ADDIS ABABA UNIVERSITY

COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES

SCHOOL OF EARTH SCINCES

A FUZZY APPROACH FOR MODELING POTENTIAL WIND FARM AREAS: A CASE OF HITOSA WOREDA, OROMIA REGION, ETHIOPIA

By

EBISA TESFAYE

Advisor: Dr. Binyam Tesfaw

A Thesis Submitted to School of Graduate Studies of Addis Ababa University In Partial Fulfillment of the Requirements for the Degree of Masters of Science in Remote sