068	0.068	0.115	0.096	0.092
Soil reaction (pH)	0.079	0.072	0.061	0.084	0.082	0.078
Gravel and stones	0.057	0.049	0.041	0.054	0.050	0.060
Soil salinity	0.052	0.054	0.046	0.047	0.054	0.056
Soil alkalinity	0.044	0.045	0.045	0.042	0.055	0.055
CR	0.062	0.047	0.065	0.050	0.042	0.046

6.6.4 Group Pairwise Comparison Matrices

As pointed out in chapter five, AHP has been adapted in order to be applied in group decisions. The AIJ method was applied to derive a new pairwise comparison matrix for the group by aggregating the individual judgements by means of geometric mean of the weights. The group pairwise comparison matrices were compiled using the geometric mean method as described in Section 2.2.2 (Group AHP). To illustrate this process, consider determining the second-level group pairwise comparison judgment a_{12}, a_{13} and a_{23}, the comparison of soil to slope, soil to erosion and slope to erosion. Let; a^{E}_{a12}, a^{E}_{13} *and* a^{E}_{23}, denote the comparison of soil to slope, soil to erosion and slope to erosion for decision maker E ($where\ E = 1,2,3,4,5,6$). Then:

Soil to Slope;

$$a_{12} = (a^{1}_{12} + a^{2}_{12} + a^{3}_{12} + a^{4}_{12} + a^{5}_{12} + a^{6}_{12})^{1/6}$$

$$a_{12} = (1/5 + 1/7 + 1/5 + 1/7 + 1/7 + 1/7)^{1/6}$$

$$a_{12} = 0.15981$$

Soil to Erosion,

$$a_{13} = (a^{1}_{13} + a^{2}_{13} + a^{3}_{13} + a^{4}_{13} + a^{5}_{13} + a^{6}_{13})^{1/6}$$

$$a_{13} = (1/6 + 1/8 + 1/7 + 1/7 + 1/7 + 1/6)^{1/6}$$

$$a_{13} = 0.1471$$

Slope to Erosion

$$a_{23} = (a^{1}_{23} + a^{2}_{23} + a^{3}_{23} + a^{4}_{23} + a^{5}_{23} + a^{6}_{23})^{1/6}$$

$$a_{13} = (1 + 1/2 + 1 + 1 + 1 + 2)^{1/6}$$

$$a_{13} = 1$$

The two groups' pairwise comparison matrices for barley and wheat (i.e. GAHP for second and third levels respectively) are given in Tables 6.11 to 6.13 and Table 6.14 to 6.15. The associated weights were calculated using the eigenvector method introduced in Chapter Five and results are presented in Chapter Seven.

Table 6.10: Group pairwise comparison matrix and resulting weight for Level 2 criteria of hierarchical for barley and wheat

AIJ	GAHP

Criteria	A	B	C	Weight
A	1	6.2573	1	0.7653
B	0.1598	1	1	0.119
C	0.1471	1	1	0.1157
				$\sum W = 1$

Table 6.11: Group pairwise comparison matrix and resulting weight for Level 2 criteria of hierarchical for barley

	AIJ												GAHP
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	weight
A1	1	1.698	1	1.122	1.701	3.015	1	1.698	2.14	2.942	2.621	2.449	0.1325
A2	0.589	1	0.891	0.891	1.07	1.698	1.122	1.201	1.07	1	1.201	1	0.0818
A3	1	1.122	1	1.26	2.335	2.621	1	1.414	1.698	2.289	2.289	2.289	0.1227
A4	0.891	1.122	0.794	1	1.782	2	1	1.26	1.587	1.587	2	1.817	0.1032
A5	0.588	0.935	0.428	0.561	1	1.26	0.63	0.693	1	2.245	2.14	3.147	0.0806
A6	0.332	0.589	0.382	0.5	0.794	1	0.55	0.794	1	1.782	0.707	0.707	0.0548
A7	1	0.891	1	1	1.587	1.817	1	1.587	1.587	2	2.449	1.587	0.1079
A8	0.589	0.833	0.589	0.794	1.442	1.26	0.63	1	1.26	2.449	1.906	3	0.0895
A9	0.467	0.935	0.589	0.63	1	1	0.63	0.794	1	1.906	1.587	3	0.0768
A10	0.34	1	0.437	0.63	0.445	0.561	0.5	0.408	0.525	1	1.442	1.414	0.0514
A11	0.382	0.833	0.437	0.5	0.467	1.414	0.408	0.525	0.63	0.693	1	1.414	0.0511
A12	0.408	1	0.437	0.55	0.318	1.414	0.63	0.333	0.333	0.707	0.707	1	0.0479
													$\sum W = 1$

Table 6.13: Group pairwise comparison matrix and resulting weight for Level 2 criteria of hierarchical for wheat

	AIJ												**GAHP**
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12**	**weight**
A1	1	1.26	1.587	2.14	1.513	2.804	1.26	2.04	2.45	3	3	3	0.1502
A2	0.794	1	1.26	1.26	1.122	1.414	2.14	1.782	1.26	1.442	1.442	1.442	0.1063
A3	0.63	0.794	1	1.122	1.587	2.449	1	1.782	1.782	2.289	2.289	2.289	0.1124
A4	0.467	0.794	0.891	1	0.794	1	1	1.26	1.26	1.414	1.782	1.414	0.0799
A5	0.661	0.891	0.63	1.26	1	1.414	0.891	1.122	1	2.289	2	3	0.0931
A6	0.357	0.707	0.408	1	0.707	1	0.833	0.891	1	1.587	1	0.891	0.0631
A7	0.794	0.467	1	1	1.122	1.201	1	1.587	1.782	2	2.449	1.414	0.0959
A8	0.49	0.561	0.561	0.794	0.891	1.122	0.561	1	1.122	2.449	1.587	3	0.0785
A9	0.408	0.794	0.561	0.794	1	1	0.561	0.891	1	1.698	1.414	3	0.0746
A10	0.333	0.693	0.437	0.707	0.437	0.63	0.5	0.408	0.589	1	1.201	1.414	0.0494
A11	0.333	0.693	0.437	0.561	0.5	1	0.408	0.63	0.707	0.833	1	1.414	0.0507
A12	0.333	0.693	0.437	0.707	0.333	1.122	0.707	0.333	0.333	0.707	0.707	1	0.0459
													$\sum W = 1$

Table 6.14: Weighting for each level of hierarchical and overall weight for each land characteristics for barley

Level 1	Level 2	Level 3	Overall weight $W = w_1 \times w_3 \times w_3$

Goal	Criteria		Sub-criteria		
Land Suitability 1.00	Topography (slope)	0.119	Slope steepness	1.00	0.119
	Soil characteristics	0.7653	Soil depth	0.1325	0.1014
			Soil texture	0.0818	0.0626
			AWHC	0.1227	0.0939
			Hydraulic conductivity	0.1032	0.079
			Soil salinity	0.0806	0.0617
			Soil alkalinity	0.0548	0.0419
			Infiltration rate	0.1079	0.0826
			$CaCO_3$	0.0895	0.0685
			Soil reaction pH	0.0768	0.0587
			Organic matter	0.0514	0.0393
			CEC	0.0511	0.0391
			Gravel and stones	0.0479	0.0367
	Erosion hazard	0.1157	Soil Erosion	1.00	0.1157
					$\sum W = 1$

Table 6.15: Weighting for each level of hierarchical and overall weight for each land characteristics for wheat

Level 1	Level 2		Level 3		Overall weight
Goal	Criteria		Sub-criteria		$W = w_1 \times w_3 \times w_3$
Land Suitability 1.00	Topography (slope)	0.119	Slope steepness	1.00	0.119
	Soil characteristics	0.7653	Soil depth	0.1502	0.1150
			Soil texture	0.1063	0.0814
			AWHC	0.1124	0.0860
			Hydraulic conductivity	0.0799	0.0611
			Soil salinity	0.0931	0.0712
			Soil alkalinity	0.0631	0.0483
			Infiltration rate	0.0959	0.0734
			$CaCO_3$	0.0785	0.0601
			Soil reaction pH	0.0746	0.0571
			Organic matter	0.0494	0.0378
			CEC	0.0507	0.0388
			Gravel and stones	0.0459	0.0352
	Erosion hazard	0.1157	Soil Erosion	1.00	0.1157
					$\sum W = 1$

6.7 Fuzzy Set theory

As pointed out in Chapter Five a number of fuzzy set models can be used to derive membership function values. The most popular are those widely used to model land evaluation for agricultural crops, bell shaped (Gusaine) including asymmetric left models, asymmetric right models and symmetric models (Burrough et al., 1992;

Davidson, 1994; Burrough and McDonnell, 1998; Baja, 2001). Fuzzy set models have been chosen in this research to standardise land characteristics to common membership grades (i.e. from 0 to 1). Tables 6.16 and 6.17 summarises the different types of fuzzy set models used to calculate membership functions (MFs) for each land characteristic after determining the value of ideal points (b1 and b2) , crossover points (UCP and LCP) and the width of transition zones (d1 and d2) in accordance with the thresholds value of land characteristics for each crop.

The aforementioned types of fuzzy set models are shown in Figures 6.6, 6.7, 6.8 and in Equations 6.2, 6.3 and 6.4.

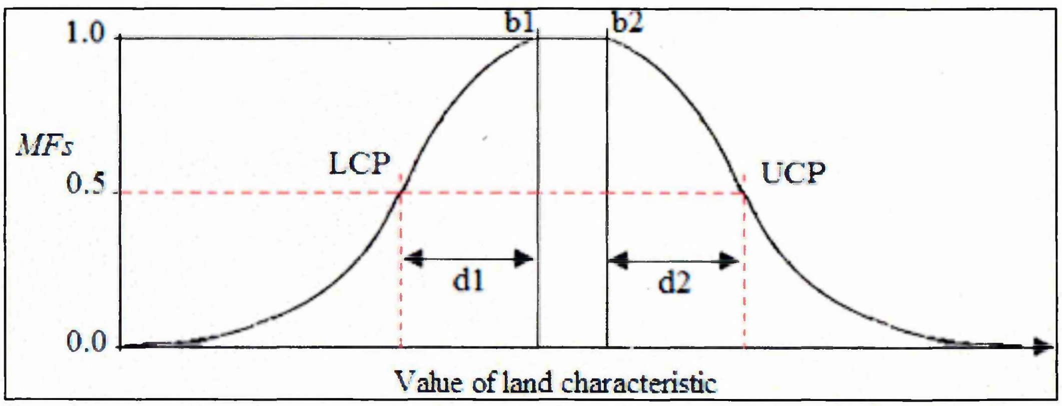


Figure 6.6: Symmetrical fuzzy membership function

The Symmetrical fuzzy membership functions is calculated using

$$\mathcal{MF}_{(xi)} = \begin{cases} 1/\left[1+\left(\frac{x-b_1}{d_1}\right)^2\right] & x < b_1 \\ & b_1 \le x \le b_2 \\ 1/\left[1+\left(\frac{x-b_2}{d_2}\right)^2\right] & x > b_2 \end{cases} \quad \text{Equation (6.2)}$$

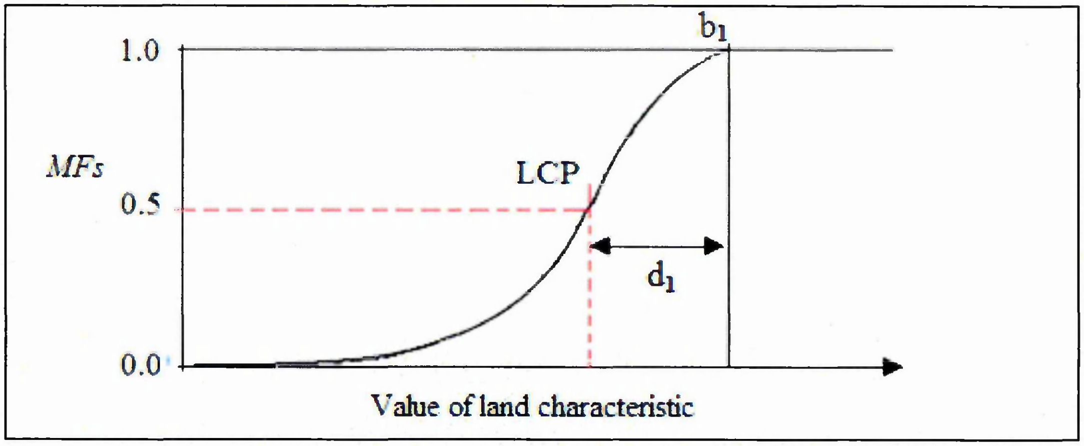


Figure 6.7: Asymmetrical left fuzzy membership function

The asymmetrical left model is calculated using:

$$\mathcal{MF}_{(x_i)} = 1/\left[1 + \left(\frac{x-b_1}{d_1}\right)^2\right] x < b_1 \qquad \text{Equation 6.3}$$

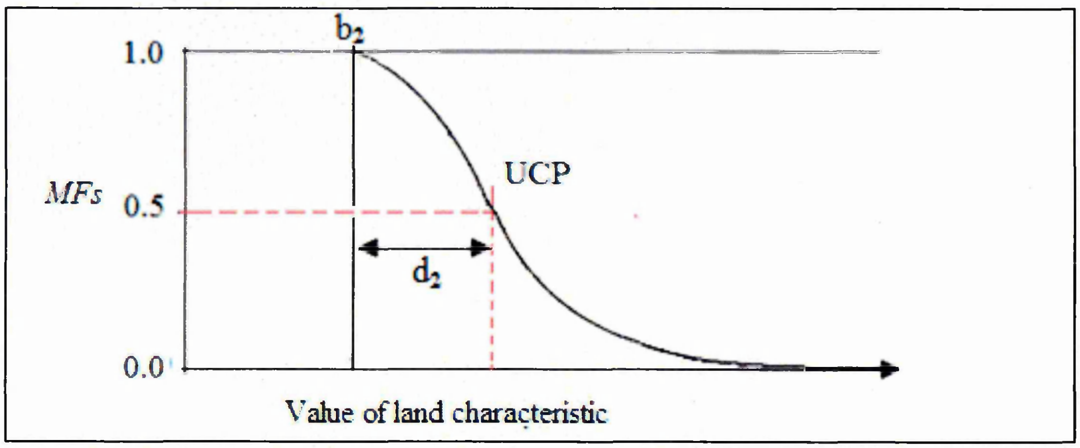


Figure 6.8: Asymmetrical right fuzzy membership function

The asymmetrical right model is calculated using:

$$\mathcal{MF}_{(x_i)} = 1/\left[1 + \left(\frac{x-b_2}{d_2}\right)^2\right] x > b_2 \qquad \text{Equation 6.4}$$

Where ***(MF)*** is the membership function of a land characteristics, ***(d)*** is the width of the transition zone, while ***(b1*** and ***b2)*** are for an ideal point level, $\boldsymbol{x}$ is the value of land characteristics and ***LCP*** and UCP are lower and upper crossover points.

For sub-criteria that appears in soil texture and soil erosion have been converted to fuzzy numbers, based on the value of the characteristics. For example, in the case of soil texture where data are ordinal consisting of four categorical classes, 1, 2, 3 and 4, the model shown in Figure 6.9 was employed.

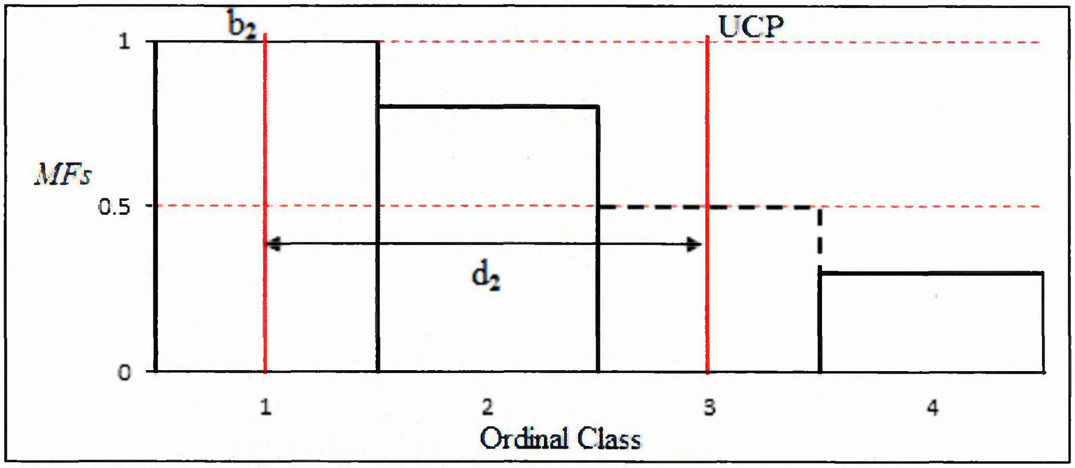


Figure 6.9: Asymmetrical right fuzzy membership function for categorical data (classes)

Table 6.16: Types of fuzzy set models and their use to calculate membership functions for each land characteristic for barley crop

Land characteristics	Type of fuzzy set	b1	LCP	d1	b2	UCP	d2
Soil depth	asymmetric left	80	50	30	-	-	-
AWHC	asymmetric left	150	110	40	-	-	-
Infiltration rate	asymmetric left	12	8	4	-	-	-
Hydraulic conductivity	asymmetric left	125	42	83	-	-	-
Organic matter	asymmetric left	1.5	1	0.5	-	-	-
CEC	asymmetric left	16	8	8	-	-	-
Calcium carbonate	asymmetric right	-	-	-	20	30	10
Soil salinity	asymmetric right	-	-	-	8	10	2
Soil alkalinity	asymmetric right	-	-	-	15	25	10
Gravel and stones	asymmetric right	-	-	-	3	9	6
Soil texture	asymmetric right	-	-	-	1	3	2
Soil reaction pH	symmetric	6.5	5.3	1.2	8	8.2	0.2
Slope steepness	asymmetric right	-	-	-	2	4	2
Soil erosion	asymmetric right	-	-	-	1	3	2

Table 6.17: Types of fuzzy set models and their use to calculate membership functions for each land characteristic for wheat crop

Land characteristics	Type of fuzzy set	b1	LCP	d1	b2	UCP	d2
Soil depth	asymmetric left	120	100	20	-	-	-
AWHC	asymmetric left	150	110	40	-	-	-
Infiltration rate	asymmetric left	12	8	4	-	-	-
Hydraulic conductivity	asymmetric left	125	42	83	-	-	-
Organic matter	asymmetric left	1.5	1	0.5	-	-	-
CEC	asymmetric left	24	16	8	-	-	-
Calcium carbonate	asymmetric right	-	-	-	20	30	10
Soil salinity	asymmetric right	-	-	-	6	7.4	1.4
Soil alkalinity	asymmetric right	-	-	-	10	25	15
Gravel and stones	asymmetric right	-	-	-	3	9	6
Soil texture	asymmetric right	-	-	-	1	3	2
Soil reaction pH	symmetric	6.5	5.5	1	8.2	8.3	0.1
Slope steepness	asymmetric right	-	-	-	2	4	2
Soil erosion	asymmetric right	-	-	-	1	3	2

For example, the membership functions for the organic matter can be calculated as follows: The ideal point (b) was set at 1.5 while LCP was set at 1 and transition zone: $(d) = b - LCP$ $(1.50 - 1 = 0.5)$.

The membership functions are: $\mathcal{MF}_{(Xi)} = 1/\left[1 + \left(\frac{x-b_1}{d_1}\right)^2\right] x < b_1$

$\mathcal{MF}_{(\mathrm{OM})} = 1$ for $\chi \geq 1.5$, $where\ (Xi), is\ the\ crisp\ value\ of\ (OM)$

Let (x) the crisp value of organic matter = 1.25, then the membership function is

$$\mathcal{MF}_{(\mathrm{OM})} = 1/\left[1 + \left(\frac{1.25 - 1.5}{0.5}\right)^2\right] = 0.8$$

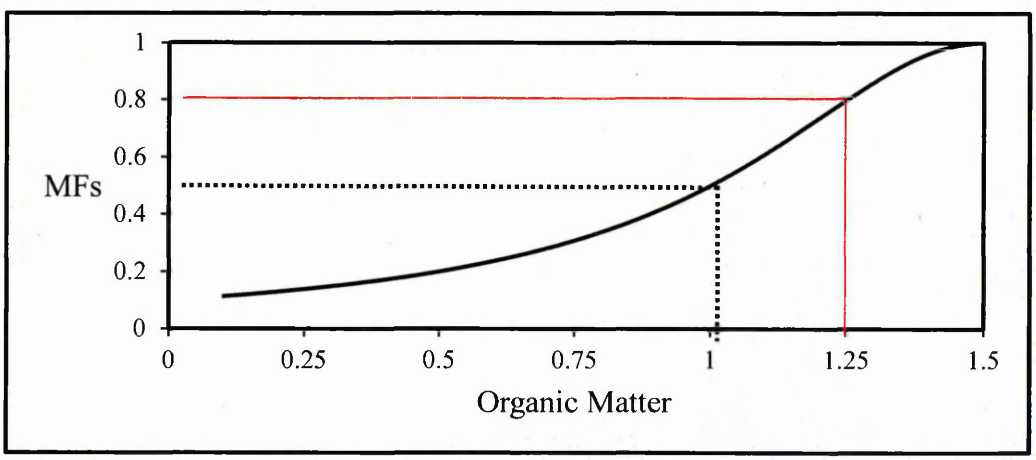


Figure 6.9: Example of calculating membership value for organic matter

6.8 Land Evaluation Models for the Study Area

Based on the above reviewed methods, three land evaluation models were applied to compute land suitability for the selection of land suitable for the production of barley and wheat. These were based on available biophysical information, but in accordance with the FAO (1976) framework for land evaluation. This information was integrated with the MCDM and the GIS functions of weighted overlay summation and the weighted overlay technique. The three models were generated as explained below:

6.8.1 Model 1 (Existing Land Evaluation Model)

In this model, weighted overlay and equal weights were applied following Nwer's (2005) study. Soil, erosion hazard and slope data were integrated into the GIS environment as information layers, and then overlaid to produce an overall land suitability assessment for barley. The steps taken are as follows. The suitability analysis of soil, slope and erosion was calculated in a spreadsheet model similar to Model 2. In the first stage, all soil characteristics were grouped to determine the overall soil suitability classes by using the limiting factor method. They were then exported into a GIS database to create soil suitability classes as thematic map layer, in addition to two thematic map layers for slope and erosion. In the second step, the three thematic map layers are assessed and reclassified according to a suitability evaluation scale between 1 and 4 as in previous studies (i.e. existing land evaluation model with equal weights for soil, erosion hazard and slope and multiplied with each map layer). In the third step, the WOT is used to generate the final land suitability map.

6.8.2 Model 2 (Weighted Overlay Summation-AHP)

In this model, the weighted overlay summation and the AHP method were applied through five stages. In the first step, the suitability analysis of soil characteristics, topography and erosion hazard was organised in a spreadsheet model using the LCs and their threshold values. The second step involves formulating 'if' functions for all LCs, setting the limits between the LCs' suitability classes for each land unit. Subsequently, the result was exported into a GIS database to create the soil suitability layer. In the third stage of the process, spatial data were converted into raster layers and processed in ArcGIS, then classified into four classes as integer rasters. These represented different suitability levels based on assigned threshold values, shown in Table 1. Each suitability class was ranked and assigned a numerical value as follows: S1 = 4.0, S2 = 3.0, S3 = 2.0 and N1 = 1.0. In the fourth step, each land characteristic of the 14 input rasters was represented as a single thematic layer and weighted by using the AHP method. In the final stage, the suitability map layers were overlaid to produce the output raster by using weighted overlay summation. The output values are a summation of value for each land characteristics suitability multiplied by the weights. The resulting output raster was standardised using equation 1.

6.8.3 Model 3 (Fuzzy - AHP)

In the Fuzzy model – AHP, four steps were executed to apply this model. In the first step, the land characteristics (LCs) and their threshold value for selected crops were identified (see Tables 6.4a and 6.4b). The second step involves the selection of the appropriate fuzzy model to calculate membership functions for each land characteristics (see Tables 616 and 6.17). Once standardised land characteristic map layers (i.e. fuzzy map layers) were derived, the third step in the Fuzzy – AHP is the production of weighted standardised land characteristic map layers (i.e. weighted fuzzy map layers) AHP via PCM analysis (Tables 6.14 and 6.15). The final stage involves overlaying the land characteristic map layers obtained on the preceding stages.

6.9 Maps Comparison

Map comparison is one of the most fundamental concepts in geographical analysis. The resulting maps from existing land evaluation model (Boolean-based category system evaluation), Boolean _AHP model and the Fuzzy_AHP modelling were compared. To perform the comparisons, or to cross-compare the results, the Model 2 and Model 3 suitability maps were reclassified or ranked into four classes (corresponding to the four suitability classes i.e. S1, S2, S3 and N), according to the guidelines (rating index) set by Sys et al. (1993) and Ben Mahmoud (2005). In these classes an area with a rating index between 1 and 0.8 is classified as highly suitable (S1), while an area with a rating index between 0.8 -0.6, 0.6-0.4 and >40 is classified as moderately suitable (S2), marginally suitable (S3) and non-suitable (N) respectively. Each map was rasterised in ArcGIS software and exported to Idrisi Andes software after converting them to a suitable format (i.e. Erdas image). To determine the correspondence between the raster maps, they were cross tabulated by means of the CROSSTAB module (IDRISI Andes software). Map comparison was possible using a set of methods, including Crosstab matrix (6.9.1) and Kappa statistics (6.9.2).

6.9.1 The CROSSTAB Matrix

The Cross-tabulation matrix, otherwise known as confusion or transition matrix, is a fundamental tool used in categorical map comparison. In this exercise, two categorical variables are shown in rows and columns – each representing variables of the two maps to be compared. In the GIS environment, the matrix records the agreement between the maps on the diagonal of the matrix and the disagreement off the diagonal. Class-by-class paired comparison between the marginal row totals and the marginal column totals allows the two maps to relate in terms of the quantity of each class. Based on Pontius (2002) and Pontius and Cheuk (2006), the result of this operation not only shows two measures of association between the maps but also gives an indication of how the two maps relate in terms of the location (i.e. the spatial distribution) of the classes in the map. Results from the Cross-tab matrix show the locations of all combinations of the categories in the original maps. Cross-classification thus produces a map representation of all non-zero entries in the cross-tabulation table (Idrisi, 2006). The matrix serves as the basis for popular statistics such as producer's accuracy, user's accuracy and Kappa – which was applied in this study as explained below.

6.9.2 Kappa Statistic

The Kappa statistic, developed by J. Cohen (1960), was used to assess the level of agreement between the models. This was calculated to measure the extent of agreement between two observations based on the difference between observed and expected agreement. The measure of agreement ranged between 0 and 1, where 0 indicates that there is a poor agreement between the maps, in other words, no relationship at all. A value of 1 indicates an almost perfect relationship or agreement between any two maps; a negative value such as -1 is indicative total disagreement (Rossiter, 2004). The resulting concordance is presented in the Kappa Index of Agreement. It should be noted that to assess agreement between two maps or to compute the value of Kappa, the two maps should have exactly the same number of categories (Idrisi, 2006).

6.10 Validation of the Models

One of the essential parts for modelling land evaluation is how to evaluate or to test the performance of resultant land suitability models. The FAO (1984) and Rossiter (2003; 1996) have earlier asserted that validation and accuracy of physical land evaluation that uses qualitative method may not be possible. However, in recent times, one of the methods that could be used for validation is investigating if the selected crops have already been produced in the region and then a comparison could be made based on crop yield (Nwer, 2005). It is anticipated that without the benefit of a land evaluation model to optimise land suitability, that crops will have been planted under a variety of land characteristics. Therefore, a range of crop yields from a number of random sites in the field would be expected. Application of the linear regression equation to assess correlation between the values of suitability of land and crop yield can be used to assess the performance of the models as has been achieved with varying degrees of success in other studies (e.g. Van Ranst et al. (1996); Baja, et al. (2001)). There are two methods to obtain crop yields: 1) controlled experiments, which are usually from field plots where researchers control the levels of the independent variable(s), and 2) uncontrolled experiments, which are usually field surveys, where the levels of the independent variables are not, controlled e.g. observation of yields on a number of different farms (Hagens, 1990; Rossiter, 1995). According to Clayton and Dent (2001) yield data may be collected from farmers' estimates and experts opinions. With the first method, the price of control is the complexity and cost of the research, whereas with uncontrolled experiments there is no guarantee the all land suitability can be sampled or that the data is accurately described. As a result, yields may vary because of fluctuation in management practice, for example, that is not accurately recorded. This latter limitation can be overcome by recording the optimum yield at all farms under the most favourable climatic and management conditions.

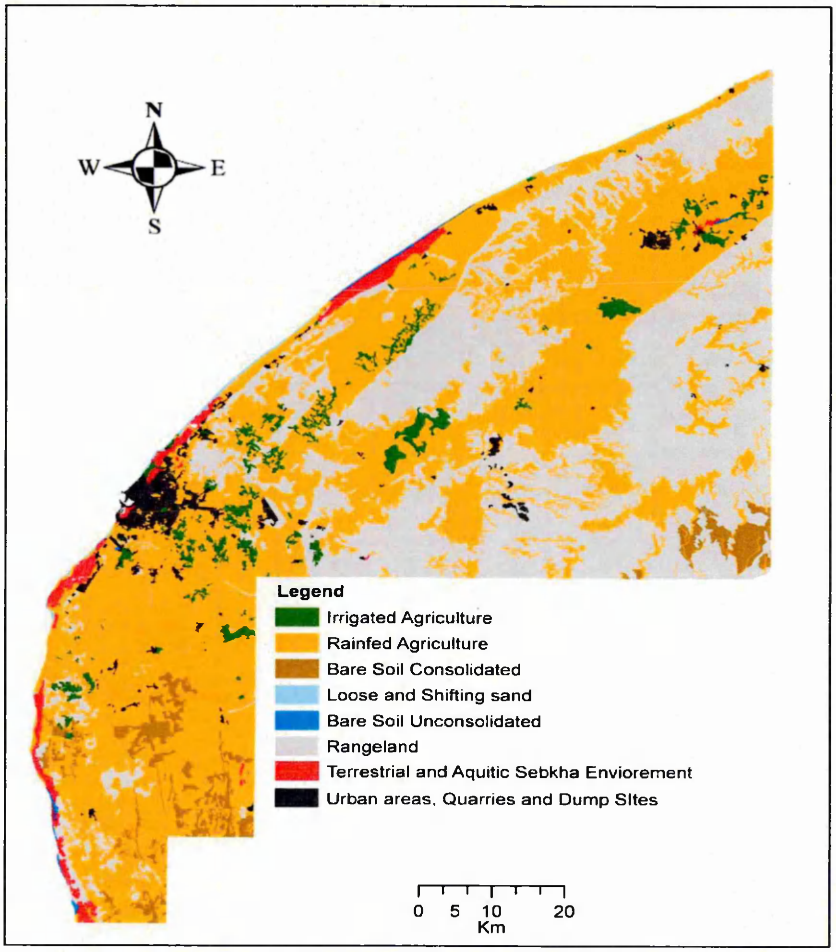
It was envisaged that equal representation of all the land suitability classes observed in the field or by stratified sampling would allow the optimum testing of the relationship between observed yield and the rangeland suitability as encountered. Traditionally this can be conducted by generating a random set of locations (i.e. to determine the locations of collecting yield data) to visit on the ground for validation or verification of the derived land suitability maps during the field visit (Idrisi, 2006). To facilitate this process the sample module in Idrisi software used through the stratified random option.

Land cover mapping was adopted to validate the findings in this thesis. The Libyan Land use Land Cover Map (LE004) covering the study area was used. A field visit to the study area was undertaken between April and May 2013 for further collection of data and ground-truthing. The land cover map in Figure 6.10 indicated that about 6.7% of total study area is on an irrigated agricultural area, whereas about of 53.4% in total of study area is rain-fed agriculture. The remaining 40% is made up of grazing land. The low proportion of irrigated land is due to absence of ground water particularly towards the northern part of the study area, lack of tributaries, water salinity especially along the coastline and no infrastructure for human habitation or for the supply or channelling of water for irrigation. These factors have contributed to the reliance on areas that support rain-fed agriculture. No doubt this explains why the GMPR was established to transfer water from the north to the south. It was also noted and important to note that the new irrigated areas were found during the field visit which were located in the south-west of the study area, but these have not been mapped in the original land cover map. This is because GMPR has established new agricultural projects on a particular site since the map was produced.

The models are designed to capture the highest yield that can be obtained from a particular plot in a specific planting season. It was not possible to capture data on observed yield for other years for model validation due to the following reasons. Firstly, farmers are not educated to keep record of yields per harvesting period. Secondly, there is often a misconception surrounding the intended use of data, which must be approached ethically to ensure data reliability i.e. some farmers believe initially that data will be transferred to government authorities for the imposition of taxes. Thirdly, some farms are under new managers and so have no productivity data for previous years. Finally, some farmers employ foreign labours or managers who are not aware of the total yield of the farm. For the above reasons, farmers were asked to provide data on the highest yield obtained with highest level of land management. It is noted that in practice, the yield per hectare is subject to change year-on-year due to changes in climate, water availability, pest invasion and management practices.

Based on the crop yield data collected from farmers and the outputs from Models 1, 2 and 3, linear regression was used to validate the performance of the models. As there appears to be no established technique that accurately and reliably quantifies crop yield from information supplied by farmers, the results were compared against those from independent researchers within the region. The latter included ARC, ICARDA, and large, state-managed, agricultural projects as suggested by Nwer (2005). For example, a trial study undertaken by ARC in cooperation with ICARDA in 2009-2010 indicated a range of yield data for wheat and barley in the Marj and Slough trial plots. The estimates collected from farmers fall within this range. For example, the yield provided by state-managed agricultural projects and private farms supervised by GMRP for barley was 5.1 tonne per hectare for barley and 5.3 tonne per hectare for wheat (within the 2009-2010 harvest season). These figures for yield fall within the ARC estimate of potential yield of between 4 and 6.5 tonne per hectare for barley and from 4.5 to 7.5 tonne per hectare for wheat. It should be noted that a follow-up conversation with Engineer Nasser Almsmary, director of the unit of irrigation and drainage in projects of Jardina in the south of study area, was invited to discuss the yield data collected from farmers during the field visit held from April to May 2013 as an independent expert. The expert assessed the accuracy of the yield data in the following way. He is a resident of the area and was worked closely with soils and productivity of the land in his capacity as an irrigation and drainage engineer. He therefore composed a description of the soil of an area with its yield. In addition . He knew seven of the farmers personally and was also able to provide information about the crop yield data of some farms under the supervision of the GMRP that has been used for validate the results of models. He was satisfied that the accuracy of the yield was estimated to be good or very good. Therefore, it can be inferred that the data obtained from farmers can be relied upon for further analysis.

The land use map was used for validating the suitability classes obtained from the models - it allows the appraisal of land suitability classes of especially the rain-fed agricultural areas and even salinity class. For example, if the low suitability classes correspond with salinity class, it makes the result more robust and realistic other than depending on linear regression alone. Because it was not possible to use linear regression for Model 1, Equation 2 was used for conversion from qualitative to quantitative similar to the procedure adopted by Van Ranst et al. (1996).



6.10: land cover for study

6.11 Summary

The MCDA includes integration of expert knowledge at different levels of decision-making. In this regard, the GIS environment has proven to be a useful tool for handling both technical and logistical problems through the construction of different thematic layers (in the form of MCDA) to define land suitability map layers. The next chapter presents the results obtained from the combination of these methods.

Chapter Seven

Results

7.1 Introduction

Assigning weight is an important step in calculating overall land suitability for agricultural purposes. However, it has often been viewed as a subjective process particularly with inadequate and inaccurate data (Dinh and Duc, 2012). Generally, the process of calculation of weights in land evaluation is dependent on the characteristics of the study area, land characteristics, type of crops, experts experience and presence of the necessary data for the analysis and choice of multi-criteria decision rules. This research has contributed to the development of the AHP method for deriving weights for selected land characteristics by utilising the experiences of experts. By constructing GAHP, attempts have been made to incorporate local knowledge from local experts from different backgrounds and experience into the model of decision making for land evaluation application.

This section of the research present the results from the methods set out in Chapter Six. The weighting factors and modelling procedure are contained in this chapter. The results and suitability models are also compared and validated following the results presentation.

7.2 Weighting Results

As pointed out in Chapters Five and Six, the AHP method was applied to assign different weights to land characteristics for barley and wheat. Six local experts used their knowledge and experiences to assign weights to the selected land for each crop. The set of results from the six local experts obtained through applied AHP method was accepted for use in land evaluation models in this research, because the consistency ratios obtained were less than or equal to the established acceptable limits of 0.1. The consistency ratio shows that the comparisons of land characteristics were perfectly consistent, and the relative weights are appropriate for applying in land suitability evaluation models. The set of weights from six local experts for each level of hierarchy were aggregated from the use of the GAHP method described in Section 6.6 (see Appendix B for all sets of pairwise comparisons).

The Eigen values or the weight of soil characteristics are higher than slope steepness and erosion hazard in the second level for barley and wheat. Table 7.1 indicates that the soil is highly sensitive in the suitability classification as attested to by all the local experts. According to them, soil was more important than slope and erosion. However, with respect to the comparison between slope and erosion, four local experts felt both criteria were equally important and one felt slope was more important than erosion and the last one felt erosion was more important than slope. This assertion is in agreement with Nwer (2005). This study has indicated that soil characteristics appears the most important factor in evaluating suitability for the production of grains especially wheat and barley.

Table 7.1: The result of weighting for Level 2 (criteria) of hierarchy for barley and wheat generated by local experts and GAHP

Level 2 (Criteria)	Local Experts						GAHP
Land Characteristics	E1	E2	E3	E4	E5	E6	AIJ
Soil Characteristics	0.7324	0.7838	0.7471	0.7778	0.7778	0.7582	0.7653
Topography (Slope)	0.1378	0.1349	0.1336	0.1111	0.1111	0.0905	0.119
Erosion hazard	0.1297	0.0813	0.1194	0.1111	0.1111	0.1512	0.1157
CR	0.0055	0.0055	0.058	0.0193	0.0001	0.095	

At the third level, the results show that soil depth, available water holding capacity and soil texture received the highest weight compared to other sub-criteria for barley while in the case of wheat the most important soil characteristics affecting growth under irrigation conditions in the study area were soil depth, soil texture, soil salinity and available water holding capacity. Tables 7.2 to 7.3 summarise the set of weights for soil characteristics for barley and wheat.

Table 7.2: Derived weighting for Level 3 (Sub-criteria) of hierarchy for barley generated by local experts

Level 3 (Sub-criteria)	Local Experts						GAHP
Soil Characteristics	E1	E2	E3	E4	E5	E6	AIJ
Soil depth	0.1262	0.1371	0.1513	0.1244	0.1135	0.1298	0.1325
Soil texture	0.1097	0.1019	0.1106	0.0703	0.0667	0.0610	0.0818
AWHC	0.1143	0.1314	0.1368	0.1223	0.1186	0.1103	0.1227
Hydraulic conductivity	0.1024	0.1104	0.1069	0.1093	0.0962	0.0835	0.1032
Soil salinity	0.0668	0.0686	0.0753	0.0758	0.1007	0.0971	0.0806
Soil alkalinity	0.0457	0.0517	0.0514	0.0457	0.0643	0.0716	0.0548
Infiltration rate	0.1005	0.1106	0.1069	0.1115	0.1023	0.1057	0.1079
Soil reaction pH	0.1023	0.0685	0.0677	0.1145	0.0963	0.0924	0.0895
$CaCO_3$	0.0792	0.0725	0.0610	0.0838	0.0823	0.0781	0.0768
Organic matter	0.0573	0.0490	0.0409	0.0536	0.0498	0.0597	0.0514
CEC	0.0515	0.0536	0.0463	0.0465	0.0542	0.0558	0.0511
Gravel and stones	0.0441	0.0448	0.0450	0.0422	0.0551	0.0552	0.0479
CR	0.0556	0.0472	0.0653	0.0503	0.042	0.0464	$\sum=1$

Table 7.3: Derived weighting for Level 3 (Sub-criteria) of hierarchy for wheat generated by local experts

Level 3 (Sub-criteria)	Local Experts						GAHP
Soil Characteristics	E1	E2	E3	E4	E5	E6	AIJ
Soil depth	0.1419	0.1773	0.1452	0.1505	0.1271	0.1565	0.1502
Soil texture	0.1035	0.0916	0.1211	0.1207	0.0821	0.1061	0.1063
AWHC	0.1107	0.1174	0.1021	0.1015	0.1187	0.1103	0.1124
Hydraulic conductivity	0.0777	0.0841	0.0830	0.0827	0.0739	0.0835	0.0799
Soil salinity	0.0941	0.0863	0.0947	0.0946	0.1046	0.0971	0.9308
Soil alkalinity	0.0512	0.0626	0.0713	0.0710	0.0713	0.0716	0.0630
Infiltration rate	0.0957	0.1056	0.0908	0.0905	0.0933	0.1057	0.0959
Soil reaction pH	0.0902	0.0678	0.0765	0.0742	0.0908	0.0924	0.0778
$CaCO_3$	0.0839	0.0714	0.0667	0.0664	0.0814	0.0781	0.0746
Organic matter	0.0579	0.0446	0.0497	0.0495	0.0478	0.0597	0.0494
CEC	0.0481	0.0488	0.0504	0.0502	0.0561	0.0558	0.0507
Gravel and stones	0.0452	0.0048	0.0485	0.0483	0.0530	0.0552	0.0459
CR	0.0524	0.0380	0.0394	0.0405	0.0448	0.0608	$\sum=1$

The final results of weighting included twelve soil characteristics as well as slope steepness and soil erosion for barley and wheat as shown in Table 7.4.

Table 7.4: Weights for barley and wheat

Land characteristics	barley	wheat
Soil depth	0.1014	0.1150
Soil texture	0.0626	0.0813
AWHC	0.0939	0.0860
Hydraulic conductivity	0.0790	0.0611
Soil salinity	0.0616	0.0712
Soil alkalinity	0.0419	0.0483
Infiltration rate	0.0825	0.0734
Soil reaction pH	0.0685	0.0601
$CaCO_3$	0.0587	0.0571
Organic matter	0.0393	0.0378
CEC	0.0391	0.0388
Gravel and stones	0.0367	0.0352
Slope steepness	0.119	0.119
Soil erosion	0.116	0.116

7.3 Modelling Land Suitability for Wheat and Barley

Different land evaluation models were implemented to produce land suitability maps for barley and wheat in the study area. Further from Section 6.8, two types of analyses were undertaken to evaluate the output of models: cross comparison and linear regression. In order to cross-compare the results, each model was ranked or converted into four suitability classes according to the rating index set by Sys et al. (1993).

7.3.1 Model 1 (Boolean) Land Suitability for Barley and Wheat

The outputs of this model were based on the weighted overlay technique. This application, based on the Boolean approach, requires the suitability mapping using a common scale of values to simplify the limiting factor method. This was applied in this context for barley and wheat following the limiting factors convention. The results obtained for barley classify about 3.2%, 53.2%, 42.7% and 0.9% of total study area as highly suitable (S1), moderately suitable (S2), marginally suitable (S3) and currently not suitable (N1) respectively for barley production. Figure 7.1 shows the percentages of suitability classes of the study area for barley, and Figure 7.2 shows the spatial distribution of these classes.

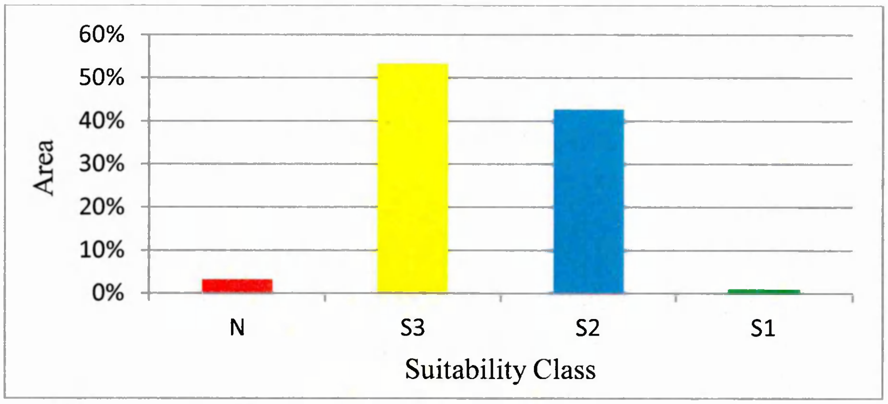


Figure 7.1 Model 1 proportions of suitability classes for barley

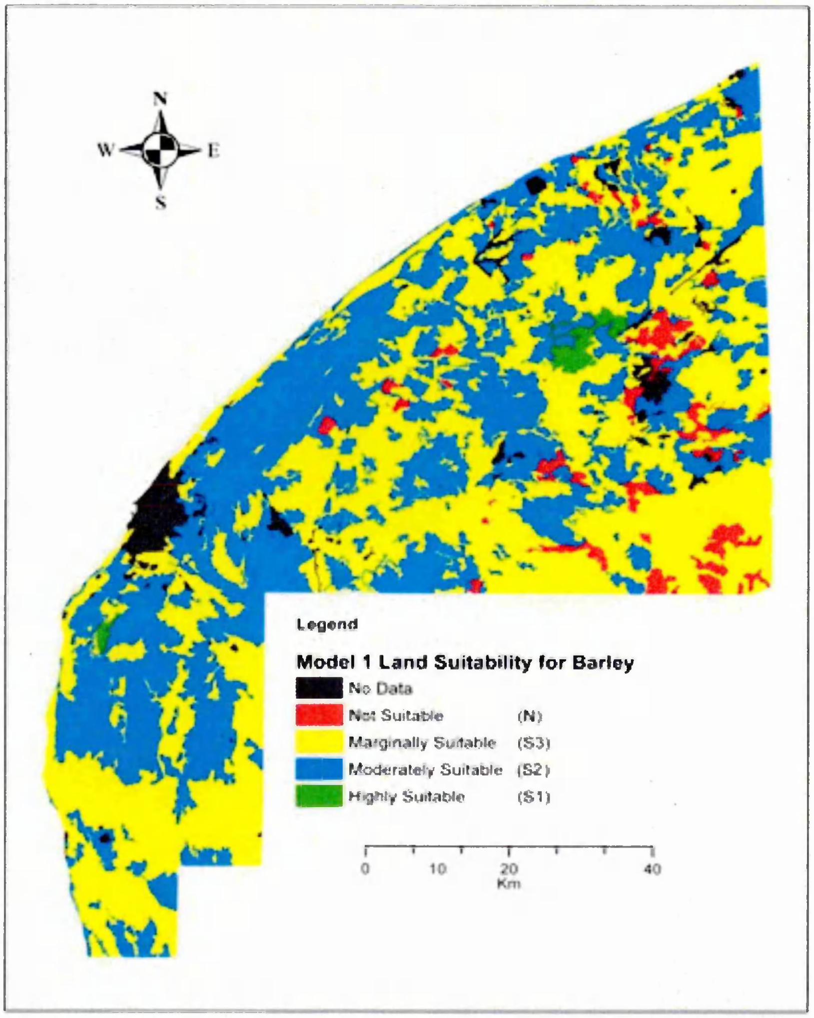


Figure 7.2 Spatial distribution of land suitability produced by Model 1 for barley

Meanwhile, the model outputs of land evaluation for wheat shows few locations of high suitability and non-suitability. Marginally suitability (S2) and moderately suitability (S3) dominates the study area, covering about 49% and 47.4%

respectively. About 4% were classified as highly suitable and less than 1% of study area is non-suitable for wheat production at all. Figure 7.3 shows the percentages of suitability classes and the spatial distribution of these classes are shown in Figure 7.4.

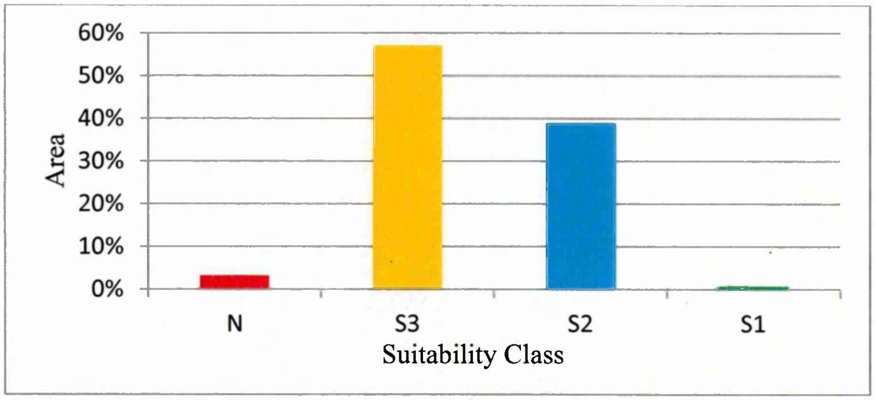


Figure 7.3 Model 1 proportions of suitability classes for wheat

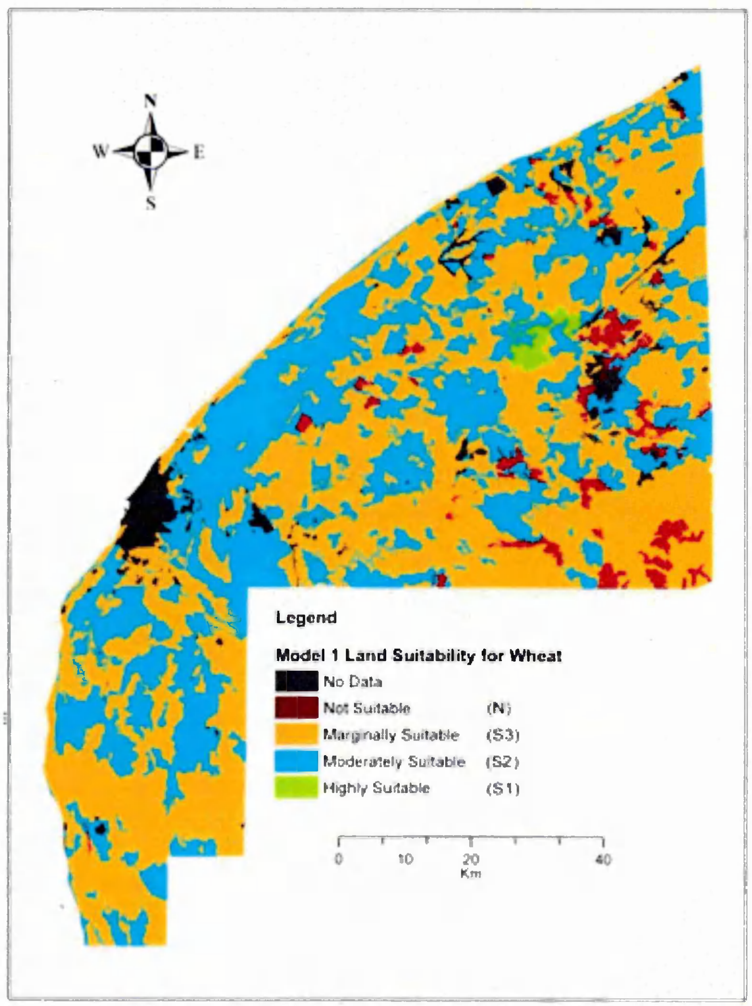


Figure 7.4 Spatial distribution of land suitability produced by Model 1 for wheat.

7.3.2 Model 2 (AHP) Land Suitability for Barley and Wheat

The outputs of this model were based on application of weighted overlay summation technique. This technique, as described in chapter five, provides the ability to combine multiple inputs (land characteristics) to create land suitability map. It is similar to the Weighted Overlay tool where multiple raster inputs, representing multiple factors (selected land characteristics) can be easily combined incorporating weights derived by group of local experts using AHP method through PCM.

Figures 7.5 and 7.6 showed the results of the land suitability evaluation for barley obtained from Model 2 AHP and application of weighted overlay sum. The figures reveal that the degree of suitability ranges from 0.37 to 0.93 where 50 suitability sub-classes have been identified for barley.

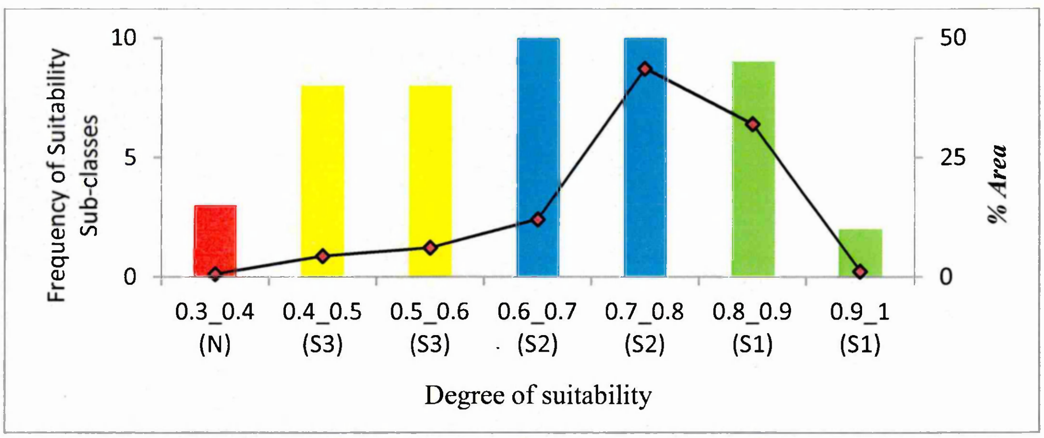


Figure 7.5 Model 2 sub-classes and area of land suitability for Barley

The degree of suitability lies between 0.8-0.9 and 0.7-0.8 and is located within class S1 and S2, which accounts for about 32% and 44% of the total study area respectively. Meanwhile, the degree of suitability lies between 0.9 and 1, and 0.3 and 0.4 and is located within class S1and N, but contains a limited number of locations accounting for about 1.2% and 0.64% of the total study area respectively.

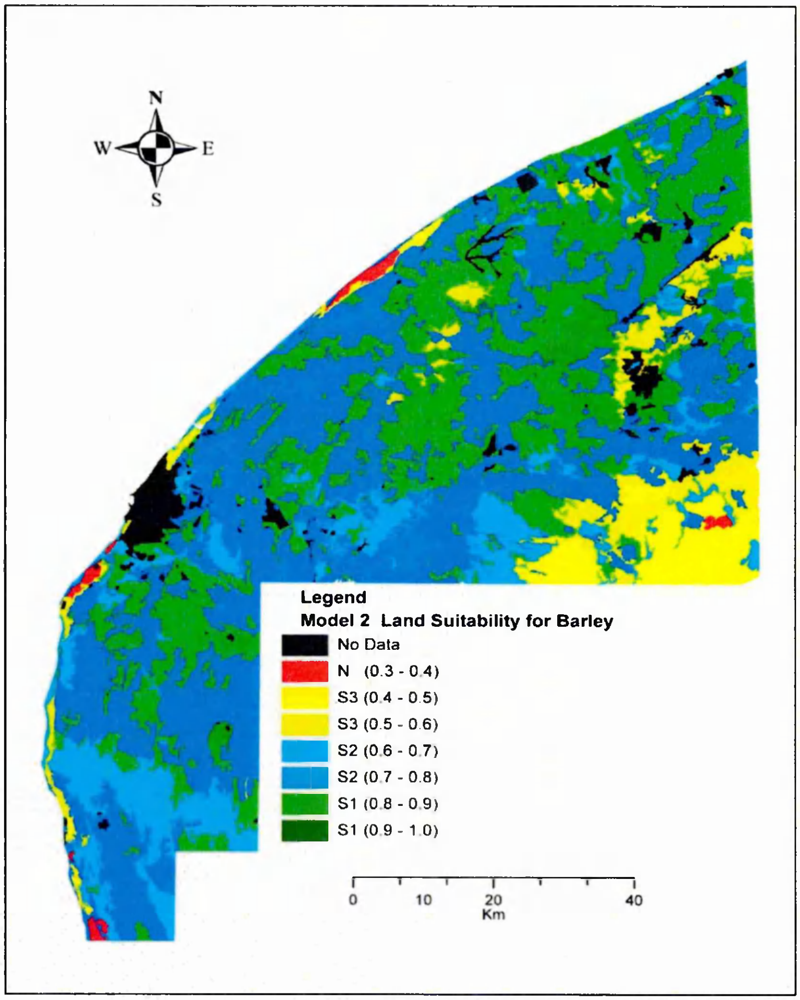


Figure 7.6 Spatial distribution of land suitability produced by Model 2 for barley

Figures 7.7 and 7.8 show the results of land suitability evaluation for barley obtained from Model 2 AHP and by the application of weighted overlay summation. The figures reveal that the degree of suitability ranges from 0.33 to 0.93 where 48 suitability sub-classes have been identified for barley. The degree of suitability lies between 0.8 and 0.9, and 0.7 to 0.8 and is located within class S1 and S2, comprising 23.3% and 45.7% of the total study area respectively. Meanwhile, the spatial distribution of the N and S1 appears in a limited number of locations in total to the samples of the study area.

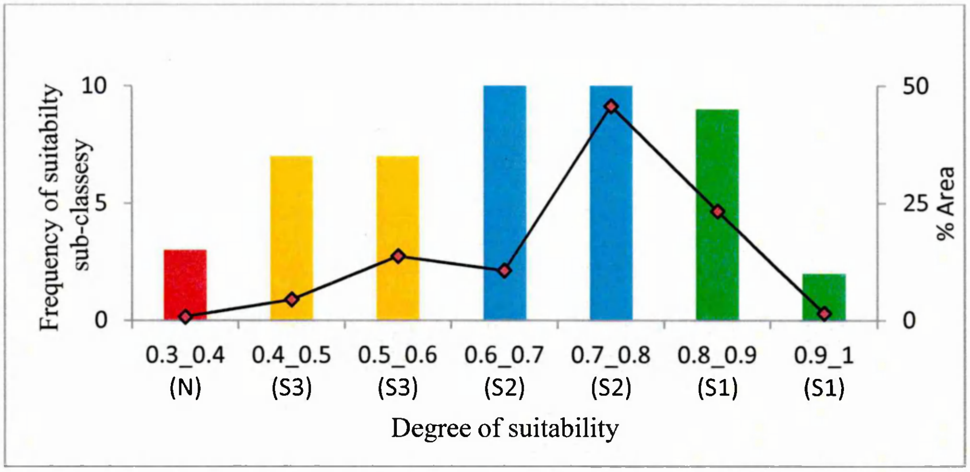


Figure 7.7 Model 2 sub-classes and area of land suitability for wheat

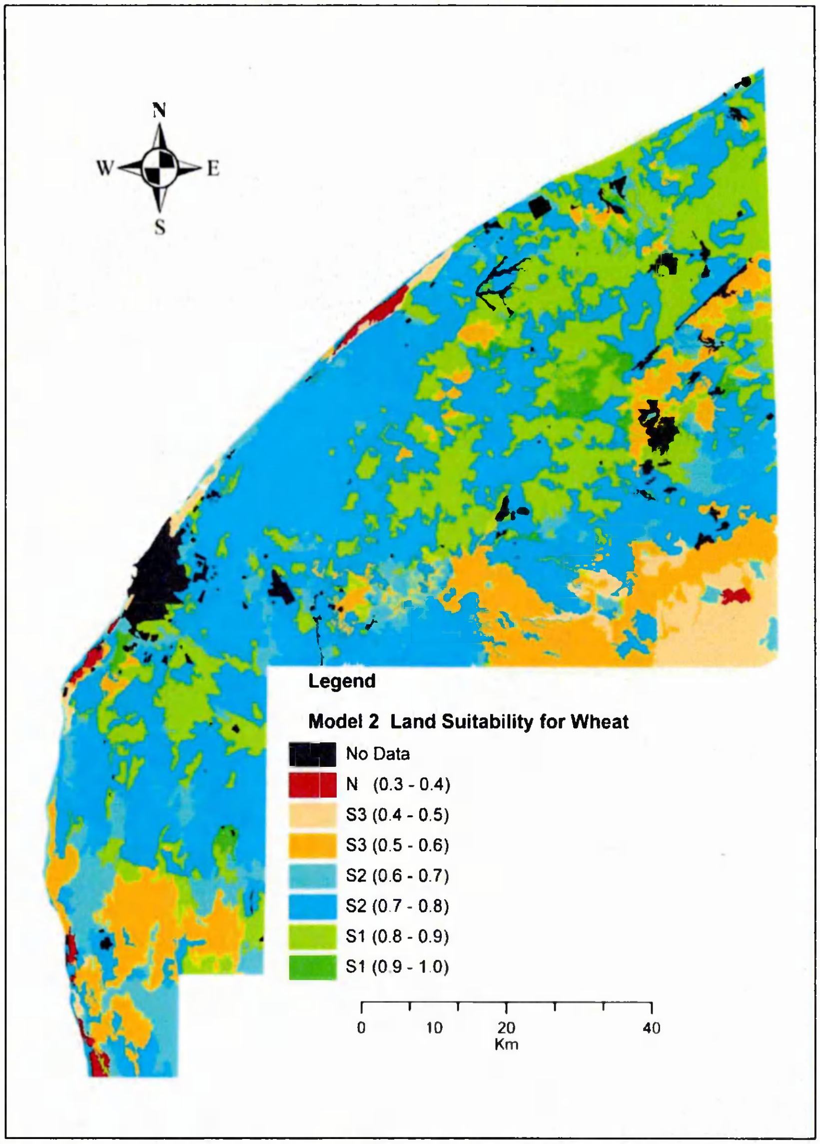


Figure 7.8 Spatial distribution of land suitability produced by Model 2 for wheat

7.3.3 Model 3 Land Suitability for Barley and Wheat

The derivation of land suitability maps using Fuzzy AHP comprises three main tasks. 1) Conversion of the selected land properties into a continuous scale or fuzzy membership; 2) derivation of the weighted fuzzy maps for the selected land characteristics by taking the weights obtained from local expertise into account; and 3) derivation of the overall suitability evaluation on the basis of joint membership functions obtained with the weights provided by local experts in Section 7.2.

The results from Model 3 (Fuzzy and AHP) for barley crop (Figures 7.9 and 7.10) indicate that the suitability of the study area ranges from 0.33 to 0.94; where 55 sub-classes were found for suitability. However, the degree of suitability ranges between 0.9 and 0.8, and 0.8 to 0.7, which are located within class S1 and S2. These classes receive the highest percentages of land suitability, accounting for about 32% and 36% of the total study area respectively. In contrast, the degree of suitability between 0.9 and 1, and 0.3 to 0.4, which are located within class S1, and N receive the lowest degree of land suitability, accounting for less than 3% of the total study area.

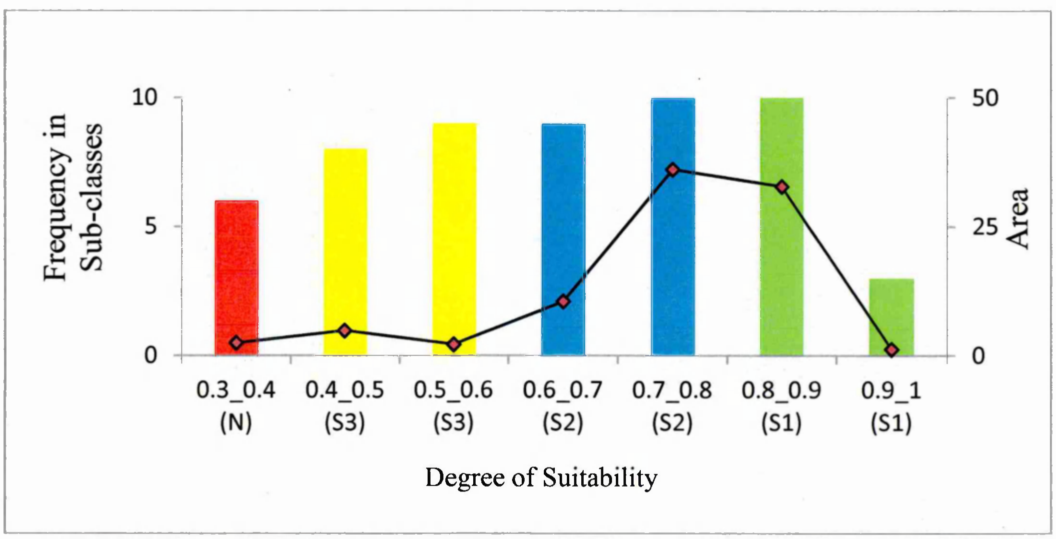


Figure 7.9: Model 3 sub-classes and area of land suitability for barley

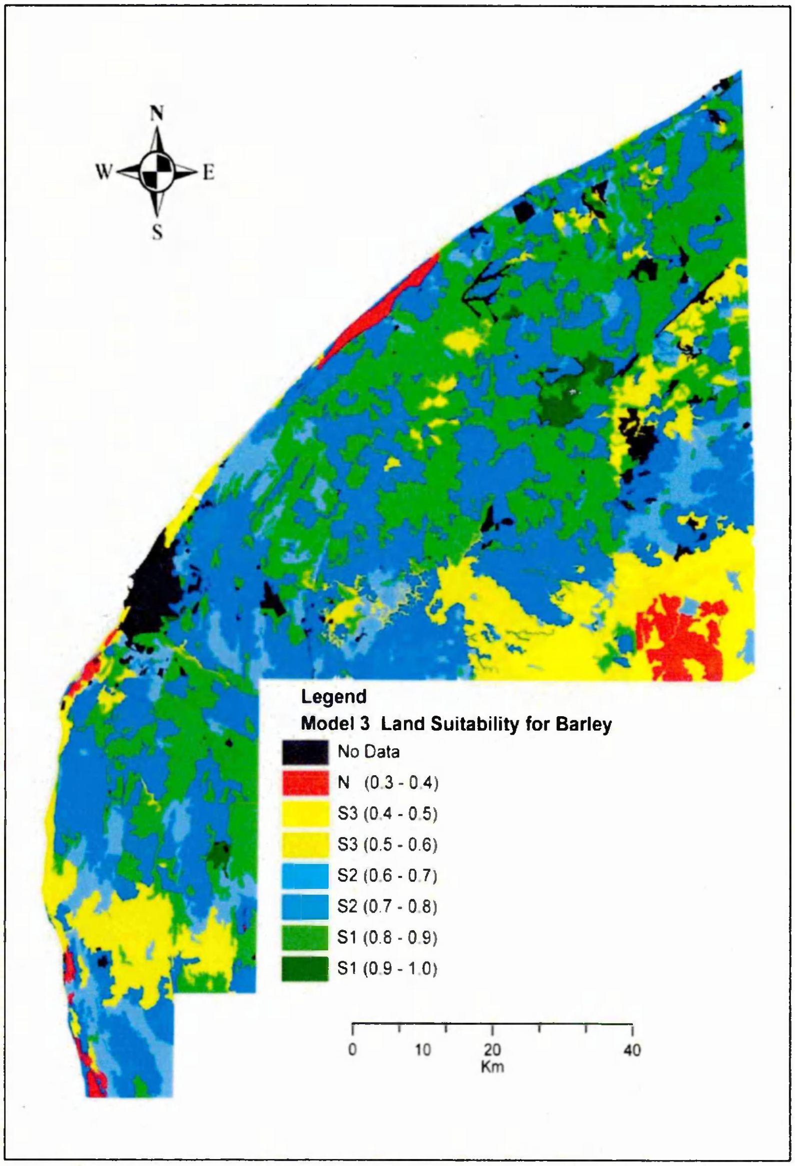


Figure 7.10 Spatial distribution of land suitability produced by Model 3 for barley

In contrast, Figures 7.11 and 7.12 show that the results from Model 1 (Fuzzy AHP) for wheat indicate that the suitability of the study area ranges from 0.28 to 0.93, where 59 degrees of subdivision in suitability ranges (i.e. suitability sub-classes) were found for barley.

The degree of suitability, located within class S2 and S1, lies between 0.7 and 0.8, 0.8 and 0.9 and 0.6 to 0.7, and receive the highest percentages of land suitability. This accounts for about 39%, 22% and 18% of the total study area respectively. This is in contrast to the degree of suitability between 0.9 and 1, 0.3 and 0.4 and 0.2 to 0.3 which are located within class S1 and N receive the lowest percentages of degree of land suitability (accounting for about 0.95 %, 3.7% and 0.6 2% of the total study). Although the degrees of suitability between 0.7 and 0.8, 0.6 and 0.7, 0.4 and 0.5, and 0.5 to 0.6, received higher proportion of subclass suitability, their total area compared to the study area was mapped with a lower percentage. Figure 7.11 shows the percentage of each suitability sub classes. Even when results from this model for barley and wheat indicated high level of suitability, however, that there is no location in the study area with a degree of suitability equal to 1.

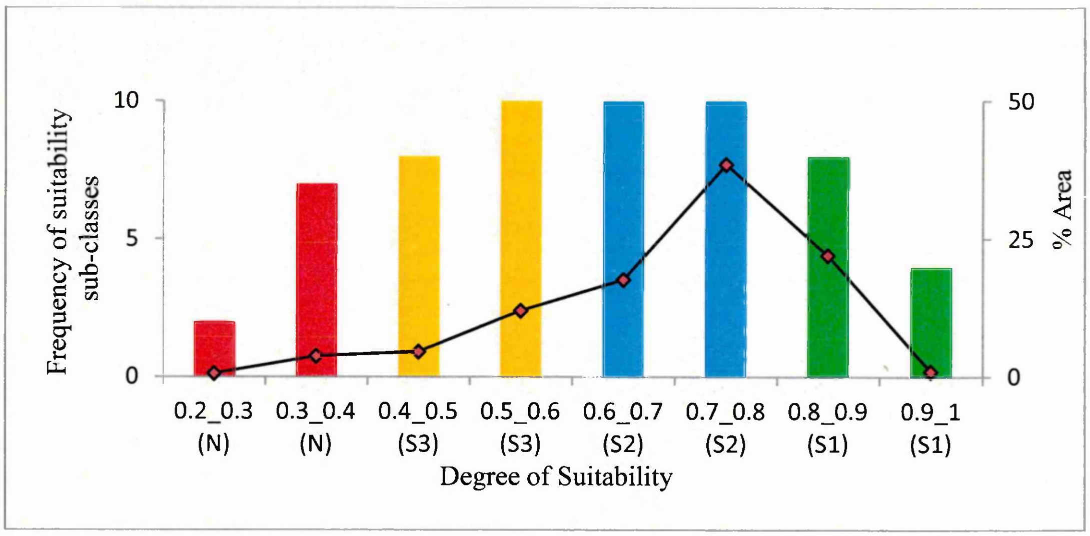


Figure 7.11: Model 3 sub-classes and area of land suitability for wheat

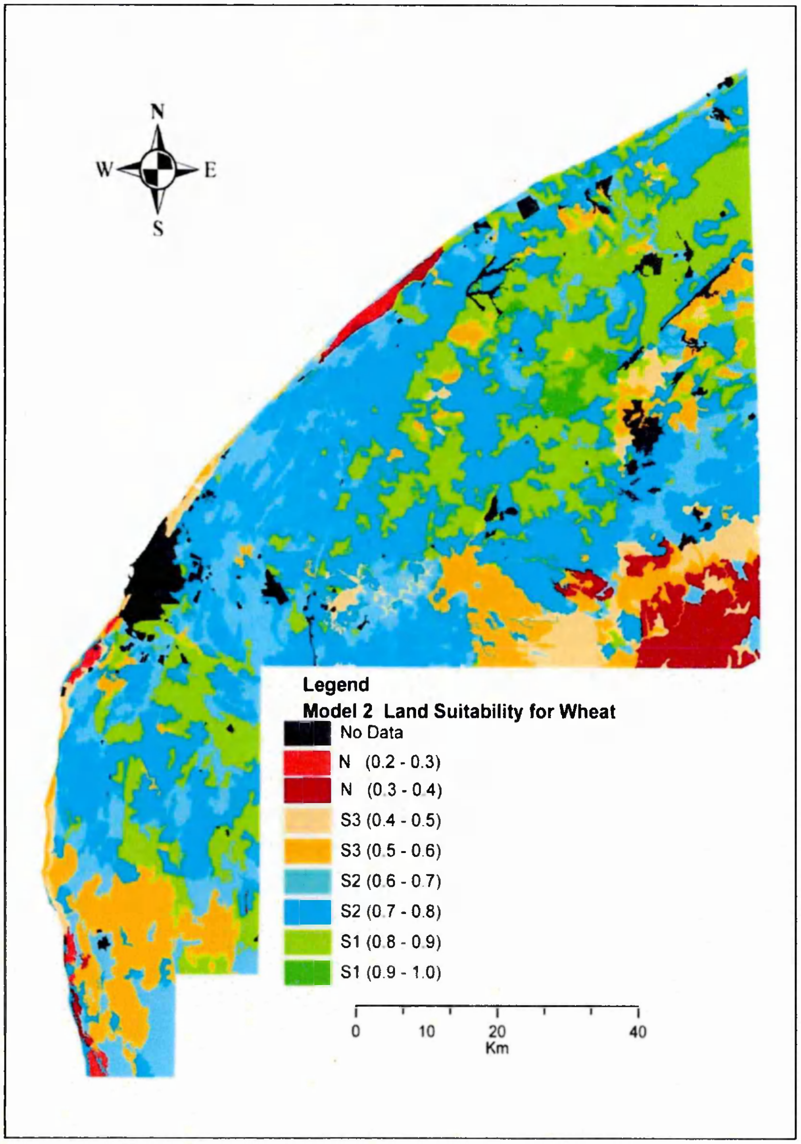


Figure 1 Spatial distribution of land suitability produced by Model 3 barley

7.4. Result Summary and Comparison

Tables 7.5 and 7.6 summarize the results of the three suitability models for barley and wheat for the study area.

Table 7.5: The results of three Models for barley

Suitability Range		Model 1 Area %	Model 2 Area %	Model 3 Area %
(N)	0.2 - 0.3		-	-
	0.3 - 0.4	3.22%	0.64%	2.44%
(S3)	0.4 - 0.5		4.42%	4.83%
	0.5 - 0.6	53.20%	6.13%	12.18%
(S2)	0.6 - 0.7		12.05%	10.45%
	0.7 - 0.8	42.71%	43.65%	36.09%
(S1)	0.8 – 0.9		31.89%	32.80%
	0.9 – 1	0.88%	1.21%	1.22%

Table 7.6: The results of three Models for wheat

Suitability Range		Model 1 Area %	Model 2 Area %	Model 3 Area %
(N)	0.2 - 0.3		-	0.62%
	0.3 - 0.4	3.25%	0.78%	3.73%
(S3)	0.4 - 0.5		4.44%	4.56%
	0.5 - 0.6	57.12%	13.70%	11.98%
(S2)	0.6 - 0.7		10.55%	17.63%
	0.7 - 0.8	38.89%	45.72%	38.52%
(S1)	0.8 – 0.9		23.32%	22.00%
	0.9 – 1	0.75%	1.50%	0.95%

7.4.1 Comparison of Results

From Tables 7.5 and 7.6, it appears that the percentage of areas of land suitability class is very close, particularly between Model 2 and Model 3. However, this does not necessarily reflect agreement or correspondence in terms of the spatial distribution of land suitability class. To discover the level of agreement between Model 1, Model 2 and Model 3, and to make comparisons between the resulting land suitability maps produced by each model, the results of Model 2 and Model 3 were ranked or converted into four classes (i.e. S1, S2, S3 and N). This was according to the guidelines (rating index) set by Sys et al. (1993), where an area with a rating index between 1 and 0.8 is classified as Highly suitable (S1), while an area with a rating index between 0.8 and 0.6, 0.6 and 0.4, and >40, is classified as Moderately suitable (S2), Marginally suitable (S3), and Non suitable (N) respectively. This procedure was done to facilitate the comparison between models by using CROSSTAB model in Idrisi software. This function offers many operations such as is a table listing the tabulation totals as well as one and possibly three measures of association between the maps. If the two maps have exactly the same number of categories, another measure of association called Kappa (also called KHAT or the Kappa Index of Agreement KIA) is performed. The second operation that CROSSTAB offers is error matrix analysis which shows the correctly classified area between maps by the User's Accuracy and Producer's Accuracy analysis. The third operation that CROSSTAB offers is cross-classification. Cross-classification of the result is a new map that shows the locations of all combinations of the categories in the original images. Cross-classification thus produces a map representation of all non-zero entries in the cross-tabulation table. How that worked out is described below.

7.5 Comparisons of Model Outputs and Level of Agreement for Barley

Table 7.7 summarises the results of comparison between land suitability models for barley. The highest overall agreement value for barley i.e. the sum of correctly classified areas, between Model 2 and Model 3 was found to be about 80% of spatial distribution of the study area. This means that the majority of suitability classes in study area are almost exact in two land suitability maps. The highest value of 41% was mapped as S2 suitability class in the two models map. Whereas the comparison between Model 1 with Model 2 and Model 3 indicating that overall accuracy is very low - about 35.3% and 39.4% - with highest value of 22% and 24% in the total study area mapped as S2 in the two models. However, disagreements were found between

Model 1 and Model 2, and Model 1 and Model 3, - accounting for 64.5% and 60.6% with the highest value of 28.9% and 21.2% respectively. In terms of coverage, Model 1 map corresponds to moderately suitable areas, for the Model 2 map and Model 3 corresponds mainly to highly suitable land for barley cultivation.

Table 7.7: Summarises the comparison between land suitability models for barley

Model 1. vs. Model 2			Model 1. vs. Model 2			Model 2. vs. Model 3		
Legend	area	%	Legend	area	%	Legend	area	%
N | N	588.4	0.10	1 | 1	3681.39	0.62	1 | 1	3748.6	0.64
N | S3	13330	2.26	1 | 2	10237.3	1.74	2 | 1	21416	3.63
N | S2	5059.8	0.86	1 | 3	5059.81	0.86	2 | 2	62550	10.60
S3 | N	3160.3	0.54	2 | 1	21483.2	3.64	2 | 3	32544.	5.52
S3 | S3	70148	11.89	2 | 2	83360.8	14.13	3 | 3	241728	40.97
S3 | S2	170336	28.87	2 | 3	125133.6	21.2	4 | 3	33569.6	5.69
S3 | S1	70215	11.90	2 | 4	83881.9	14.22	3 | 4	28577	4.84
S2 | S3	487.5	0.08	3 | 2	1496.1	0.25	4 | 4	165848	28.11
S2 | S2	132446	22.45	3 | 3	140111.4	23.75	-	-	-
S1 | S1	119032	20.18	3 | 4	110358	18.71	-	-	-
S1 | S1	5177.5	0.88	4 | 4	5177.48	0.88	-	-	-
Overall accuracy		**35.3%**	Overall accuracy		**39.4%**	Overall accuracy		**80.3%**

Where: 1= non-suitable (N), 2 = moderately suitable (S3), 3 = moderately suitable (S2) and 4 = highly suitable

7.5.1 Results of crosstab model for barley

This section shows the result of crosstab matrices between three land suitability maps and levels of agreements and disagreements between suitability classes.

7.5.2 Model 1 Map vs. Model 2 Map

Table 7.8 shows the results of crosstab matrix resultant from the comparison of Model 1 and Model 2, where 35.3% (overall accuracy or agreement) of the study area was mapped with the same classes in both models, with an overall Kappa statistic of 7.34%. The highest value of Kappa per class and Producer's Accuracy was equal to 1 were found in areas that have been mapped as highly suitable (when Map 1 was referenced). This means that the whole area of highly suitable class (S1) classified in Model 1 map corresponds to the same area in Model 2 map (or not being classified randomly). In contrast, the value of Producer's Accuracy indicates that only 2.7% of the area in the highly suitable class mapped by Model 2 corresponds to the same area in Model 1 with a very low Kappa value (1.8%). The rest of this class (i.e. highly suitability class in Model 2 map) was mapped as moderately suitable (S2) and marginally suitable (S3) in the Model 1 map. Figure 7.13 shows the spatial distribution of the agreement and disagreement between suitability classes.

Table 7.8: Crosstab Matrix for Barley. Model 1 vs. Model 2

		Map 1 as reference				
	Category	N	S3	S2	S1	Row Total
Map 2	N	0.000997	0.005357	0	0	0.006354
	S3	0.022595	0.118899	0.000826	0	0.14232
	S2	0.008576	0.288714	0.224492	0	0.521782
	S1	0	0.119013	0.201755	0.008776	0.329544
	Column Total	0.032168	0.531983	0.427074	0.008776	1

	Map 1 as reference		Map 2 as reference	
class	Producer's Accuracy	Kappa value	User's Accuracy	Kappa value
N	0.031	0.0248	0.157	0.129
S3	0.224	0.0947	0.835	0.649
S2	0.526	0.0081	0.430	0.0055
S1	1	1	0.027	0.0180
The overall Kappa agreement 7.3%				
The overall accuracy 35.3%				

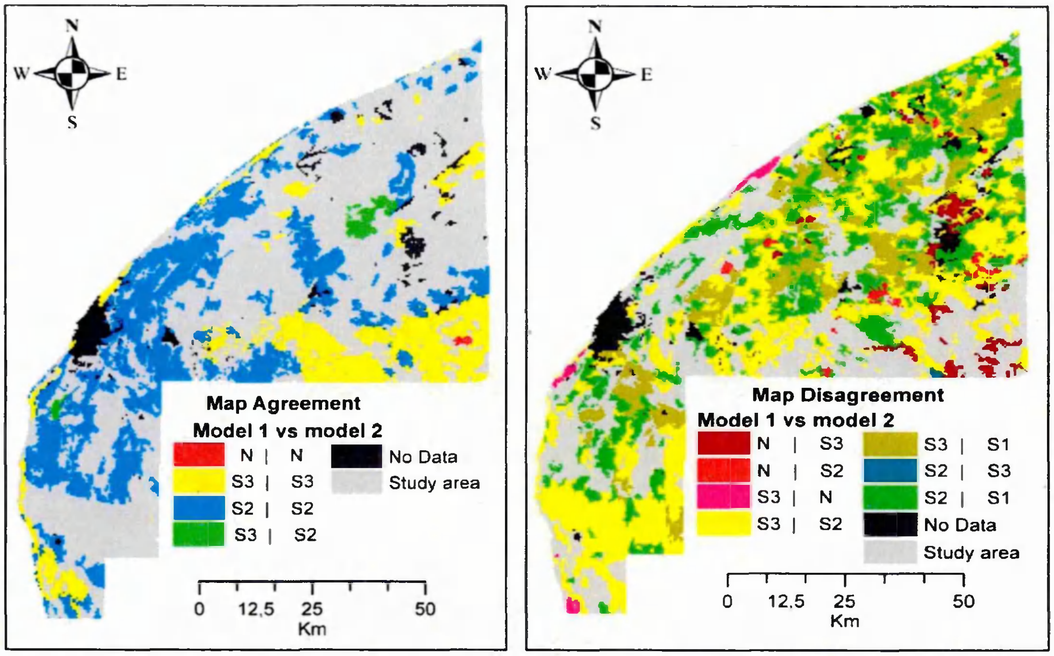


Figure 7.13: Level of agreement and disagreement between suitability classes (Model 1 vs. Model 2) for barley

7.5.3 Model 1 Map vs. Model 3 Map

The results of comparison between Model 1 and Model 3 are shown in Table 7.9. It is similar to the comparison between Model 1 and Model 2. The overall accuracy between Model 1 against Model 3 was about 39.4%, with very low overall Kappa of 15%. The highest value of Kappa per class equal to 1 were found in areas that have been mapped as highly suitable class (S1) in two models map (when map 1 was referenced) and the value of Producer's Accuracy (100%) value equal to 1. Figure 7.14 shows the spatial distribution of the agreement between suitability classes.

Table 7.9: Crosstab Matrix for Barley. Model 1 vs. Model 3

		Map 1 as reference				
	Category	N	S3	S2	S1	Row Total
Map 3	N	0.00624	0.036413	0	0	0.04265
	S3	0.017352	0.141294	0.002536	0	0.16118
	S2	0.008576	0.212098	0.237485	0	0.45816
	S1	0	0.142177	0.187053	0.008776	0.33801
	Column Total	0.032168	0.531983	0.427074	0.008776	1

	Map 1 as reference		Map 3 as reference	
class	Producer's Accuracy	Kappa value	User's Accuracy	Kappa value
N	0.193977	0.1581	0.146293	0.1179
S3	0.265599	0.1245	0.876613	0.7364
S2	0.556074	0.1807	0.518346	0.1593
S1	1	1	0.025963	0.0173
The overall Kappa agreement15.1%				
The overall accuracy 39.4%				

However, when Map 3 was set as reference, the value of Kappa and User's Accuracy for highly suitable class (S1) was very low about 1.7% and 2.6% respectively. Whereas, the rest of proportions of this class i.e. highly suitability class in Model 3 map were mapped as moderately suitable (S2) and marginally suitable (S3) in Model 1 map about 55.3% and 42.1% in total of high suitable class respectively. This means that highly suitability class mapped from the model 3 is associated with high, moderate and marginally suitable in Model 1 and vice versa as can be seen in the disagreement map in Figure 7.14.

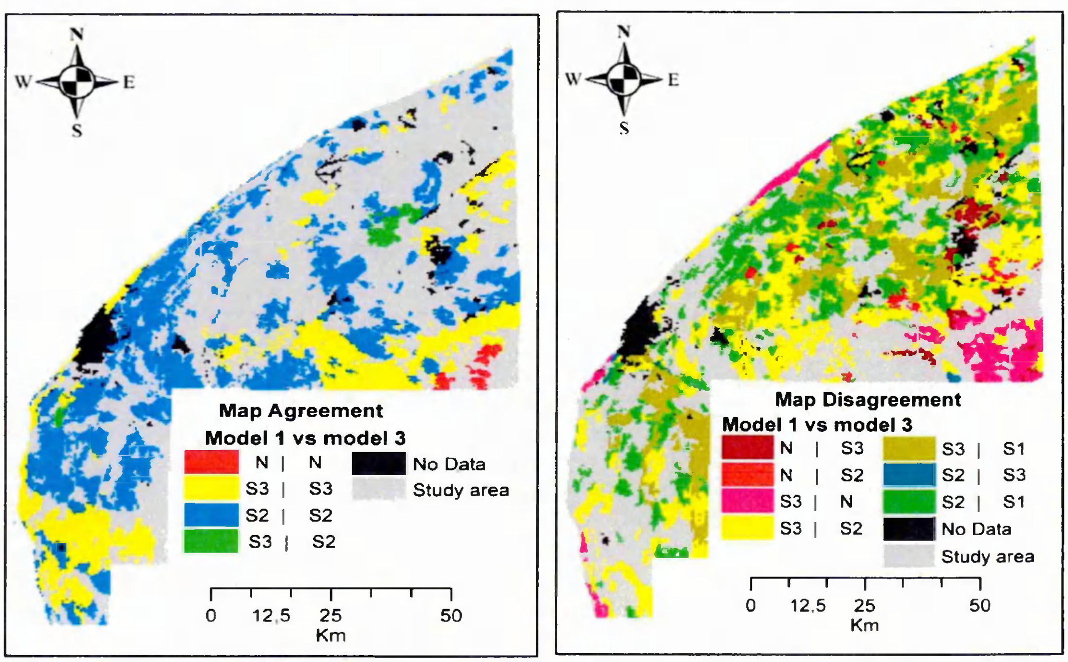


Figure 7.14: Level of agreement and disagreement between suitability classes (Model 1 vs. Model 3) for barley

7.5.4 Model 2 Map vs. Model 3 Map

The comparison in this section illustrates that the results of model 3 are more comparable to the Model 2 map than those from Model 1 map. The overall Kappa agreement between Model 2 and Model 3 is considered very high. From the Kappa values per class it can be seen that only the non-suitable or currently not suitable (N) area has a high probability of not being classified randomly. This means that the whole area of non-suitable class classified in Model 2 map corresponds to the same area in Model 3map as shown in Figure 7.15. The Producer's Accuracy for non-suitable area (N) is 100%. While in the case of map of Model 3, the value of Kappa for this class is very low, about 14%, and the 15% non-suitable area (N) of User's Accuracy refers to a certain non-suitable area in Model 3. The rest 85% of that class (i.e. N) were mapped as marginally suitable (S3) by Model 2. Table 7.10 shows Cross tabulation matrix analysis of Model 2 map (in columns) against Model 3 map (in rows).

Table 7.10: Crosstab Matrix for Barley. Model 2 vs. Model 3

		Map 2 as reference				
	Category	N	S3	S2	S1	Row Total
Map 3	N	0.006354	0.036299	0	0	0.042653
	S3	0	0.10602	0.055161	0	0.161182
	S2	0	0	0.409722	0.048437	0.458159
	S1	0	0	0.056899	0.281107	0.338006
	Column Total	0.006354	0.14232	0.521782	0.329544	1

	Map 2 as reference		Map 3 as reference	
class	Producer's Accuracy	Kappa value	User's Accuracy	Kappa value
N	1	1	0.148965	0.1435
S3	0.6959	0.696	0.657769	0.6959
S2	0.6036	0.604	0.894279	0.7789
S1	0.778	0.778	0.831661	0.7489
The overall Kappa agreement. 68.6%				
The overall accuracy 80.3%				

Moreover, the values of Kappa per class are considered relatively high mainly because most of study area (i.e. suitability classes) was mapped or classified correctly by both models where, Kappa per class is 1, 0.69, 0.60 and 0.77 for class N, S3, S2 and S1 respectively when map of model 2 is reference. Likewise, when the map of Model 3 was referenced, the values of Kappa per class are high except in case of non-suitable class. Figure 7.15 shows the spatial distribution of the agreement and disagreement between suitability classes.

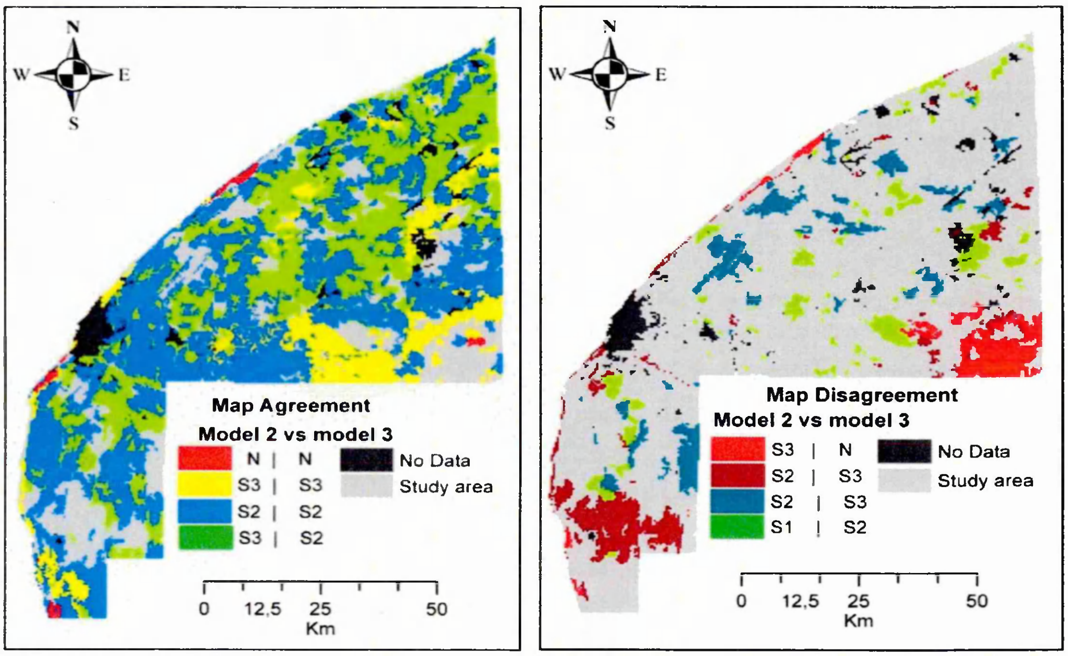


Figure 7.15: Level of agreement and disagreement between suitability classes (Model 2 vs. Model 3) for barley

7.6 Comparison of the Models and Level of Agreement for Wheat

In the case of wheat, the results of comparisons for the three land evaluation models are similar to the barley comparison results in terms of the percentages of the overall accuracy and overall Kappa, mainly due to the difference between the threshold values for each suitability classes and land characteristic for barley and wheat (see Tables 6.4a and 6.4b). However, there are slight differences. One of the reasons for the difference in results between the wheat and barley is the difference in the threshold values as well as the weights given.

The results of comparisons reveal that the highest overall accuracy value among the comparisons of three land suitability maps for wheat (of about 88%) was found between Model 2 against Model 3 with the highest value of 54.48% identifying the total of study area as moderately suitability class (S2) by two models. Table 7.12 below compare and summarise land suitability class for wheat production from three models. The crosstab matrix for the models is further explained in Sections 7.6.1 to 7.6.4.

Table 7.11: Summarises the comparison between land suitability models for wheat

Model 1. vs. Model 2			Model 1. vs. Model 3			Model 2. vs. Model 3		
Legend	Area	%	Legend	area	%	Legend	area	%
1 | 1	588.35	0.10	1 | 1	3681:39	0.62	1 | 1	4589.13	0.78
1 | 2	13330	2.3	1 | 2	10405.4	1.76	2 | 1	21096.6	3.58
1 | 3	5227.9	0.89	1 | 3	5059.8	0.86	2 | 2	85882.3	14.6
2 | 1	4000.78	0.68	2 | 1	22004.2	3.73	2 | 3	11750.2	2
2 | 2	92539.1	15.7	2 | 2	85058.6	14.4	3 | 3	306765.7	52
2 | 3	182557	30.9	2 | 3	162838.5	27.6	4 | 3	13431	2.3
2 | 4	57910.5	9.8	2 | 4	67105.5	11.4	3 | 4	24492.2	4.2
3 | 2	487.49	0.083	3 | 2	2168.5	0.37	4 | 4	121973.4	20.7
3 | 3	143961	24.4	3 | 3	163359.6	27.7	-	-	-
3 | 4	84974.5	14.4	3 | 4	63894.8	10.8	-	-	-
4 | 4	4404.2	0.75	4 | 4	4404.2	0.75	-	-	-
Overall accuracy		40.93%	Overall accuracy		43.48%	Overall accuracy		88.00%

Where: 1= non-suitable (N), 2 marginally suitability (S3), 3 = moderately suitable (S2) and 4 = highly suitable

7.6.1 Results of Crosstab Model for Wheat

Tables 7.12 to 7.14 and Figures from 7.16 to 7.18, show the results of crosstab matrices between three land suitability maps and levels of agreements and disagreements between suitability classes in the models map.

7.6.2 Model 1 Map vs. Model 2 Map

The result of comparison between Model 1 map and Model 2 map for wheat are shown in Table 7.12 and Figure 7.16. The values of overall accuracy between the two models map were about 41%, with a low overall Kappa value of 13%. The highest value of Kappa per class was found in the high suitable class when map of model 1 was referenced and the value of Producer's Accuracy values equals 1. This means that the whole area classified as high suitable in Model 1 map corresponds to the same area on the Model 2 map (Table 7.12).

Table 7.12: Crosstab Matrix for Wheat Model 1 vs. Model 2

		Map 1 as reference				
	Category	N	S3	S2	S1	Row Total
Map 2	N	0.0010	0.0068	0.0000	0.0000	0.0078
	S3	0.0226	0.1579	0.0008	0.0000	0.1813
	S2	0.0089	0.3084	0.2454	0.0000	0.5626
	S1	0.0000	0.0982	0.1426	0.0075	0.2483
	Column Total	0.0325	0.5712	0.3889	0.0075	1.0000

	Map 1 as reference		Map 3 as reference	
class	Producer's Accuracy	Kappa value	User's Accuracy	Kappa value
N	0.031	0.0231	0.128	0.099
S3	0.276	0.1162	0.871	0.6988
S2	0.631	0.1565	0.436	0.0774
S1	1.000	1	0.030	0.0228
The overall Kappa agreement 12.92%				
The overall accuracy 41%				

In contrast, the lowest values of Kappa and User's Accuracy 2.3% and 0.3% were found in the same class i.e. high suitable class (S1) when map of Model 2 was referenced. This means that only 2.3% in total of the high suitability class in the Model 2 map corresponds to that suitability class in the Model 1. The rest of the areas classified as moderately suitable and marginally suitable in Model 1 map are about 50.2% and 39.5% respectively in total of the high suitable class as mapped by

Model 1. This is because few areas have been mapped in Model 1 map as the high suitable class (S1) is less than 1% when compared to other classes in the same model map (see Table 7.12).

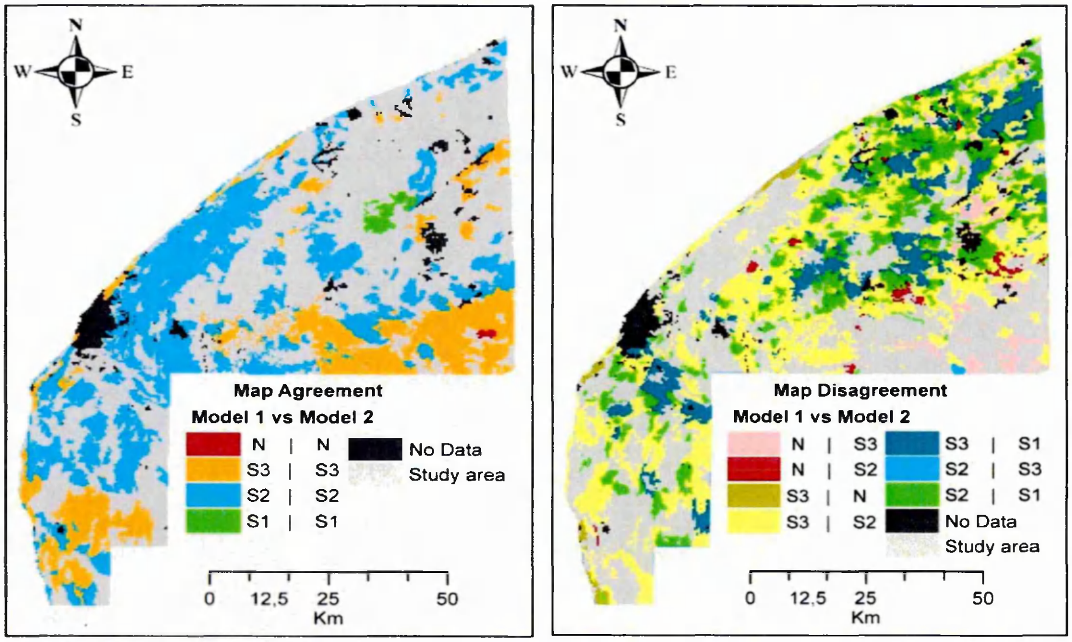


Figure 7.16: Level of agreement and disagreement between suitability classes (Model 1 vs. Model 2) for wheat

7.6.3 Model 1 Map vs. Model 3 Map

The result of comparison between Model 1 map and Model 3 map for wheat are shown in Table (7.13) and the spatial distribution of the agreement and disagreement between suitability classes are shown (7.17).

Table 7.13: Crosstab Matrix for Wheat. Model 1 vs. Model 3

		Map 1 as reference				
	Category	N	S3	S2	S1	Row Total
Map 3	N	0.0062	0.0373	0.0000	0.0000	0.0435
	S3	0.0176	0.1442	0.0037	0.0000	0.1655
	S2	0.0086	0.2760	0.2769	0.0000	0.5615
	S1	0.0000	0.1137	0.1083	0.0075	0.2295
	Column Total	0.0325	0.5712	0.3889	0.0075	1.0000

	Map 1 as reference		Map 3 as reference	
class	Producer's Accuracy	Kappa value	User's Accuracy	Kappa value
N	0.192	0.1555	0.143325	0.1146
S3	0.252	0.1041	0.87	0.6996
S2	0.712	0.3434	0.434	0.1706
S1	1.000	1	0.03	0.0252
The overall Kappa agreement 17.36%				
The overall accuracy 43.5%				

The results indicate that the values of overall accuracy were about 44%, with a low overall Kappa value about 17 %. The highest values of Kappa per class were found in the high suitable class when map of Model 1 was set as reference as well as the value of Producer's Accuracy where both values equal to 1. Meanwhile, the lowest Kappa value (10.4) was found for areas mapped as marginally suitable (S3). This is mainly because most of study area was classified as marginally suitable (S3) with 57% of the total study area compared to only 16.5% mapped as marginally suitable (S3) in the Model 3 map. Whereas, the agreement between the two models for this class e.g. marginally suitable (S3) is about 14.4%. This explains why value of Kappa and User's Accuracy when Model 3 was set as reference in marginally class rose to 73% and 87%. This also means that the majority of marginally suitability class mapped in Model 3 map correspond to the same area of S3 mapped in Model 1.

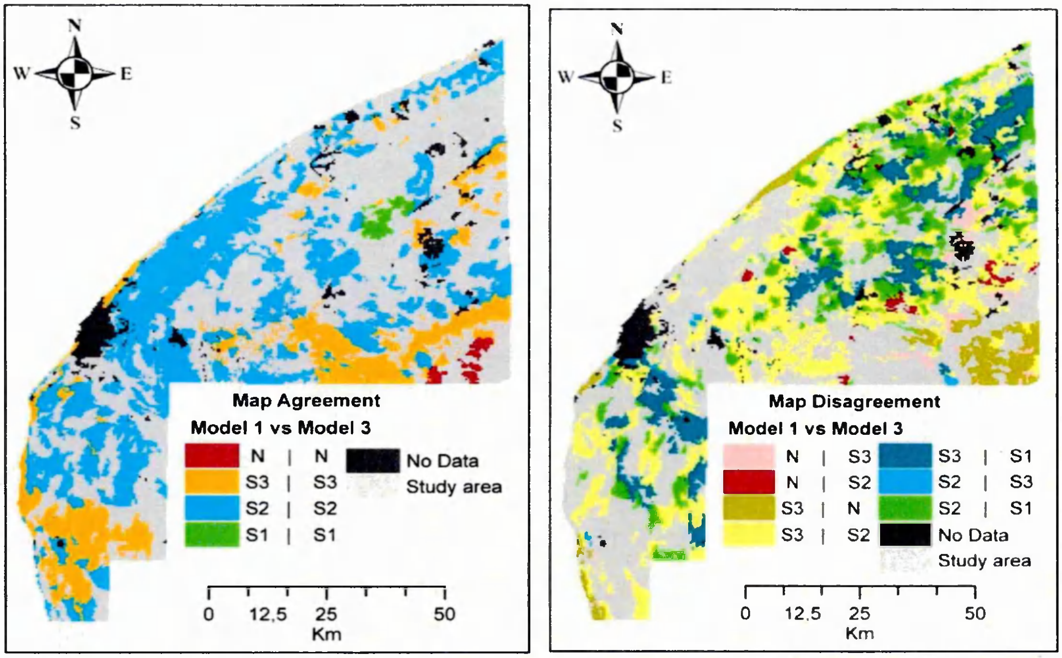


Figure 7.17: Level of agreement and disagreement between suitability classes (Model 1 vs. Model 3) for wheat

7.6.4 Model 2 Map vs. Model 3 Map

Table 7.14 and Figure 7.18 show the results of comparison between the results of land suitability obtained from Model 2 and Model 3 maps. The results of comparison reveal that the agreement between two models is high where the values of overall Kappa and overall accuracy about (0.793) and (0.88) respectively compared to those obtained from comparing Model 1 and Model 2, and Model 1 and Model 3. This explained that the suitability classes due to the highest of Kappa values per class were found within non suitable (N) area where it can be seen that only the non-suitable (N) area has a high probability of not being classified randomly. This means that the whole area of non-suitable class classified in Model 2 map corresponds to the same area in the Model 3 map, where the Producer's Accuracy for non-suitable area (N) is 100% while the value of User's Accuracy is only 17.8% for non-suitable area (N).

Table 7.14: Crosstab Matrix for Wheat. Model 2 vs. Model 3

		Map 2 as reference				
	Category	N	S3	S2	S1	Row Total
Map 3	N	0.007778	0.0358	0	0	0.0435
	S3	0	0.1456	0.01992	0	0.1655
	S2	0	0	0.52	0.0415	0.5615
	S1	0	0	0.0228	0.2067	0.2295
	Column Total	0.00778	0.18133	0.56264	0.24825	1

	Map 2 as reference		Map 3 as reference	
class	Producer's Accuracy	Kappa value	User's Accuracy	Kappa value
N	1	1	0.1787	0.1722
S3	0.8028	0.7637	0.8796	0.8530
S2	0.9241	0.8270	0.9261	0.8309
S1	0.8328	0.7830	0.9008	0.8680
The overall Kappa agreement 79.99%				
The overall accuracy 88%				

Moreover, the Kappa per class is considered relatively high mainly because most of study area was mapped or classified correctly. The values of Kappa per class are 1.0, 0.8, 0.92 and 0.83 for classes, S3, S2 and S1respectively.

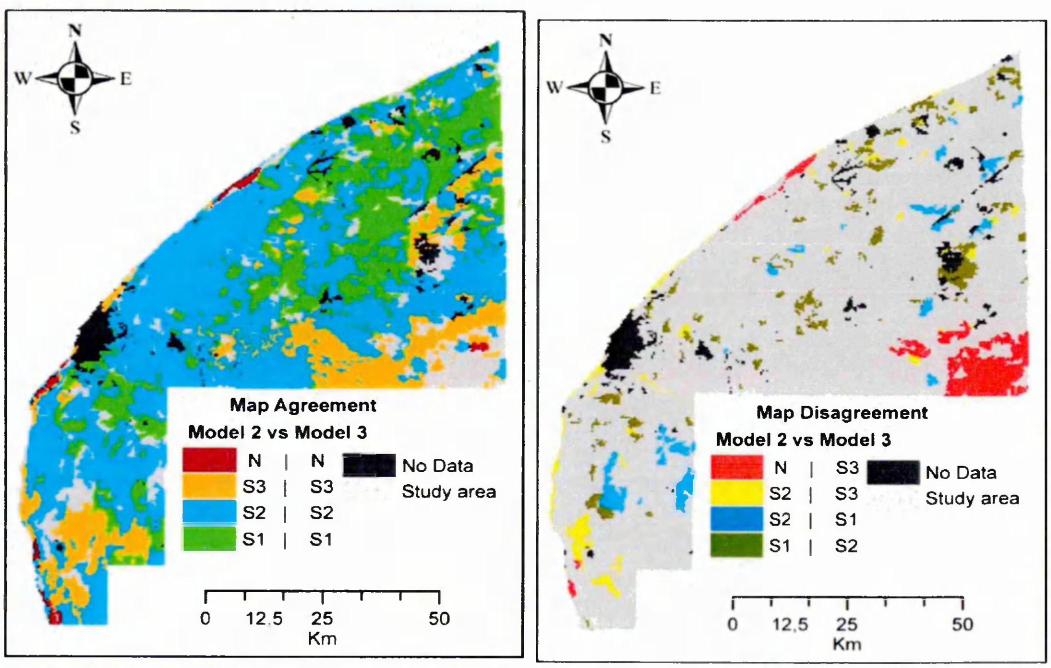


Figure 7.18: Level of agreement and disagreement between suitability classes (Model 2 vs. Model 3) for wheat

7.7 Models validation

The results of the three land evaluation models were explored by comparing the suitability classes with the field results, similar procedures previously have been employed (e.g. Tang and van Ranst, 1992; van Ranst et al., 1996; Triantafilis et al., 2001; Braimoh et al., 2004; Baja et al., 2011). According to Hangens (1990), validation of model results based on one year of crop yield is not enough in land evaluation studies. This is because of variation in crop management, climate, pests and crop diseases affecting productivity, all of which means that crop yields from a number of seasons are needed. Data can be obtained from trial plots (Hangens, 1990; Nwer, 2005), or from surveys of farmers (Clayton and Dent, 2001). As has been presented in the previous chapter, the results of land suitability for study area for barley and wheat obtained from applying model 3 are wider in terms of degree of land suitability than those obtained from Models 1 and 2. So, the results of spatial distribution of land suitability obtained from Model 3 for barley and wheat were chosen as basis for gathering crop yield data. The data on the optimum yield for a particular location being obtained via personal interview and consulting with local experts. Whilst the suitability index depends on the model applied, the suitability of the study area is generally very good, as might be expected for a region that has been identified for agricultural production.

7.7.1 Results of Field Visit

It was found from the Libyan land cover map and the field visit to the study area that was conducted that about 6.7% of the study area had irrigated agriculture compared to about 53.4% of rain-fed agriculture. However, a newly irrigated area on the south-west of study area was not mapped on the original land cover map but was found during the field visit. This is because GMPR has established new agricultural projects during the period of producing this map.

Although 55 and 59 Land suitability sub-classes were identified by Model 3 for barley and wheat respectively, in the field, only 33 and 27 of these classes respectively were obtained. The lack of whole coverage for all the classes was due to variety of reasons. There is still a dominance of rain-fed crops (figure 6.10). Supplemental irrigation from drilled wells, mainly 200-300m deep, is often only undertaken in the absence of sufficient rainfall as result of the high cost of groundwater extraction. Also in some farms, a great deal of fuel is needed to pump the water to the surface for storage and distribution (FAO, 2011). Furthermore, in the coastal areas of Libya seawater intrusion is a problem or a potential problem, limiting the opportunity for groundwater extraction and irrigation. Similarly, there is an absence of crops due to high soil salinity in some locations particularly in the coastal area and in shallow soil depth. The most productive agricultural fields are in the northern coastal areas of the country where irrigation predominantly relies on groundwater (Rashid, et al. 2010). Furthermore, the civil war and insecurity also restricted the full access to all the sites identified by the random sampling operation. The insecurity of the situation at the time of data collection also discouraged farmers to be present in their farms for discussion. Amidst these limitations, as much information as possible that could be useful for the study was collected.

It should be noted that despite of the degree of land suitability, wheat has wide range from (0.28 to 0.93) with 59 suitability sub classes. Data were obtained for only 27 of these classes for wheat was because, for many reasons, most farmers prefer to cultivate barley than wheat. According to Elbeydi et al. (2007), the Libyan people on a regular basis traditionally consume barley. It is most commonly found in the rural areas, where wheat is less readily available for bread making but the urban population also uses it less regularly. Barley plays a major role in Libya's agricultural sector. It is considered as a principal food grain in the daily life of the Libyan people and is always a feature of meals on special occasions. Moreover, barley is more adaptable in the marginal climate and soil. Therefore, this crop is not only suitable for farmers located in the drier hinterland but also for reasons mentioned above.

7.7.2 Results of Validation

The correlations between the land indices obtained by the three models and the observed yields for barley and wheat are shown in Figures 7.17 to 7.22. The correlation coefficients are high for the linear regression of Model 2 and Model 3 land suitability. However, the results obtained with the latter models are in better agreement (R^2 = 0.834) with the observed yields compared to those obtained with the other two models: Model 1 (R^2 = 0.159); Model 2 (R^2 = 0.661) for barley. Likewise, the correlation coefficients for wheat are also high for the linear regression where: R^2 = 0.812, 0. 61 and 0.134 for Model 3, Model 2, and Model 1 respectively.

The variation in the scatter plots of the linear regressions in Figure 7.17-7.22 is largely attributed to the structure of the models and variation in land management practices. As a result, there are variations in the land suitability map produced by each model. However, certain conditions can be noticeable. Models within the same location could have the same observed yield. Likewise, the land index within the same model could be varied. For example, the land indexes of 0.88 in Model 3 and 0.83 in Model 2 have the same proportion of five tonnes per hectare. The main reason for the high yield in this area is that the area is supervised by GMRP irrigation scheme. The areas under GMRP appear to have high management practices like mechanised ploughing, sowing, harvesting and transportation. Also, variation could arise within the same model. For example, in Model 3 the land indexes of 0.71 and 0.65 have the same observed yield of 2.8 tonnes per hectare but are in different location. This is also attributed to the level of farm input such as fertilizer, improved seedlings, timing of cropping and the amount of water available for irrigation. Field visits confirmed that the locations with lower productivity relates to the level of management practice like supplementary irrigation while those with higher yields rely on the GMRP full irrigation and extension services.

The nature of the relationship between suitability and yield could follow a number of forms. Previous work uses linear regression, although with an intercept set to zero (Keshavarzi et al., 2010). However, this is not advocated here, as there seems no a priori reason why zero yields should correspond to zero suitability, thus regression was used to obtain the optimum correlation for the range of suitability encountered.

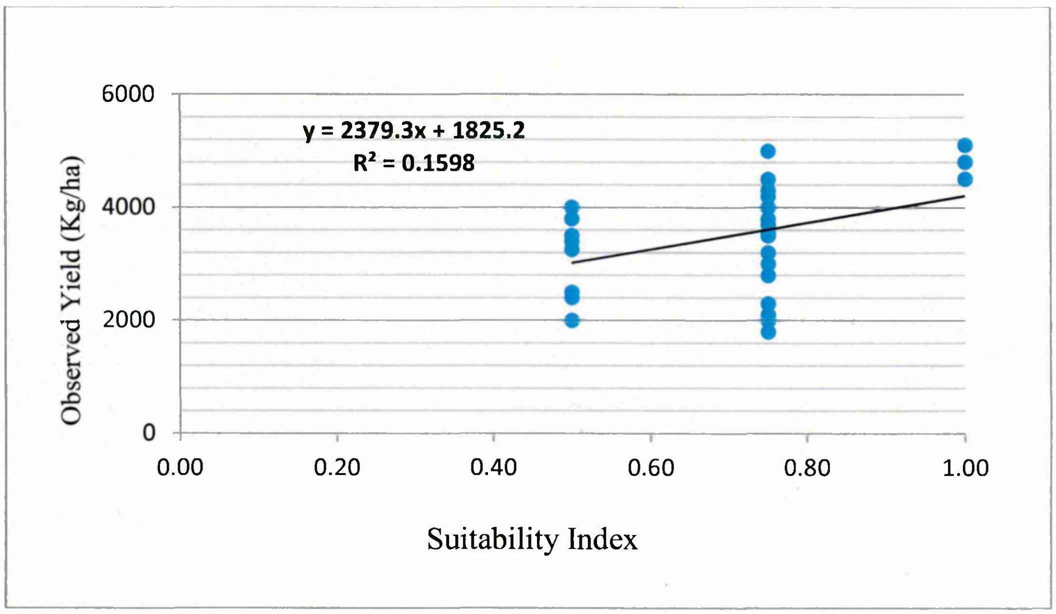


Figure 7.19: Linear regression between land suitability index obtained with Model 1 and observed irrigated barley yield in study area

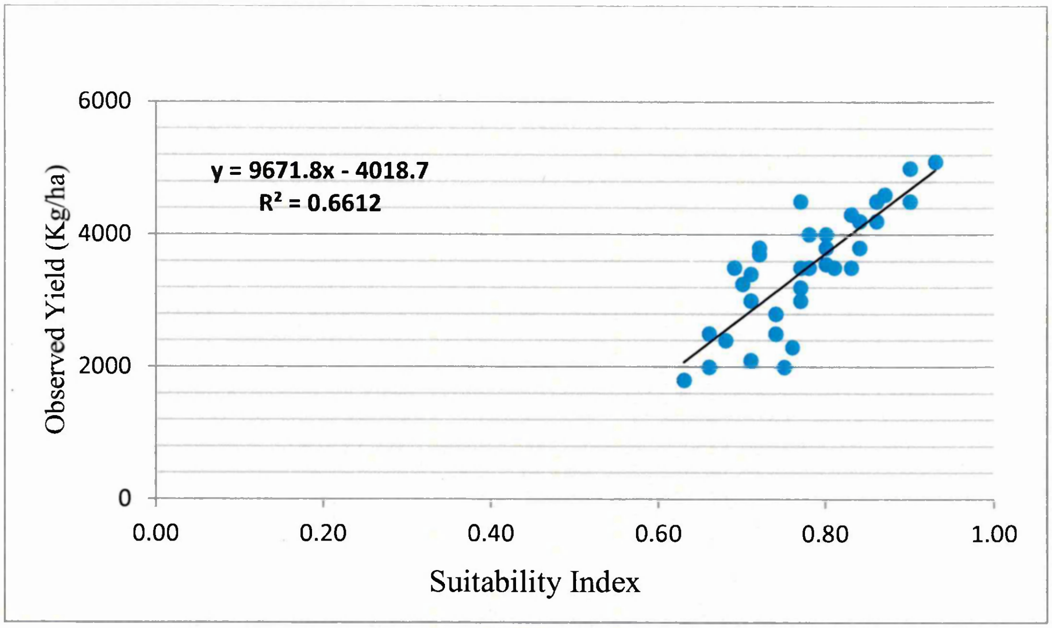


Figure 7.20: Linear regression between land suitability index obtained with Model 2 and observed irrigated barley yield in study area

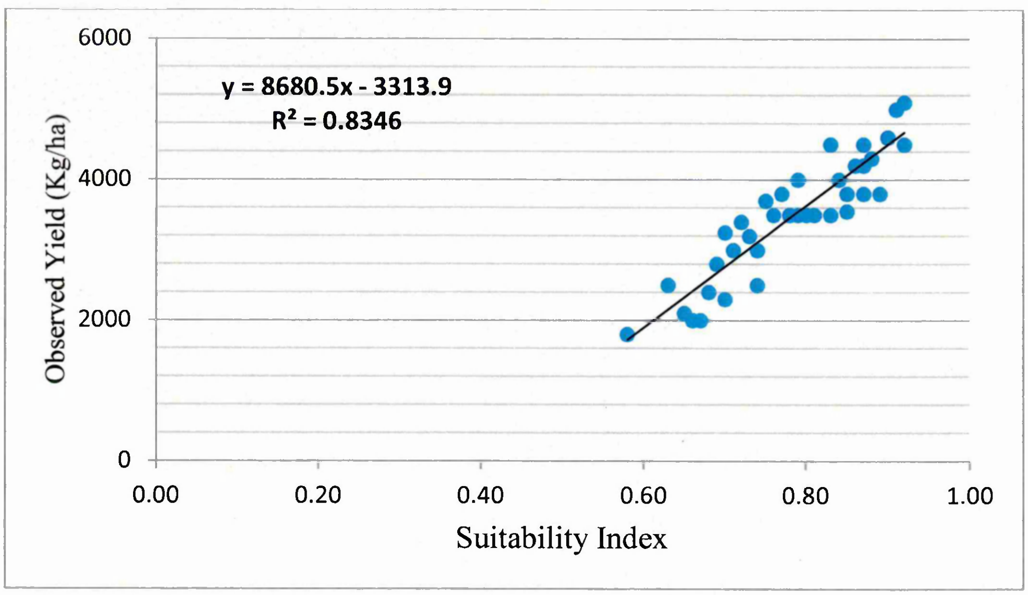


Figure 7.21 Linear regression between land suitability index obtained with Model 3 and observed irrigated barley yield in study area

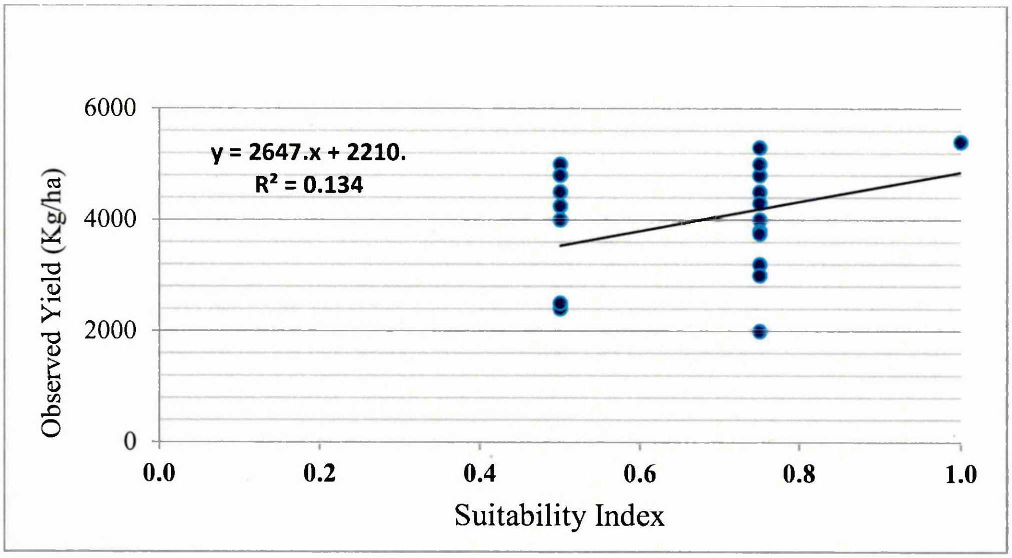


Figure 7.22 Linear regression between land suitability index obtained with Model 2 and observed irrigated wheat yield in study area

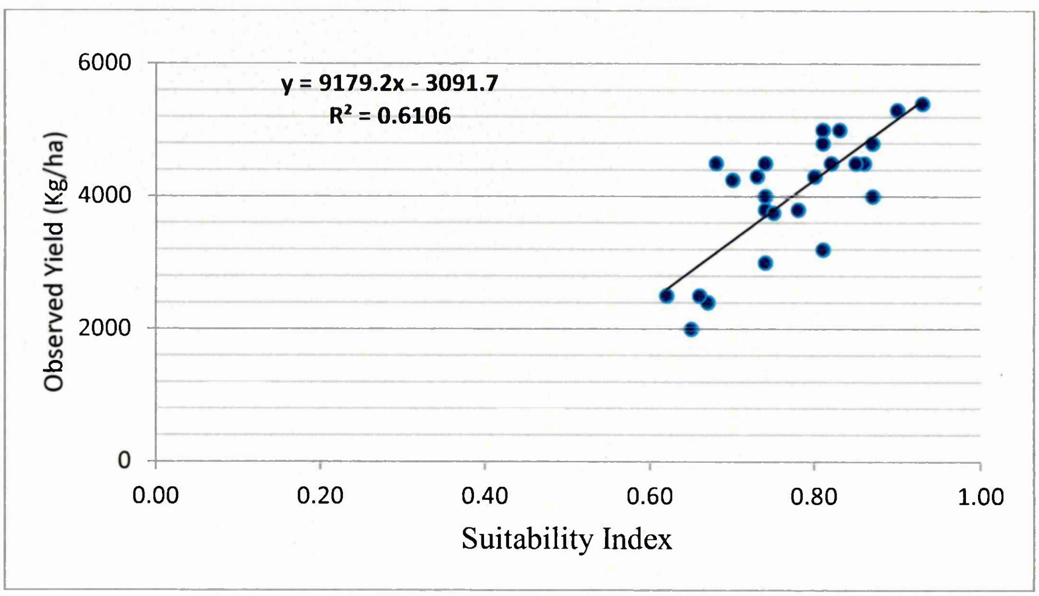


Figure 7.23 Linear regression between land suitability index obtained with Model 2 and observed irrigated wheat yield in study area

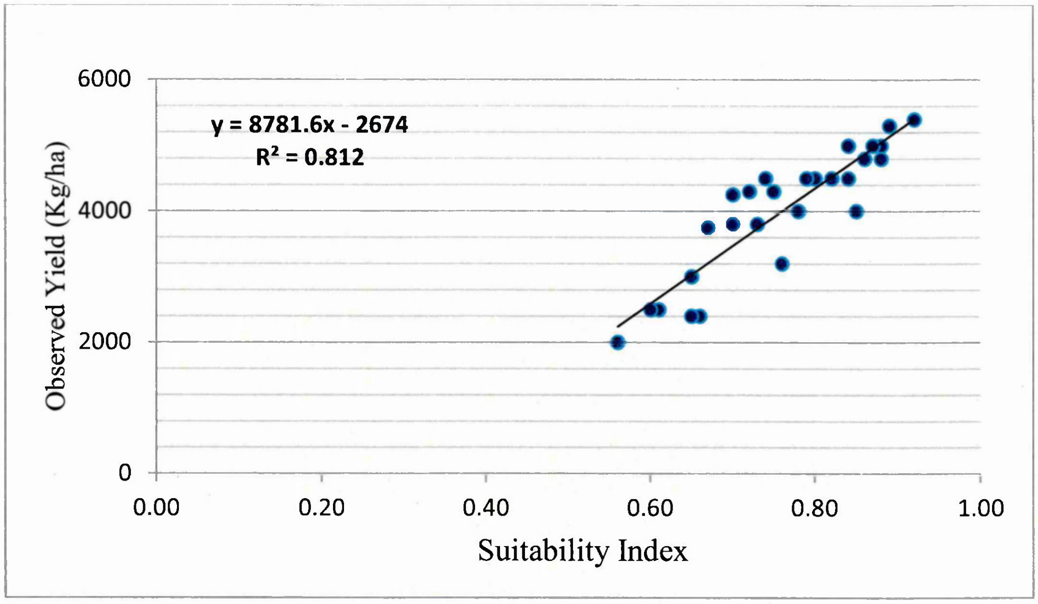


Figure2 7.24 Linear regression between land suitability index obtained with model 3and observed irrigated wheat yield in study area

7.8 Summary

This chapter contributes to the use of AHP method for deriving weights for selected land characteristics. By constructing GAHP, it was possible to incorporate local knowledge and local experts from different backgrounds and integrate their experiences into land suitability modelling i.e. to define and set threshold values for land utilization types, land qualities and land characteristics. The set of weights from six local experts for each level of hierarchy was aggregated from the use of the GAHP method.

Three models have been established for the study – Model 1, Model 2 and Model 3. These land suitability models are based on Boolean, Fuzzy AHP and the integration of MCDM and the GIS functions of WOS and WOT to the FAO framework for land evaluation in study area that have been established for wheat and barley crops. The Boolean model for land evaluation has been developed by taking into consideration the weights resulting from the pairwise comparison analysis after discussion with local staff. Furthermore, the Fuzzy AHP has been used to explore and address the uncertainty associated with the traditional methods. All three land evaluation models were analysed and two types of analyses were undertaken to evaluate the output of models; cross comparison and linear regression. In order to cross-compare the results, each model was ranked or converted into four suitability classes (i.e. S1, S2, S3 and N) according to the guidelines (rating index) set by Sys et al. (1993). The overall accuracy and level of agreement and disagreement between the maps has been computed. The results of the three land evaluation models were validated by comparing the suitability classes with field results; where correlation between the land indices obtained by the three models and the observed yields for barley and wheat was computed.

Chapter Eight

Discussion of Results

8.1 Introduction

The results obtained from Model 1 (existing land evaluation) indicate that the study area has good potential to grow and produce irrigated barley and wheat. Suitability analysis in Model 1 indicated moderately (S2) and marginally suitable (S3) areas for barley and wheat. In addition, the results reveal that a few locations have been found within the study area which are classified as highly suitable (S1) and not suitable or currently not suitable (N1) for barley and wheat. This is less so in the case of Models 2 and 3 for barley and wheat. The suitability analysis indicated Models 2 and 3 indicated as areas of high suitable (S1) and moderately (S2) for barley and wheat. In addition, a few locations within the study area are not suitable or currently not suitable (N1) for the barley and wheat.

This chapter therefore demonstrates the applicability of the three models derived from the study (Models 1, 2, 3) and relates them to existing work (Model 1), why the result is different between models and the effect of structure of each models on the results.

8.2 Discussion of Model 1

The reasons why most of the study area is classified as being between S2 and S3 for both barley and wheat is as a result of using the weighted overlay technique, where the outputs of weighted overlay technique depend on the numeric evaluation scale chosen. Additionally, the discrete output of WOT and the integer value have an effect on the final land suitability output of WOT. Moreover, as pointed out by Davidson et al. (1994) and Van Ranst and Tang (1996), the structures of the land suitability evaluation in the FAO (1976) methodology classifies the suitability of land in terms of two suitability orders (suitable and unsuitable) where the high, moderate and marginal for suitable order and non-suitable order.

The use of Boolean methodology for land evaluation is simple in its application and built on the principle of limiting factor of Liebig`s law of the minimum. Furthermore, the use of the weighted overlay technique with limiting factor method makes the assessment rigorous or discrete. Only one low factor is enough to reduce the suitability from high to moderately suitable or not suitable, even if the relevance of this factor is lower compared to the others. Of course, this is true only in the case of using the limiting factor method to produce the final overall land suitability, which is considered a straightforward process (i.e. without allocation of weights to land characteristics). Using this land suitability classification approach, studies by Burrough et al. (1992) and Baja et al (2001) found that use of a Boolean-based categorical system of land suitability analysis had resulted in the rejection of considerable suitable areas - where the poorer the suitability class, the higher the land suitability index variations.

Additionally, a Boolean-based categorical system was only applied for deriving or producing the suitability for a set of thematic layers (i.e. for the soil layer, all soil characteristics were grouped to determine the overall soil suitability classes as one thematic layer) based on threshold values of selected crops (Tables 6.4a and 6.4b). However, equal weights were given to these sets of thematic layers. Allocating equal weights to sets of thematic layer is unrealistic or arbitrary because the land characteristics can vary in terms of importance and impact on the production and cultivation of the crop. Each characteristic will also differ in terms of its degree of importance depending on the crop, as is the case in the threshold values of barley and wheat.

Giving land characteristics equal weights has led to lower proportion of high suitability class (S1). For the purpose of demonstration, a given parcel of land could be regarded as being moderately suitable for irrigated wheat and barley if the suitability of soil and erosion is marginally (S3 = 2.0) and suitability of slope is moderately (S2 = 3.0), then the overall suitability of parcel of land is marginally suitable (S2). This is because the resultant land suitability by the weighted overlay is based on multiplying each suitability class by allocated weight; in this case, equal weights were given for each suitability layer as follows:

(S3, 2 * 0.333) + (S2, 3 * 0.333) + (S3, 2 * 0.333) = (0.666+1+0.666) = 2.333, which is rounded to an integer value of 2.

Model 1 showed that the use of the weighted overly technique (i.e. converting the decimal value to an integer) is misleading and misrepresentation of reality. The results of Model 1 confirm with ESRI, (2010) in terms of using weighted overly technique: "the use of weighted overlay technique can result in a loss of information which inaccurately reflects reality". This is clear from comparison between Model 1 versus Model 2, and Model 1 versus Model 3. . For barley and wheat the overall accuracy for Model 1 map compared to Model 2 map and Model 3 map was 35%, 39% and 41%, 44% respectively, while the overall accuracy between Model 2 versus Model 3 was high with about 80% and 88% for barley and wheat respectively. Meanwhile, the overall kappa values are very low (poor agreement) when comparing Model 1 vs. Model 2 and Model 1 vs. Model 3, where about 7.4%-12.5% is for barley and 13% - 17.4% for wheat. Comparing the overall kappa between Model 2 and Model 3 shows high agreement, about 69% and 80% for barley and wheat respectively.

The low agreement between Model 1 and Model 2 is due to the lack of non-suitable areas in Model 2 map, which represents about 1% of the study area for both barley and wheat. When compared to the Model 1 map that represent about 3% in total of study area for both barley and wheat. For barley, the user accuracy for non-suitable area (N) was 3.1% with Kappa as 2.5%. This means that if a small proportion of unsuitable area was classified by Models 1 and 2 compared with other classes, only 3.1% (user accuracy) of this class in Model 2 corresponded to the same class in Model 1 map.

The comparison between Model 1, Model 2, Model 3 has shown that suitability classes as determined by Model 1 (highly suitable, moderately suitable, marginally suitable and currently not suitable) was associated with low and high degree of suitability (sub suitability classes) obtained by model 2 and 3 as can be seen in the case of non-suitable class. About 70% and 27% of non-suitable class with Model 1 were mapped Model 2 as marginally suitable and moderately suitable by for barley. However, it is undeniable that most of spatial distributions of areas mapped as non-suitable are located in the coastal area, where the soil is characterised by a high proportion of salinity as well as the high level of ground water known as sebkha (soil with high salinity) in the land cover map for study area. In addition, areas characterized as having a shallow depth of soil are located in the south of the study area. These same shallow areas are mapped in land cover map as Bare Soil Consolidated.

The correlation between crop yields and the suitability of land obtained by Model 1 was very low with $R^2 = 0.16$ and $R^2 = 0.13$ for barley and wheat respectively. This is due to a number of reasons. Firstly, the model output are represented by four numbers, which is because of using the weighted overlay technique process. Second, the imprecision caused by the method used to select the weighting for all criteria or factors (i.e. three thematic layers) that affect the suitability of land for the selected crops. This ascribes equal weighting to each thematic layer as reported in many studies (such as Davidson, 1994; Groenemans et al., 1997; Van Ranst and Tang, 1999; Elaalem et al., 2012; Sarmadian et al. 2010) that clearly affirmed that the selection of weights have a major effect on the model outputs. Third, the weighted overlay tool is applied to solve multi-criteria problems suitability models (ESRI, 2010) and allows for the consideration of geographical problems, which may often require the analysis of different factors. Such is the case with land suitability analysis where determination of overall land suitability of an area for a particular agricultural crop requires consideration of many criteria e.g. soil pH, depth and texture etc (Van Diepen et al., 1991). Each criterion or sub-criterion is represented by a separate map, (a single thematic layer), in terms of the degree of suitability for each land unit. But in the existing land evaluation model for the study area, the land characteristics related to soil, are grouped and represented as one thematic layer. Arguably, this process results in the loss of interaction between factors, particularly when weights are assigned to each land characteristic.

8.3 Discussion of Model 2

The structure in Model 2 is similar to both Model 1 and Model 3. The similarity between Model 2 and Model 1 is that both models applied the same scale (i.e. 1 to 4) with each suitability class ranked and assigned a numerical value. However, the difference between the two models was that the final suitability was derived by only three layers in Model 1. In Model 2, each land characteristic was represented as a layer by itself. In addition, different weights were given for each land characteristics instead of equal weights as has been applied in Model 1. Moreover, the outputs of Model 2 were standardised using Equation 5.17. This procedure allows the suitability of land for barley and wheat to be given values between 0 and 1, where 1 is a highly suitable location and 0 is an unsuitable one.

These differences (i.e. the number of input layers or land characteristics where each LC is considered as a map layer by itself to give fourteen input layers; weights allocated to layers or land characteristics; and techniques being used for deriving the final land suitability) led to clear variations in outputs of two models for barley and wheat. In addition, the results of Model 2 reveal the importance of assigning different weights to the selected land characteristics. For example, the same parcel of land in the previous example classified as marginally suitable (S3) for producing barley was classified as highly suitable (S1) by Model 2 as follow:

(4*0.101) + (2*0.039) + (4*0.039) + (4*0.0617) + (4*0.0419) + (3*0.0939) + (3*0.0825) + (3* 0.0790) + (4* 0.0587) + (3*0.0367) + (4*0.0685) + (4*0.0626) + (3* 0.1190) + (2* 0.1157) = 3.278, then, dividing the resulting suitability by 4 using equation 5.17 3.278/4 = 0.81 based on Sys et al. (1991) and Ben Mahmoud (1995). This resulting suitability class becomes highly suitable (S1). From the previous illustrative example the effect of using the weighted overlay technique and the number of input layers (i.e. land characteristics) and weights assigned to these layers.

The results obtained by this model for barley show that the suitability of the study area ranged between 0.37 – 0.93. The dominant suitability sub-classes are S1 and S2 with the range of the degree of suitability lying between 0.8 and 0.9, and 0.7 to 0.8 and accounting for about 32% and 44% of the total study area respectively. Small amounts of land of about 1.2% and 0.64% of the total study area were mapped at between 0.30 and 0.40, and between 0.9 and 1, which is located within classes N and S1. Similarly, the degree of suitability of land for wheat ranged from 0.28 to 0.93. The majority of the study area has a degree of suitability lying between 0.8 and 0.9 (23.3% of the study area) and 0.7 to 0.8 (45.7% of the study area) thus located within classes S1 and S2 respectively. A small amount of the study area (0.78%) has been mapped with suitability between 0.28 and 0.40; thus non-suitable or currently unsuitable class N.

The results of Model 2 show that no locations in the study area were mapped with a degree of suitability values equal to 1 for barley or wheat. The highest degree of suitability value was 0.93 for both crops. This does not mean the selected land characteristics in the suitability classification for barley and wheat were not assigned or ranked with high suitability rating which in this case is S1 = 4.0 in the study area. In Model 1 where soil characteristics are matched with crop requirements and rated on a scale of 1 to 4, the final soil suitability value is given by the lowest numerical rating value representing the soil thematic layer. This is combined with the results of the soil erosion layer and slope layer.

Layers were produced from the suitability analysis results and integrated in a weighted overlay within the GIS. Although, the same scale of 4 to 1 was used, each land characteristic is itself represented by a thematic layer. The derivation of overall suitability with Model 2 was not only based on the rating values assigned to land characteristics that are based on the structure of the land suitability evaluation in the FAO framework, but also took weighting values derived from applying GAHP method through PMC as shown in Table 7.4. The overall land suitability values and allocated weights were integrated within the GIS (weighted overlay sum).The resulting land suitability values are a direct result of the summation for land characteristics of the multiplication of the suitability value for each land characteristic and its allocated weight. This means that land suitability maps from the use of Model 2 show the interaction between the suitability values and the weights for the selected land characteristics.

The results of Model 2 show that it is possible to identify a wide range of land suitability for barley and wheat, instead of only four suitability classes. Land suitability maps derived from applying Model 2 are like land suitability maps derived from using the fuzzy approach and AHP method in Model 3, although the structure of Model 2 is close to that of Model 1 (i.e. both models apply same scale i.e. 1 to 4). However, comparison of the results from these three models showed very interesting findings. It illustrated that the overall correspondence or accuracy and overall kappa are very low between Model 1 and Model 2 (Table 7.8; Figure 7.13) and between Model 1 and Model 3 (Table 7.9; Figure 7.14) as demonstrated in previous sections. The comparison between the results from Model 2 and Model 3 showed very good agreement for barley (Table 7.10; Figure 7.15) and wheat (Table 7.14; Figure 7.18). This can also be clearly seen when a comparison is made between the two models maps in terms of sub-classes (i.e. comparison between the degrees of suitability values in continuous instead of four category classes). A similarity between land suitability maps produced by Model 2 and Model 3 was found in many sites in the study area. Much of this similarity was found in areas that were mapped at between 0.7 and 0.8 and between 0.8 and 0.9 for both crops. The highest spatial distribution and larger areas were found in those suitability sub-classes, which constitute about almost 44% and 32% respectively in the Model 2 map for barley and 46% and 23% respectively in the Model 2 map for wheat. Likewise, in the case of the Model 3 map, about 36% and 33% respectively for barley and about 37% and 22% for wheat in the study area. Tables 7.5 and 7.6 show the percentages of areas under each sub-class.

The explanation of this similarity is that the numbers of input layers are the same i.e. each land characteristics represented as a thematic layer by itself and are allocated the same weights. On the contrary, Model 1 has only three thematic layers. The differences in the results between Model 2 and Model 3 are mainly because the Boolean approach does not have the ability to allow for the effect of characteristics which happen to have values near to class boundaries. The process of matching between land characteristics with crop requirements rated on a scale of 1 to 4 does not possibly take into consideration the effect of properties that have values near to class boundaries. This means the inputs of Model 2 are based on Boolean logic even if the limiting factor method was not applied. However, Model 3 has shown flexibility when dealing with the membership values according to the degree of suitability or closeness to class boundaries. This is the advantage of using fuzzy approaches in the process of land suitability evaluation.

For validation, the land cover for study area and linear regressions were used to show correlation between the land indices obtained by the different models and observed yields. The linear regression between land suitability indices obtained with Model 2 and observed irrigated barley and wheat yields in the study area were calculated and shown in Figures 7.18 and 7.21 for barley and wheat respectively.

Although the square of the coefficient of correlation (R^2) is relatively low for barley (0.66) and wheat (0.61), a positive gradient shows that the higher the land suitability index, the better the yield in the study area. However, there appear outliers indicating that even as some points have shown high land suitability value, the area produces low yields. The variation in yield could be attributed to differences in land management practices (e.g. irrigation system, fertiliser, timing, mechanisation and seedlings) carried out by different farmers even if the land parcels under consideration have similar biophysical characteristics.

8.4 Discussion of Model 3

As pointed out in previous chapters, the use of a Boolean approach was criticised by many researchers (e.g. Burrough, 1989; Burrough et al., 1992; Hall et al., 1992; Davidson et al., 1994; McBratney and Odeh, 1997; Baja et al., 2001). The results obtained from model 3 were based on the FAO framework but applying the multi criteria method, Fuzzy and AHP methods. The Analytic Hierarchy Process (AHP) was employed to obtain the different weights for the fuzzy calculation (Chapter 6) and to resolve the problem associated with the existing land evaluation model where an equal weight was given to the land characteristics. AHP relies on pairwise comparisons between different parameters to assign importance levels. This process may be subjective and requires expert knowledge and common sense. For this reason, a number of local experts assigned different weights to allow making the most effective decisions.

To reduce the subjectivity of the process and to collect data rigorously, efforts were made in this research to gather all interested groups to land suitability evaluation. While Fuzzy approaches were applied to overcome the limitations of traditional land evaluation systems, a Boolean or rule-based approach was adapted to the principle of maximum limiting factors. The impact of using the Boolean approach was seen clearly in the results from Models 1 and 2, and through the comparisons between Model 1 and Model 3 (Kappa value 0.15 and 0.173 for barley and wheat respectively), and Model 2 with Model 3 (Kappa value 0.686 and 0.79 for barley and wheat respectively). In addition, the result revealed the importance of assigning different weights to selected land characteristics. In addition, the results of linear regression between land suitability index and observed crop yield confirm that high correlation were found in the case of Model 3 (R^2 = 0.83 and 0.81 for barley and wheat respectively) compared to those obtained from Models 1 and 2 (R^2 = 0.66 and 0.61) and (R^2 = 0.16 and 0.13).

There are a number of possibilities that may cause the improvement in the ability of the model 3 to predict the land suitability for crop growth compared to model 2. For this discussion, it is assumed that the measurement of observed yield is correct, despite potential limitations as mentioned previously. Error may occur from inaccurate weighting of criteria, but the weightings have been established as consistent and are applied to both models and are therefore set aside. Therefore attention is focused on the effect of the contribution of each criterion and its magnitude, depending on what model is used, to the land suitability. Wheat land suitability is investigated because the largest improvement in correlation is observed as the sophistication of the theory employed is increased from model 2 to model 3. From inspection of figures 7.23 and 7.24, it can be seen that for an observed wheat yield of 5300 kg/ha, the land suitability obtained by model 2 and 3 is 0.9 and 0.89 respectively. This is only a small change. The raw data used for the criteria to calculate this land suitability is reviewed. This shows that the either the majority of the data for model 2 is in the middle of the classification class, which means that when the same farm is analysed using model 3, there is little change in land suitability. There may be some criteria that are at the edge of a classification e.g. S1/S2, but the impact of this maybe offset against another criteria that is at the other end of the classification i.e. S2/S1 boundary, or that the criterion that is not in the centre of a model 2 classification only has a small weight, therefore does not provide a large contribution to the overall land suitability.

Other farms experience may experience a change in the land suitability, as the model type is changed. For example for an observed yield of 4500 kg/ha, the land suitability increases from 0.68 to 0.74 as model 2 is changed to model 3. This is caused primarily by the values of organic matter, cation exchange capacity and soil texture. These land characteristics were classified S3 but close to the S3/S2 boundary using Model 2. For example, here the value of organic matter = 0.96 according to the FAO (1976) framework which means that the suitability is S3 or marginally suitable (as S3 is >0.5 to 1), whilst the magnitude of the fuzzy membership function of 0.48 is appropriately approximately midway in the range of values (a value of organic matter of 0.5 or less is not suitable and a value of 1.5 or greater is highly suitable. This gives a working range of 1 between not suitable and highly suitable, hence 0.48 is roughly at the midpoint of this range). Alternatively, for an observed wheat yield of 2000 kg/ha, the land suitability decreases from 0.65 to 0.56 as the theoretical model is changed from 2 to 3. This is caused by principally by soil depth, infiltration rate and organic matter. Here the magnitudes of the classification of these variables are S2, but are close to the S3 boundary. Similar behaviour is also observed for the barley data.

The results suggested there were no locations in the study area with a high degree of suitability range 1. Meanwhile the results showed that certain locations in the study area are between 0.9-1.0 for barley and wheat, in contrast there is a low degree of suitability of 0.3 to 0.4 for barley and 0.2 to 0.3 for wheat. The difference between barley and wheat in terms of the low degree of suitability is based on crop requirements. When you compare wheat and barley, wheat is less tolerant to salinity and a larger depth of soil is required in addition to other land properties i.e. cation exchange capacity CEC and soil pH. Furthermore, these factors also explain why both crops have a high degree of suitability and the same values of suitability in some locations. For example, if the depth of soil is higher than or equal to 150cm the value of membership function will be equal to 1 or the suitability rating will be highly suitable S1 or 4 for barley and wheat (see Tables 4.6a and 6.4b for crop requirements). However, if the soil depth is less than 100cm then the membership function equals 0.5 because the optimum soil depth for barley is higher than or equal to 80cm. At this level of soil depth the membership function is equal to 1 (highly suitable S1~ 4) for barley, while for wheat is 0.5.

The results of Model 3 in this research also confirm that the Fuzzy_AHP method is a credible and accurate approach. This could be applied to integrate data from various domains and sources and to delineate an area in diverse suitability classes for a specific land utilisation type through the MCE technique in a GIS context. This is in agreement with a study by Triantaphyllou and Lin (1996). They applied five fuzzy multi-attribute decisions making methods and concluded that the Fuzzy_AHP approach is more accurate than Boolean. Besides, in this methodology, expert knowledge has been very vital in obtaining reliable results. Using fuzzy set methodology, the rigid Boolean logic of suitability as determined by suitable or non-suitable land characteristics are replaced by fuzzy membership functions or membership values. Land characteristics that exactly match the strictly defined suitable situation are assigned a membership value that has worked in this research.

The attractions of fuzzy set methodology to land evaluation are explained by Burrough (1989) and Tang et al. (1991). Case studies are given by Wang et al. (1996), Hall et al. (1992), Burrough et al. (1992), Tang and Van Ranst (1992a, b), Davidson et al. (1994), Van Ranst et al. (1996), Lark and Bolam (1997), Mays et al. (1997), and Dobermann and Oberthtir (1997).

8.5 Summary

This chapter shows the different models used to produce land suitability maps for barley and wheat. In doing so, it has outlined the specific strengths and limitations of each of the three models developed. Furthermore, the models were compared for validation, reliability and robustness. Whether the combination of methods for land suitability modelling has been achieved can be seen in the concluding chapter of this thesis, Chapter Nine.

Chapter Nine

Conclusions and Recommendations

9.1 Introduction

The final land suitability can be ascertained by either more or less complex means by using different GIS analytical functions (i.e. weighted overlay analyses). Unfortunately, many who use the weighted overlay technique for modelling land suitability evaluation for agricultural crops do not fully appreciate the current approaches that convert the decimal value of model output to an integer. Furthermore, they are not aware of the full potential of the weighted overlay technique in terms of producing accurate and insightful results. This research has bridged that gap by presenting a GIS-based multi-criteria evaluation decision analysis method for land suitability evaluation use of the GAHP method with fuzzy set models for effectively solving problems associated with Boolean logic. Indeed, this comes with strict assumptions and the absence of uncertainty or vagueness associated with land suitability models in terms of measurement and imprecision. In reality, especially as in the case of this study, these assumptions are incorrect.

There are three main reasons for using fuzzy set methodology rather than the traditional Boolean method in land evaluation studies. First, Boolean defines an exact boundary as a crisp set - an element or suitability level is either included or excluded in a set. Second, a fuzzy set permits flexibility in defining the boundary of the object in the set to represent and deal with ambiguity. From the above, Boolean cannot take account of partial membership of an element in a set, as would fuzzy technique. Therefore, this study, in addition to other authors like Davidson et al. (1994) recommends fuzzy set methodologies as a tool for overcoming vagueness and uncertainties in land evaluation modelling, and assigning weights for selected factors. This also applies to employing different approaches for assigning weight i.e. by either giving equal weight to different land characteristics (existing land evaluation model) or deriving weight by applying AHP method via PCM. Moreover, it has shown that indigenous knowledge from local experts can be a supporting tool in decision-making in land evaluation studies. The AHP method with fuzzy set is capable of capturing qualitative and quantitative information which the decision maker or analyst may have regarding his/her perceived relationship between the different evaluation criteria.

In summary, a key element in this study was the use of multi-criteria methods integrated with a Geographic Information System. This integration of the study enabled the evaluator to produce specific land information maps for each land utilisation type. This study has shown how to gather, compile and integrate indigenous knowledge of different land owners/farmers and local experts opinion. There was varied opinions and convergence of ideas between and among farmers and experts, although the land parcels under consideration have similar biophysical characteristics in terms of the selection of land characteristic, land qualities and land use requirements. This process was done in Nwer's study and re-evaluated in this study by building a group of local experts based on their experience to allocate different weights for LC for wheat and barley.

Section 9.2 of this chapter presents the key conclusions of the thesis by relating them to the research questions and objectives of the study. Section 9.3 provides policy recommendations for options for land evaluation studies in Libya and considers potential areas for future research.

9.2 General Conclusions

The general conclusions are listed according to the Research Questions and objectives set out for this study in Chapter One are as follows:

1. How do results change when different approaches such as multi-criteria methods and GIS functions are applied to land suitability model?

From the comparison between the resultant land evaluation models, it can be clearly seen that there are big differences between the results of three models in terms of percentages of land suitability classes and in terms of spatial distributions of these classes. As already described, the variation in the overall land suitability given by three models was not caused only by the suitability values for each LC that was based on Boolean logic following the principle of limiting factor. For example, in Models 2 and 3, it was not possible to classify the values close to class boundaries i.e. suitability class ratings (threshold value). Following the Fuzzy method, model 1 shows the flexibility when dealing with the membership values according to the degree of suitability or closeness to class boundaries. Also, applying weighted values allocated to each LC and GIS analytical functions (i.e. WOT and WOS) have major effect on the model's output, where the resulting land suitability values are a direct result of the summation of the multiplication of each value by the weights.

It should be recalled that the resultant land suitability values derived by WOT are rounded to an integer, which leads to a loss of precision and invariably affects the overall land suitability output, as indicated in Table 7. When Models 2 and 3 were compared the overall land suitability was graded into four classes, due to the rounding process, instead of having a range of suitability as in the case of Models 1 and 2. Moreover, the number of input layers was shown to affect the land suitability results. To emphasise this, the land suitability map generated from Models 1 and 2 shows there is more interaction between the suitability of LCs values and their weights, compared with Model 3 where the resultant land suitability map was calculated from three input layers.

2. Is it possible to develop existing land suitability model?

Yes, results of this research have demonstrated that it is possible to develop the existing land suitability model by more than one way even under the use of Boolean approach as in the case of Model 2. In this model the logic of Boolean was applied to determine suitability ratings for individual land characteristics based on the FAO framework as well as in the case of Model 1. The results of Model 2 showed that it was possible to improve existing land suitability model even under the use of Boolean logic because, the results of the Boolean approach also depends on the functions and rules which can easily be employed in GIS environment, such as weighted overlay or weighted sum. It is suggested however, that the use of Boolean logic with limiting factor should be discontinued. This is because it unnecessarily converts continuous measurement of all data used to a coarse classification of one of four choices, based on the variable that is evaluated as being the worst. This potentially results in land use not being optimised, although the analysis procedure is straightforward. An improvement in the theoretical model results compared to field yield data is obtained if the Boolean technique is used. This is caused primarily by the inclusion of more data in the theoretical evaluation of land suitability. However, the quality of the model results are limited by the allocation of continuous data into discrete classifications. Here, four classifications from highly-suitable to non-suitable are used. It is recognised that an improvement of the theoretical land suitability would occur if, for example 8 or 16 or perhaps 32 classifications were used for each criterion and each factor. However, there is likely to be potential problems in establishing systematic techniques to determine the boundaries of such classes. A much more elegant approach is to create a continuous classification scale for data measured on a continuous scale using Fuzzy membership functions. Fuzzy methods require the selection of membership functions and weights that are not pre-established and require expertise. In this research the AHP method were applied to derive weights for selected land characteristics. Furthermore, this research illustrate that one can use AHP method to offer guidance when group of local experts participate in the research process.

3. Which land evaluation system is most suitable for use taking into account Libyan land conditions?

The results of this research indicated that the use of the FAO framework for land evaluation based on Fuzzy logic and GAHP methods for the selected crops under irrigation conditions, gave satisfactory results. These appear more realistic than those obtained from Model 1 and Model 2. The results of this research as described in chapter seven are in agreement with many studies such as (Elaalem, 2010) based on the use Fuzzy logic and AHP method.

4. How will the newly developed (land suitability) model help the Libyan government in decision-making process for land use planning?

The results of this research would be useful to the Libyan authorities in planning to achieve the optimum use of available land for strategic production of barley and wheat crops for food security. Since the results of land suitability from the use of FAO framework based on Fuzzy and AHP methods were presented as a continuous scale 0-1; it is considered by many scholars as a more realistic classification in nature (e.g. Burrough, 1989; Davidson et al., 1994; McBratney and Odeh, 1997; Baja et al., 2001). The high land suitability values refer to highly suitable classes and the low values refer to less suitable classes. The implication of these findings is that locations, which were mapped with low suitability values for wheat and high suitability values for barley, should be designated for barley production, and vice versa. However, as pointed out by many researches (e.g. Baja, 2006; Elaalem, 2010; Nwer, 2005), this will require designating some small farms or small agricultural projects within these locations for trial crop production. This will help the GMPR project and the decision makers in Libya towards improving the management of the arable lands in the study area and for planning agricultural land development in the study area.

5. What are the problems or limitations from the use of multi-criteria methods and how can that be resolved?

In general, there are many problems from the use of multi-criteria methods, such as availability, quantity and quality of data. For example, methods that rely on Boolean logic require high accuracy and data detail that is difficult if not impossible to find in reality. This limitation can be resolved using fuzzy-set methodology that can be considered as a new phase in the quantification trend as have been done in this study. This is true in the case of quantitative data i.e. numerical data being used in land evaluation analysis. However, the use of fuzzy logic with qualitative data i.e. categorical data, as in the case of soil texture may be somewhat inaccurate, because the result is still in rigid values as in Boolean logic. The overall suitability assessment of land units has to be based on a weighting factor of the relevant land characteristics. Furthermore, the use of the Analytic Hierarchy Process (AHP) to obtain the different weights through pair wise comparisons for the fuzzy calculation process may be subjective especially when it relies on the contribution of one expert. It is possible to solve this problem with the help of participants of all interested groups to land evaluation - such as local experts, farmers, owners - and other stakeholders on the basis of expert knowledge and local advice, experimental data, previous land evaluation methods etc. to assign importance levels for different parameters. As illustrated in Chapter Five and Six it is possible to construct or use GAHP. This will lower subjectivity and biases of process and will allow making the most effective decisions.

9.3 Recommendations and future work

This study is concentrated on two main crops (barley and wheat) that are dominant in the study area. The same methodology (i.e. FAO framework for land evaluation based on using Fuzzy and AHP) employed in this research can be applied to more food and even cash crops in Libya. However, it should be noted that in this study the climate factor i.e. mean temperature in growing season were ignored because the mean temperature in the growing season for the study area is homogenous and does not influence barley and wheat production. Therefore, it should be taken into account for other crops. Moreover, the values of weights designed for selected land characteristics for barley and wheat may not be suitable for other areas and crops.

This research is considered to be the first study that alerted to the limitations of applying WOT in land suitability classification for agriculture, and the full potential of WOT in terms of producing accurate and insightful results. This problem should be considered when using WOT in land suitability evaluation and addressed in further research. In addition, this study shows the importance of using AHP method for deriving weights for selected land characteristics by constructing GAHP. The GAHP process has allowed the incorporation of local knowledge with fuzzy approach into the model of decision making for land evaluation application. Moreover, the number of input layers affected the land suitability results. To emphasise this, the resultant land suitability map from Model 2 and Model 3 showed more interaction between the suitability of LCs values compared with Model 1 where the resultant land suitability map was calculated from three input layers.

In light of this, it is proposed that the models presented in this research provide important tools by which to study land evaluation for the suitability of growing wheat and barley in Libya at a low scale. If this notion is adopted, it must too be accepted that information gathered in this way can help fill some of the knowledge gaps and help to link land and crop production for maximum production. The approaches adopted in the thesis can together provide data for further application and validation of the models. The evaluations of land using complex multi-criteria approach for selected crops at this scale provides a valuable alternative and help to illuminate the scaling issues.

The following are suggestions on areas for further extension of this research and to improve food production and agricultural land management in Libya.

1. The evaluation carried out in this research is in terms of physical suitability of land for irrigated crops. A further extension of this research can integrate the appraisal of environmental, economic and social indices in particularly Model 3. This will show the not only physical suitability of the land but also the economic benefit resulting from the use of a scientifically proven land evaluated for a particular crop production. Furthermore, as GMRP is opening new lands for irrigation, the models developed by this research can be used to establish trial plots before the full implementation of the irrigation scheme.

2. It was reported in Chapter Two that the major agricultural activities in Libya, particularly in the study area, are the cultivation of barley and wheat crops. Field visits indicated that activities are being done in small plots of land with poor management, traditional tools and often for subsistence. As a result, agricultural production fell short of that needed for a growing population – hence the food security problem faced by Libya. Suitable management of land and water by using the most suitable land for the most suitable crop is very necessary for food security,

self-sufficiency and improving the quality of life for rural populations and the country as a whole. In this case, therefore, this research argues for the application of this study to achieve the afore-mentioned benefits. Therefore, land-use policy in general must take account of land suitability in relation to the expected future societal needs and the possibility of meeting demands for environmental protection, food sufficiency and sustainability.

3. The agricultural land use system of the country should meet local demands of food. This research advocates the development of infrastructure in areas classified as highly suitable for wheat and barley production. This is because the reduced availability of lands highly suited to agricultural production reduces the sustainability of existing agricultural systems and encourages the use of more marginal lands for agriculture. Likewise, the areas classified as non-suitable for wheat and barley can be tested for other crops if the physical conditions allow. This is because the mountain and desert areas may not be suitable for any food crops.

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APPENDICES

Appendix A

A. 1. The definitions of Soviet terminology of class, subclass, type, subtype and genera.

- **Class**: A class unites soils of similar mineral part composition, the similarity being caused by the nature and direction of soil formation, as well as by peculiarities of origin and age of parent materials (weathering crusts).
  - **Subclass:** A subclass unites soil types with similar combinations of the conditions of their formation connected with the development processes which are conditioned by the composition and properties of the soil-forming rock, as well as peculiarities of climatic regimes.
- **Type:** A type unites soils which develop under similar (typical) biological, climatic and hydrological conditions, and which have a similar soil profile structure and, generally, similar properties. Soils of a single type are characterised by common origin, migration, transformation and accumulation of substances. Their genesis is connected with a distinct manifestation of the soil formation processes, with possible combinations with other processes.
  - **Subtype:** A subtype embraces soils within a type, varying in quality as far as the intensity of manifestation of the main and secondary elementary processes of soil formation is concerned. Subtypes represent stages of an evolutionary transition of one type into another. While reflecting the peculiarities of soil development, subtypes preserve a general typical structure of the profile, but, at the same time, possess some specific features of their own.
- **Genera:** A genus includes soil groups within a subtype. A genus reflects soil properties connected with the influence of local factors, manifestation of the features caused by a peculiar character of parent material influence, chemical composition of groundwater. The given classification distinguishes soils into genera according to their calcareousness, leachedness, solonetzicity, and salinity, as well as to the combination of these properties.

A2. Classification of the soils and their codes of the study area

Type	**Subtype**	**Genera**	**Code**
Red Ferrisiallitic	Typical	Carbonate, carbonate saline Leached, leached saline.	F-t-ca, F-t-cas, F-t-l, F-t-ls
	Concretionary	Carbonate saline, Leached, leached saline.	F-c-cas, F-c-l, F-c-ls
	Crust	Carbonate, carbonate saline Leached, leached saline.	F-cr-ca, F-cr-as, F-cr-l, F-cr-ls
	Hydrated	Carbonate, Leached, Leached saline.	F-hd-ca, F-hd-l, F-hd-ls
	Hydromorphic	Carbonate solonetzic-saline	F-h-casna
	Of a truncated profile	Leached, leached saline	F-i-l, F-i-ls
Yellow Ferrisiallitic	Typical	Leached	Y-t-l
	Concretionary	Leached	Y-c-l
Siallitic Cinnamon	Typical	Carbonate	CS-t-ca
Rendzina	Dark	Carbonate,	Rz-ca,
	Red	Carbonate, carbonate saline Leached, leached saline.	Rz-r-ca, Rz-r-cas Rz-r-l, Rz-r-ls,
Reddish Brown Arid	Differentiated	Carbonate, carbonate saline Carbonate solonetzic-saline	FB-d-ca, FB-d-cas, FB-d-casna,
	Differentiated Crust	Carbonate, carbonate saline Carbonate solonetzic, Carbonate solonetzic-saline.	FB-dcr-ca, FB-dcr-cas FB-dcr-cana, FB-dcr-canas
	Slightly Differentiated	Carbonate	FB-sd-ca
	Slightly Differentiated Crust	Carbonate, carbonate saline Carbonate gypsic.	FB-sdr-ca, FB-sdr-cas FB-sd-cag
	Non-Differentiated	Carbonate	FB-nd-ca
	Hydromorphic Crust	carbonate saline Carbonate solonetzic-saline	FB-hcr-cas, FB-hcr-casna
Brown Arid	Differentiated	Carbonate, carbonate saline	B-d-ca
	Slightly Differentiated	Carbonate, carbonate saline	B-sd-ca, B-sd-cas
Lithosols	Reddish Brown	Carbonate, carbonate saline	L-fbl-ca, Lfb-cas
	Brown	Carbonate, carbonate saline	L-bl-ca, L-bl-cas
Crusts	Non-Monolithic	Carbonate, Carbonate saline Siallitic carbonate, Siallitic carbonate saline	CR-nm-ca, CR-nm-ca CR-nm-sica, CR-nm-sicas,
Solonchaks	Automorphic		Sa
	Hydromorphic		Sh
	Hydromorphic crust		Shcr
	Hydromorphic sebkha		Shs

A3. A brief description for the soil in study area

A. 3.1.1 Red ferrisiallitic Typical soils (Ft)

The red ferrisiallitic typical soils are fairly common in the eastern .They develop on parent materials whose properties are scribed in the foregoing characteristic of soil types. The soil-forming processes common to the whole type are most pronounced in the red ferrisiallitic typical soils. In the wet period intensive weathering takes place under the conditions of the neutral and alkaline reaction which leads to de-carbonation of the soil profile, formation of secondary minerals high in silica, liberation of iron oxides. In the dry period due to intensive moisture evaporation there is a pronounced upward movement of alkali-earth bases, rube faction of iron compounds take place. The following sequence of genetic horizons is observed in the red ferrisiallitic typical soils with a fully developed profile: A_1, B_1ox, B_2ox, B_3ox, BC, C, R (or CR). An Ap horizon is distinguished in arable soil.

A. 3.1.2. Red Ferrisiallitic Concretionary Soils

The parent material is represented by eluvial-deluvial loamy and clayey deposits of limestone of small thickness (50-120). The profile of the red ferrisiallitic concretionary soils usually falls into the following horizons: A_1, B_1ox, B_2ox, B_3ox, and R. additional horizons BCox and C are differentiated in the soils with a tick profile. In ploughed up soils Ap horizon is singled out. The red ferrisiallitic concretionary soils are represented by genera Leached and Leached saline.

A. 3.1.3. Red Ferrisiallitic Curst Soils

These are spared in the western and central parts eastern zone in the regions of Daryanh, Benghazi, Al Marj and Tukrah. The parent materials here are eluvium and deluvium of lime stones or, in places, proluvial deposits which are mainly of clay loamy and clay texture. The soils a deeply developed profile exhibit the following sequence of horizons: A_1, B_1ox, B_2ox, B_3ox, BC and CR. No B2ox, B3ox, and BC horizons have been generally observed in the soils of weakly developed profile. The Ap horizon is distinguished in the ploughed soils. The following genera have been distinguished the subtype of the red ferrisiallitic curst soils: carbonate, carbonate saline, leached and leached saline soil. The most common is genus of the leached soils it is followed by that of the carbonate soils, their saline analogues being spread to a considerably lesser extent.

A. 3.1.4. Red Ferrisiallitic Hydrated Soils

The red ferrisiallitic hydrated soils occupy a small area of study area about 0.91% of study area. They occur in the regions of Al Marj and Jardas Al Abid and Al Abyar. Clay loamy and clayey alluvial-proluvial and eluvial-deluvial limestone deposits represent the parent material. The red ferrisiallitic hydrated are the characterised by the main features of the ferrisiallitic type soil formation accompanied by the hydration processes (accumulation of hydrated iron forms) and to a certain extent, by the process of concretion formation, i.e., segregation of free forms of iron and formation of ferruginous concretion. The red ferrisiallitic hydrated soil profile is characterised by the horizon sequence of A_1, B_1hox, B_2hox, B_3hox, BC, C and sometime R. the Ap horizon is distinguished in the ploughed soils. The subtype of the red ferrisiallitic hydrated soils is divided into the following genera: carbonate, carbonate saline, leached and leached saline.

A. 3.1.5. Red Ferrisiallitic Soils of a Truncated Profile

The red ferrisiallitic soils of a truncated profile are wide spared on the territory of the eastern zone. The soils of the subtype under retain the principal features and properties of the red ferrisiallitic soils. At the same time they are distinguished from the other soil subtypes by their truncated profile (from 5 to 30 cm), slight differentiation into genetic horizons and erodibility of the upper horizon. The profile of the red ferrisiallitic soils of a truncated profile is characterised by sequence of the following genetic horizons: A_1, Box and R or A_1 and R. the genus of the leached and leached saline soils have been singled out in the subtype of the red ferrisiallitic soils of a truncated profile.

A. 3.2.1. Yellow Ferrisiallitic Typical Soils

The yellow ferrisiallitic typical soils cover small area and they occur as two large tracts of land on the lower step of the Jabal akhdar upland: north-west, north and north-east of Al Marj. The peculiarities common to the type of the yellow ferrisiallitic soils as a whole with inconsiderable deviations, in color intensity depending upon the amount of iron oxides and degree of their hydration show most conspicuously in the subtype under consideration. The common horizon sequence in the yellow ferrisiallitic typical soils comprises Ap, B_1hdox, B_2hdox, B_3hdox, and R or BC and C horizons. The parent material (horizon C) is characterised by a yellowish brown or brownish yellow color, often with red mottles; clay texture, general structure lessens, firm consistence.

A. 3.3.2. Yellow Ferrisiallitic Concretionary Soils

The yellow ferrisiallitic concretionary soils have a limited occurrence on the territory of the eastern zone,. The parent materials of the soils are eluvial-deluvial deposits of limestone weathering products and alluvial-proluvial deposits transferred from the territory of the upper step of the Jabal Akhdar upland. the general typical peculiarities of the yellow ferrisiallitic soils the subtypes under consideration is characterised by a considerable development of the concertinaing processes usually in the horizons A_1, and B_1hdox, the iron concretions forming in these horizons often make up 5% and more of the horizon volume. As to the nature of leaching from carbonates only one genus of leached soils is singled out in subtype. The following profiles are distinguished in the soils with a thick profile: Ap, (or Ap and A_1cn), B_1cnhdox, B2hdox, B3hdox, C.

A. 3.4.1 The Siallitic Cinnamon Typical Soils

The Siallitic cinnamon typical soils are found in eastern zone on upper plateau of Al Jabal Akhdar upland the in area of Al Abyar. These soils lie on the flat undulating plains. The main parent materials of the soils are alluvial, alluvial proluvial, eluvial-deluvial and proluvial deposits of chiefly heavy texture. The profile of the fully developed Siallitic cinnamon typical soils is subdivided into following horizons: A_1, B_1ca, B_2ca, B_3ca, BCca, Cca and R. in soils with limited thickness of the fine-earth layer the possibility of profile development is restricted by close bedding of hard bedrocks. The horizons are designated by additional indices of “ca” or “sa”, respectively. The leached genus of this soil is characterised by a higher content of silica and sesquioxides and a low amount of total calcium and magnesium.

A. 3.5.1. Dark rendzina

The soil forming process in the dark rendzina proceeds under a cardinal influence of the lithomorphic factor. High calcareousness of the parent materials, present of clay minerals in the limestones determines an increased accumulation of humus in these soils, formation of a stable flocculated humus-mineral complex, development of crumbly granular water stable structure. The dark rendzina with the horizons sequence of A_1, AR, and R, are most common. The dark rendzinas with a weakly and moderately developed profile have of A_1, B_1ca (sometimes B_2ca), and R horizons. In subtype of the dark rendzinas, four genera are singled out: carbonate, carbonate saline, leached, and leached saline.

A. 3.5.2. Red rendzina

The red rendzinas are predominantly soils of the slopes, eluvial deposits and various combinations of eluvial and deluvial deposits of calcareous rocks serve as basic parent material. The basic morphologic features of the red rendzinas include a truncated slightly differentiated profile of the A1, AR, R, or AR, and R type (the profile of the A1, B1ca, and R type occurs very rarely). The following genera are singled out within the subtype of the red rendzinas: carbonate, carbonate saline, leached and leached saline.

A. 3.6.1 Reddish Brown Arid Differentiated soils

The reddish brown arid differentiated soils have developed on various types and forms of relief. In the littoral plain it is a flat terrain on alluvial-proluvial deposits. The parent materials are predominantly represented by alluvial, alluvial-proluvial, proluvial-deluvial and, occasionally, eluvial-deluvial deposits of limestones. The subtypes of the reddish brown arid differentiated soils have the following genetic structure of the profile: A_1 or A_P, B_1ca (occasionally B_1), B_2ca, B_3ca (or BCca), Cca occasionally R or CRca (at a depth of over 120 cm). The subtypes of the reddish brown arid differentiated soils have the following genera: carbonate, carbonate saline, carbonate solonetzic-saline, leached, and leached saline.

A. 3.6.2 Reddish Brown Arid Differentiated Crust soils

The most of reddish brown arid differentiated curst soils they occur as homogenous, a few soils in associations with the reddish brown arid differentiated and slightly differentiated soils. The parent materials are alluvial, alluvial-proluvial, deluvial-proluvial, and carbonate, occasionally saline and gypsic deposits of loamy, rarely clayey and loamy sandy texture. Depending on the depth of the crust horizon bedding the vertical profile is differentiated into the following horizons: A_1, B_1ca, B_2ca, BCca, CRca; A_1, B_1ca, CRca; A_1, BCca, CRca; A_1, B_1ca, CRca. The subtypes of the reddish brown arid differentiated curst soils the following genera are singled out: carbonate, carbonate saline, carbonate solonetzic, and carbonate solonetzic-saline.

A. 3.6.3. Reddish Brown Arid Slightly Differentiated soils

The reddish brown arid slightly differentiated soils occupy a small % of the study area. On the soil map these soils are delineated as homogenous mapping units or in associations with other subtypes of the reddish brown arid soils. The parent materials of the soil are alluvial, alluvial-proluvial deposits, less frequently those deluvial-proluvial, and eolian. The reddish brown arid slightly differentiated soils generally have the following sequence of horizons: A_1, B_1ca, B_2ca and (sometimes B_3ca), BCca, Cca. The reddish brown arid slightly differentiated soils subtypes is divided into the genera of carbonate and carbonate saline soils.

A. 3.6.4. Reddish Brown Arid Slightly Differentiated Crust soils

These soils are speared in south western part of the study area and covers about 1.8 of the total of study area. About 40% of these soils are delineated as mapping units of various sizes and self-contained mapping units the remaining part of soils 60% has been distinguished in association with other subtypes of the reddish brown arid soils and with non-monolithic crusts. The principal parent materials of the soils are alluvial, alluvial-proluvial and-proluvial-deluvial deposits of loamy and less frequently loamy sandy and clay texture.

A. 3.6.5. Reddish Brown Arid Non-Differentiated soils

These soils occur only on the littoral in the south-western part of the study area (in the area of the town of Qaminis). The parent materials are mainly eolian and sand deposits, which are often enriched in shell fragments of the ground mollusks. These soils are in the initial stage of soils formation and represent the "youngest" soils of reddish brown arid soil type. The reddish brown arid non-differentiated soil subtype is divided into the genera of carbonate and carbonate saline soils.

A. 3.6.6. Reddish Brown Arid Hydromorphic Crust Soils

The reddish brown arid hydromorphic crust soils are very inconsiderably spared in the eastern zone, occurring south west of the Benghazi city. They occupy about 0.02% of the study area. The soils occur as small homogeneous mapping units mainly along the fringes of the solonchak distribution. The parent material is represented by deluvial and deluvial-proluvial deposits. This soil fall into two genera: carbonate saline and carbonate solonetzic-saline. The profile of the soils in question has the following form: A_1, B_1, B_2ca, and BCcag.

A. 3.7.1 Brown Arid Slightly Differentiated Soils

These soils are less spared on the territory of the eastern zone as compared with the brown arid differentiated soils. They are singled out in the southern part of the territory question among the brown Lithosols both as homogeneous individuals and in associations with brown arid differentiated soils, brown lithosols and Automorphic solonchaks. The subtypes of these soils are subdivided into the following genera: carbonate, carbonate saline. The soils with weakly developed profile display the following sequence of horizons: A_1, B_1ca, B_2ca, and R. however, in number of profiles the B_2ca horizon is messing and the B_1ca horizon is immediately followed by the bedrock

A. 3.8.1 Cinnamonic Lithosols

The geographic distribution of this soil is mainly south-east of the town of Taknis they develop under conditions of the sub-humid climate. The parent materials of these soils are eluvial-deluvial and eluvia deposits of limestones and marls. The profile of cinnamonic lithosols soils is subdivided into the A_1, AR, R genetic horizons of the AR, R ones. The R bedrock is represented by limestones or marls slightly affected by soil formation and weathering. The subtype of cinnamonic lithosols is subdivided into carbonate, carbonate saline and carbonate gypsic genera.

A. 3.8.2. Reddish Brown Lithosols

These soils are most common among the soils of this type. They are most widespread in the areas of Albyar and Taknis. The parent materials are represented by predominantly eluvial-deluvial and eluvial limestone deposits, less frequently by proluvial deposits. The parent materials, containing water-soluble salts, are also found. The most characteristic sequence of horizons in the profile is as follows: A1, AR, R, or AR and R. The following genera are singled out within the subtype of the reddish brown lithosols: carbonate, carbonate-saline, carbonate gypsic, carbonate solonetzic ones. According to the nature of bedrocks there distinguished the reddish lithosols on limestones.

A. 3.9.3. Brown Lithosols

The brown lithosols are found among the brown arid soils and in places, at the elevated relief elements in the zone of reddish brown arid soils. The parent materials are eluvial and deluvial-eluvial loamy deposits of a brown or light brown color with a large amount of limestone fragments. The most characteristic sequence of horizons in the profile is as follows: A1, AR, R, or AR and R. the AR horizon is a transitional one between the A1 and R and the R horizon is the parent rock represented by hard limestone slightly affected by soil formation and weathering. The brown lithosols subtype is subdivided into following genera: carbonate, carbonate saline and carbonate solonetzic-saline.

A. 3.10. 1 Monolithic Crusts Soils

The geographic distributions of these soils in eastern and western parts of the study area and are confined to the areas of the loose sedimentary formation. The monolithic crust profile is characterized by the presence of the genetic horizons of A1 and CRca or CRsica. According to the chemical composition of the crust horizon the following genera have been established within the monolithic crust: siallitic carbonate, siallitic carbonate saline and carbonate.

A. 3.10.2 Non-Monolithic Crusts Soils

The non-monolithic crusts are confined to the depressions of the littoral plain, piedmont alluvial-proluvial accumulative trains in the surveyed zone; the non-monolithic crusts develop mainly on the loamy and, less frequently, on the loamy sandy deposits. The profile of the non-monolithic crusts, there have been differentiated the following horizons: A1, CRca, or A1, B1ca, and CRca. Silicate or gypsic composition of the crust horizon is indicated by the additional symbols of "si" or "cs". The parent rock (Cca) has been exposed in number of the profiles. Depending on the chemical composition of the crust horizon, the non-monolithic crusts are subdivided into the following genera: carbonate, carbonate saline, siallitic carbonate and siallitic carbonate saline.

A. 3.11. Saline Soils and Solonchaks

Saline soils and Solonchaks cover about 1 % of the study area. The most intensive process of salt accumulation and formation of saline soils and solonchaks are observed within the close depressions of the coastal plain. The basic salts involved in the salinization of soils of the study area are NaCl and Na_2So_4 with $CaCl_2$, $MgCl_2$, $NaHCo_3$, $MgSo_4$ and$NaCo_3$.

According to Ben Mahmoud (1995) there are three main source of the salt may be distinguished. Firstly, marine .i.e., the infiltration of seawater and accumulation of its salts in the soil and subsoil, secondly, continental, which is conditioned by the groundwater lying close to the surface and thirdly, eolian slat accumulation, i.e., enrichment of soil and rocks with toxic salts of marine or continental origin through their transfer of air masses. This type of saline soils and solonchaks is subdivided into the following sub - types: automorphic (Sa), hydromorphic (Sh), hydromorphic crust (Shcr) and hydromorphic sebkha (Shs).

A. 3.11.1 Automorphic Solonchaks

These soils are mainly located close to the southern boundary of the study area. The principal morphologic-genetic peculiarities of the Automorphic solonchaks are the following: absence of the soil horizons, reddish brown, reddish yellow or yellowish red coloring; presence of visible readily salts, weak crumbly structure; high rate of skeletal.

A. 3.11.2 Hydromorphic Solonchaks

The hydromorphic solonchaks are developed in the coastal area of the maritime plains, being localized in the vast flat solonchaks depressions of sebkha type which represent former marine lagoons. The parent materials include marine lagoon sediments, eluvial-deluvial and deluvial deposits of a different granulometric composition. Lagoon deposits are strongly saline, carbonate enriched, being in some cases gypsiferous. The hydromorphic solonchaks are formed under the conditions of limited ground water drainage.

A. 3.12. Non-Soil Formation

It occupies 1 % of the study area. The genesis of this soil is distinguished by very weak evidence of biological process of rock transformation as well as by preponderance of physical weathering. The main non-soil formation in the study area is maritime sands (SM). The thickness of these formation is varies from 0.3 m to several metres.

Appendix B

B. 1. Second- Level pairwise comparison matrices and weights for barley and wheat generated by local experts 1; where A is Soil, B, Slope and C, Erosion.

1. Local expert 1; Prof Khalil Suliman (Soil physics and conservation)

Local Expert 1					
Criteria	A	B	C	Sum	Weight
A	1	5	6	12	0.7324
B	1/5	1	1	2.2	0.1378
C	1/6	1	1	2.167	0.1297
sum	1.3667	7	8	16.3667	∑=1
CR= 0.0001					

2. Local expert 2; Dr. Ezzaldin Rahoma (Soil Mineralogy and Classification)

Local Expert 2					
Criteria	A	B	C	Sum	Weight
A	1	7	8	16	0.7838
B	1/7	1	2	3.143	0.1349
C	1/8	1/2	1	1.625	0.0813
Sum	1.2679	8.5	11	20.77	∑=1
CR= 0.0194					

3. Local expert 3; Prof Khaled Ben Mahmoud (Soil Pedology and Land Evaluation)

Local Expert 3					
Criteria	A	B	C	Sum	Weight
A	1	5	7	13	0.7471
B	1/5	1	1	2.2	0.1336
C	1/7	1	1	2.143	0.1194
Sum	1.3428	7	9	17.343	∑=1
CR= 0.0014					

4. Local expert 4; Dr. Yones Daw (Soil physics and Irrigation Science)

Local Expert 4					
Criteria	A	B	C	Sum	Weight
A	1	7	7	15	0.7778
B	1/7	1	1	2.1429	0.1111
C	1/7	1	1	2.1429	0.1111
Sum	1.286	9	9	19.2857	∑=1
CR= 0.0					

5. Local expert 5; Dr. Bashir Nwer (Soil classification and Land Evaluation)

Local Expert 5					
Criteria	A	B	C	Sum	Weight
A	1	7	7	15	0.7778
B	1/7	1	1	2.1429	0.1111
C	1/7	1	1	2.1429	0.1111
Sum	1.286	9	9	19.26	∑=1
CR= 0.0					

6. Local expert 6; Dr. Ahmed Khmaj Suliman (Soil Fertility and Plant Nutrition)

Local Expert 5					
Criteria	A	B	C	Sum	Weight
A	1	7	6	14	0.7582
B	1/7	1	0.5	1.643	0.0905
C	1/6	2	1	3.167	0.1512
Sum	1.31	10	7.5	18.81	∑=1
CR= 0.0092					

B .2. Group pairwise comparison matrix and resulting weight for Level 2 criteria of hierarchical for barley and wheat

Aggregate Individual Judgement (AIJ)					GAHP
Criteria	A	B	C	Sum	Weight
A	1	6.257	6.799	14.056	0.7653
B	0.1598	1	1	2.1598	0.1190
C	0.1471	1	1	2.1471	0.1157
Sum	1.0306	8.257	8.799	18.362	∑=1

B.3.1 The Pairwise comparisons for Level 3 (Sub-criteria) of hierarchy for barley generated by local experts:

Local Expert 1 (E 1)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	1	1	1	2	3	1	2	2	3	3	3.0	0.1265
A2	1	1	1	1	2	2	2	2	1	1	3	1.0	0.1090
A3	1	1	1	2	3	3	1	1	1	2	2	2.0	0.1138
A4	1	1	1/2	1	2	2	1	1	2	2	2	3.0	0.1023
A5	1/2	1/2	1/3	1/2	1	2	1/2	1/3	1	2	2	3.0	0.0675
A6	1/3	1/2	1/3	1/2	1/2	1	1/3	1/2	1	2	1/2	0.5	0.0456
A7	1	1/2	1	1	2	3	1	1	1	2	3	2.0	0.1005
A8	1/2	1/2	1	1	3	2	1	1	2	2	2	3.0	0.1028
A9	1/2	1	1	1/2	1	1	1	1/2	1	2	2	3.0	0.0792
A10	1/3	1	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1	3	2.0	0.0581
A11	1/3	1	1/2	1/2	1/2	2	1/3	1/2	1/2	1/3	1	2.0	0.0512
A12	1/3	1	1/2	1/3	1/3	2	1/2	1/3	1/3	1/2	1/2	1.0	0.0434
	7.8	10.0	8.7	9.8	17.8	23.5	10.2	10.7	13.3	19.8	24.0	25.5	∑=1
CR=0.062													

Local Expert 2 (E 2)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weights
A1	1	1	1	1	2	3	1	3	3	3	3	3.0	0.1371
A2	1	1	1	1	2	2	2	2	1	1	1	1.0	0.1019
A3	1	1	1	1	3	3	1	2	2	3	3	3.0	0.1314
A4	1	1	1	1	2	2	1	2	2	2	2	2.0	0.1104
A5	1/2	1/2	1/3	1/2	1	1	1/2	1	1	2	2	3.0	0.0686
A6	1/3	1/2	1/3	1/2	1	1	1/2	1	1	2	1/2	0.5	0.0517
A7	1	1/2	1	1	2	2	1	2	2	2	3	2.0	0.1106
A8	1/3	1/2	1/2	1/2	1	1	1/2	1	1	2	2	3.0	0.0685
A9	1/3	1	1/2	1/2	1	1	1/2	1	1	2	2	3.0	0.0725
A10	1/3	1	1/3	1/2	1/2	1/2	1/2	1/2	1/2	1	1	2.0	0.0490
A11	1/3	1	1/3	1/2	1/2	2	1/3	1/2	1/2	1	1	2.0	0.0536
A12	1/3	1	1/3	1/2	1/3	2	1/2	1/3	1/3	1/2	1/2	1.0	0.0448
Sum	7.50	10.00	7.67	8.50	16.33	20.50	9.33	16.33	15.33	21.50	21.00	25.5	∑=1
CR=0.047													

Local Expert 2 (E 3)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weights
A1	1	2	1	1	3	3	1	4	4	4	2	2.0	0.1516
A2	1/2	1	1	1	3	3	1	3	3	1	1	1.0	0.1105
A3	1	1	1	1	3	3	1	3	3	3	3	3.0	0.1367
A4	1	1	1	1	2	2	1	2	2	2	2	2.0	0.1069
A5	1/3	1/3	1/3	1/2	1	1	1/2	1	1	4	3	4.0	0.0752
A6	1/3	1/3	1/3	1/2	1	1	1/2	1	1	2	1	1.0	0.0514
A7	1	1	1	1	2	2	1	2	2	2	2	2.0	0.1069
A8	1/4	1/3	1/3	1/2	1	1	1/2	1	1	3	3	3.0	0.0677
A9	1/4	1/3	1/3	1/2	1	1	1/2	1	1	2	2	3.0	0.0610
A10	1/4	1	1/3	1/2	1/4	1/2	1/2	1/3	1/2	1	1	1.0	0.0409
A11	1/2	1	1/3	1/2	1/3	1	1/2	1/3	1/2	1	1	1.0	0.0462
A12	1/2	1	1/3	1/2	1/4	1	1/2	1/3	1/3	1	1	1.0	0.0450
Sum	6.91	10.33	7.33	8.50	17.86	19.53	8.50	19.00	19.33	26.00	22.00	24.0	∑=1
CR=0.065													

Local Expert 4 (E 4)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	2	1	1	1	3	1	1	2	2	2	2	0.1135
A2	1/2	1	1	1	1/2	1	1	1/2	1	1	1	1	0.0667
A3	1	1	1	1	2	2	1	2	2	2	2	2	0.1186
A4	1	1	1	1	2	2	1	1	1	1	2	1	0.0962
A5	1	2	1/2	1/2	1	1	2	1	1	2	2	3	0.1007
A6	1/3	1	1/2	1/2	1	1	1/2	1	1	2	1	1	0.0643
A7	1	1	1	1	1/2	2	1	2	2	2	2	1	0.1023
A8	1	2	1/2	1	1	1	1/2	1	1	3	2	3	0.0963
A9	1/2	1	1/2	1	1	1	1/2	1	1	3	1	3	0.0823
A10	1/2	1	1/2	1	1/2	1/2	1/2	1/3	1/3	1	1	1	0.0498
A11	1/2	1	1/2	1/2	1/2	1	1/2	1/2	1	1	1	1	0.0542
A12	1/2	1	1/2	1	1/3	1	1	1/3	1/3	1	1	1	0.0551
Sum	8.83	15.0	8.50	10.5	11.3	16.5	10.5	11.7	13.7	21.0	18.0	20.0	∑=1
CR=0.050													

Local Expert 5 (E 5)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	2	1	2	1	3	1	1	1	3	3	2	0.1248
A2	1/2	1	1	1	1/2	1	1	1/2	1/2	1/2	3	1	0.0695
A3	1	1	1	1	1	2	1	1	1	2	2	2	0.0978
A4	1/2	1	1	1	1	2	1	1	1	1	2	1	0.0838
A5	1	2	1	1	1	1	1/2	1	1	2	2	3	0.0977
A6	1/3	1	1/2	1/2	1	1	2	1	1	1	1	1	0.0731
A7	1	1	1	1	2	1/2	1	2	2	2	2	1	0.1062
A8	1	2	1/2	1	1	1	1/2	1	1	3	1	3	0.0942
A9	1/2	2	1/2	1	1	1	1/2	1	1	1	1	3	0.0798
A10	1/3	2	1/2	1	1/2	1	1/2	1/3	1	1	1	1	0.0607
A11	1/3	1	1/2	1/2	1/2	1	1/2	1	1	1	1	1	0.0568
A12	1/2	1	1/2	1	1/3	1	1	1/3	1/3	1	1	1	0.0555
Sum	8	17	9	12	10.8	15 .5	10.5	11. 2	11.8	18.5	20	20	∑=1
CR=0.042													

Local Expert 6 (E 6)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	3	1	1	2	3	1	1	1	3	3	3.0	0.1244
A2	1/3	1	1/2	1/2	1/2	2	1/2	1	1	2	3	1.0	0.0703
A3	1	2	1	2	3	3	1	1	1	2	2	2.0	0.1223
A4	1	2	1/2	1	2	2	1	1	2	2	2	3.0	0.1093
A5	1/2	2	1/3	1/2	1	2	1/2	1/3	1	2	2	3.0	0.0758
A6	1/3	1/2	1/3	1/2	1/2	1	1/3	1/2	1	2	1/2	0.5	0.0457
A7	1	2	1	1	2	3	1	1	1	2	3	2.0	0.1115
A8	1	1	1	1	3	2	1	1	2	2	2	3.0	0.1145
A9	1	1	1	1/2	1	1	1	1/2	1	2	2	3.0	0.0838
A10	1/3	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1	3	2.0	0.0536
A11	1/3	1/3	1/2	1/2	1/2	2	1/3	1/2	1/2	1/3	1	2.0	0.0465
A12	1/3	1	1/2	1/3	1/3	2	1/2	1/3	1/3	1/2	1/2	1.0	0.0422
Sum	8.17	16.3	8.17	9.33	16.3	23.5	8.67	8.67	12.3	20.8	24.0	25.5	∑=1
CR=0.046													

B.3.2. The Pairwise comparisons for Level 3 (Sub-criteria) of hierarchy for wheat generated by local experts:

Local Expert 1 (E 1)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	1	1	3	2	3	1	2	2	3	3	3	0.1419
A2	1	1	1	1	1	2	3	2	1	1	1	1	0.1035
A3	1	1	1	2	2	3	1	1	1	2	2	2	0.1107
A4	1/3	1	1/2	1	1	1	1	1	1	2	2	2	0.0777
A5	1/2	1	1/2	1	1	2	1	2	1	2	2	3	0.0941
A6	1/3	1/2	1/3	1	1/2	1	1/3	1/2	1	2	1	1/2	0.0512
A7	1	1/3	1	1	1	3	1	1	1	2	3	2	0.0957
A8	1/2	1/2	1	1	1/2	2	1	1	2	2	2	3	0.0902
A9	1/2	1	1	1	1	1	1	1/2	1	2	2	3	0.0839
A10	1/3	1	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1	3	2	0.0579
A11	1/3	1	1/2	1/2	1/2	1	1/3	1/2	1/2	1/3	1	2	0.0481
A12	1/3	1	1/2	1/2	1/3	2	1/2	1/3	1/3	1/2	1/2	1	0.0452
Sum	7.17	10.3	8.83	13.5	11.3	21.5	11.7	12.3	12.3	19.8	22.5	24.5	∑=1
CR=0.054													

Local Expert 2 (E 2)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	2	2	2	3	3	2	3	3	3	3	3	0.1773
A2	1/2	1	2	2	2	2	2	2	1	1	1	1	0.0916
A3	1/2	1/2	1	1	2	3	1	2	2	3	3	3	0.1174
A4	1/2	1/2	1	1	1/2	1/2	1	2	2	2	2	2	0.0841
A5	1/3	1/2	1/2	2	1	2	1/2	1	1	3	2	3	0.0863
A6	1/3	1/2	1/3	2	1/2	1	1/2	1	1	2	1	1	0.0626
A7	1/2	1/2	1	1	2	2	1	2	2	2	3	2	0.1056
A8	1/3	1/2	1/2	1/2	1	1	1/2	1	1	2	2	3	0.0678
A9	1/3	1	1/2	1/2	1	1	1/2	1	1	2	2	3	0.0714
A10	1/3	1	1/3	1/2	1/3	1/2	1/2	1/2	1/2	1	1	2	0.0466
A11	1/3	1	1/3	1/2	1/2	1	1/3	1/2	1/2	1	1	2	0.0488
A12	1/3	1	1/3	1/2	1/3	1	1/2	1/3	1/3	1/2	1/2	1	0.0403
Sum	5.33	9.25	9.83	13.5	14.2	18.0	10.3	16.3	15.3	22.5	21.5	26.0	∑=1
CR=0.047													

Local Expert 3 (E 3)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	1	2	2	1	3	1	2	3	3	3	3	0.1452
A2	1	1	1	1	1	1	2	2	2	3	3	3	0.1211
A3	1/2	1	1	1	1	2	1	2	2	2	2	2	0.1021
A4	1/2	1	1	1	1	2	1	1	1	1	2	1	0.0830
A5	1	1	1	1	1	1	1	1	1	2	2	3	0.0947
A6	1/3	1	1/2	1/2	1	1	2	1	1	1	1	1	0.0713
A7	1	1/2	1	1	1	1/2	1	2	2	2	2	1	0.0908
A8	1/2	1/2	1/2	1	1	1	1/2	1	1	3	1	3	0.0765
A9	1/3	1/2	1/2	1	1	1	1/2	1	1	1	1	3	0.0667
A10	1/3	1/3	1/2	1	1/2	1	1/2	1/3	1	1	1	1	0.0497
A11	1/3	1/3	1/2	1/2	1/2	1	1/2	1	1	1	1	1	0.0504
A12	1/3	1/3	1/2	1	1/3	1	1	1/3	1/3	1	1	1	0.0485
Sum	7.17	8.50	10.0	12.0	10.3	15.5	12.0	14.7	16.3	21.0	20.0	23.0	∑=1
CR=0.039													

Local Expert (E 4)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	1	2	2	1	3	1	3	3	3	3	3	0.1505
A2	1	1	1	1	1	1	2	2	2	3	3	3	0.1207
A3	1/2	1	1	1	1	2	1	2	2	2	2	2	0.1015
A4	1/2	1	1	1	1	2	1	1	1	1	2	1	0.0827
A5	1	1	1	1	1	1	1	1	1	2	2	3	0.0946
A6	1/3	1	1/2	1/2	1	1	2	1	1	1	1	1	0.0710
A7	1	1/2	1	1	1	1/2	1	2	2	2	2	1	0.0905
A8	1/3	1/2	1/2	1	1	1	1/2	1	1	3	1	3	0.0742
A9	1/3	1/2	1/2	1	1	1	1/2	1	1	1	1	3	0.0664
A10	1/3	1/3	1/2	1	1/2	1	1/2	1/3	1	1	1	1	0.0495
A11	1/3	1/3	1/2	1/2	1/2	1	1/2	1	1	1	1	1	0.0502
A12	1/3	1/3	1/2	1	1/3	1	1	1/3	1/3	1	1	1	0.0483
Sum	7.00	8.50	10.0	12.0	10.3	15.5	12.0	15.7	16.3	21.0	20.0	23.0	∑=1
CR=0.04													

Local Expert 5 (E 5)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	1	1	2	1	3	1	1	2	3	3	3	0.1271
A2	1	1	1	1	1/2	1	2	1	1	1	1	1	0.0821
A3	1	1	1	1	2	2	1	2	2	2	2	2	0.1187
A4	1/2	1	1	1	1	1	1	1	1	1	1	1	0.0739
A5	1	2	1/2	1	1	1	2	1	1	2	2	3	0.1046
A6	1/3	1	1/2	1	1	1	1	1	1	2	1	1	0.0713
A7	1	1/2	1	1	1/2	1	1	2	2	2	2	1	0.0933
A8	1	1	1/2	1	1	1	1/2	1	1	3	2	3	0.0908
A9	1/2	1	1/2	1	1	1	1/2	1	1	3	1	3	0.0814
A10	1/3	1	1/2	1	1/2	1/2	1/2	1/3	1/3	1	1	1	0.0478
A11	1/3	1	1/2	1	1/2	1	1/2	1/2	1	1	1	1	0.0561
A12	1/3	1	1/2	1	1/3	1	1	1/3	1/3	1	1	1	0.0530
Sum	8.33	12.5	8.50	13.0	10.3	14.5	12.0	12.2	13.7	22.0	18.0	21.0	∑=1
CR=0.045													

Local Expert 6 (E 6)													
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	2	2	2	2	2	2	2	2	3	3	3	0.1565
A2	1/2	1	2	2	2	2	2	2	1	1	1	1	0.0933
A3	1/2	1/2	1	1	2	3	1	2	2	3	3	3	0.1197
A4	1/2	1/2	1	1	1/2	1/2	1	2	2	2	2	2	0.0853
A5	1/2	1/2	1/2	2	1	2	1/2	1	1	3	2	3	0.0898
A6	1/2	1/2	1/3	2	1/2	1	1/2	1	1	2	1	1	0.0655
A7	1/2	1/2	1	1	2	2	1	1	2	2	3	2	0.1076
A8	1/2	1/2	1/2	1/2	1	1	1/2	1	1	2	2	3	0.0708
A9	1/2	1	1/2	1/2	1	1	1/2	1	1	2	2	3	0.0745
A10	1/3	1	1/3	1/2	1/3	1/2	1/2	1/2	1/2	1	1	2	0.0470
A11	1/3	1	1/3	1/2	1/2	1	1/3	1/2	1/2	1	1	2	0.0493
A12	1/3	1	1/3	1/2	1/3	1	1/2	1/3	1/3	1/2	1/2	1	0.0530
Sum	6.00	9.25	9.83	13.5	13.2	17.0	10.3	15.3	14.3	22.5	21.5	26.0	∑=1
CR=0.053													

B.2.3. Group pairwise comparison matrix and resulting weight for Level 2 criteria of hierarchical for barley

Aggregate Individual Judgement (AIJ)													GAHP
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	1	1	1	2	3	1	2	2	3	3	3	0.1325
A2	1	1 2/3	1	1 1/8	1 5/7	3	1	1 2/3	2 1/7	3	2 5/8	2 4/9	0.0818
A3	3/5	1	8/9	8/9	1	1 2/3	1 1/8	1 1/5	1	1	1 1/5	1	0.1227
A4	1	1 1/8	1	1 1/4	2 1/3	2 5/8	1	1 2/5	1 2/3	2 2/7	2 2/7	2 2/7	0.1032
A5	8/9	1 1/8	4/5	1	1 7/9	2	1	1 1/4	1 3/5	1 3/5	2	1 4/5	0.0806
A6	3/5	1	3/7	5/9	1	1 1/4	5/8	2/3	1	2 1/4	2 1/7	3 1/7	0.0548
A7	1/3	3/5	3/8	1/2	4/5	1	5/9	4/5	1	1 7/9	5/7	5/7	0.1079
A8	1	8/9	1	1	1 3/5	1 4/5	1	1 3/5	1 3/5	2	2 4/9	1 3/5	0.0895
A9	3/5	5/6	3/5	4/5	1 4/9	1 1/4	5/8	1	1 1/4	2 4/9	2	3	0.0768
A10	1/2	1	3/5	5/8	1	1	5/8	4/5	1	2	1 3/5	3	0.0514
A11	1/3	1	3/7	5/8	4/9	5/9	1/2	2/5	1/2	1	1 4/9	1 2/5	0.0511
A12	3/8	5/6	3/7	1/2	1/2	1 2/5	2/5	1/2	5/8	2/3	1	1 2/5	0.0479
Sum	7.59	12	7.98	9.44	13.9	19.1	9.10	11.7	13.8	20.6	20.1	22.8	∑=1

B.2.4. Group pairwise comparison matrix and resulting weight for Level 2 criteria of hierarchical for wheat

Aggregate Individual Judgement (AIJ)													GAHP
	A1	*A2*	*A3*	*A4*	*A5*	*A6*	*A7*	*A8*	*A9*	*A10*	*A11*	*A12*	weight
A1	1	1 1/4	1 3/5	2 1/7	1 1/2	2 4/5	1 1/4	2	2 4/9	3	3	3	0.1502
A2	4/5	1	1 1/4	1 1/4	1 1/8	1 2/5	2 1/7	1 7/9	1 1/4	1 4/9	1 4/9	1 4/9	0.1063
A3	5/8	4/5	1	1 1/8	1 3/5	2 4/9	1	1 7/9	1 7/9	2 2/7	2 2/7	2 2/7	0.1124
A4	1/2	4/5	8/9	1	4/5	1	1	1 1/4	1 1/4	1 2/5	1 7/9	1 2/5	0.0799
A5	2/3	8/9	5/8	1 1/4	1	1 2/5	8/9	1 1/8	1	2 2/7	2	3	0.0931
A6	1/3	5/7	2/5	1	5/7	1	5/6	8/9	1	1 3/5	1	8/9	0.0631
A7	4/5	1/2	1	1	1 1/8	1 1/5	1	1 3/5	1 7/9	2	2 4/9	1 2/5	0.0959
A8	1/2	5/9	5/9	4/5	8/9	1 1/8	5/9	1	1 1/8	2 4/9	1 3/5	3	0.0785
A9	2/5	4/5	5/9	4/5	1	1	5/9	8/9	1	1 2/3	1 2/5	3	0.0746
A10	1/3	2/3	3/7	5/7	3/7	5/8	1/2	2/5	3/5	1	1 1/5	1 2/5	0.0494
A11	1/3	2/3	3/7	5/9	1/2	1	2/5	5/8	5/7	5/6	1	1 2/5	0.0507
A12	1/3	2/3	3/7	5/7	1/3	1 1/8	5/7	1/3	1/3	5/7	5/7	1	0.0459
Sum	7.51	12.12	8.02	9.61	13.81	18.81	9.22	11.78	13.68	20.75	19.99	21.2	∑=1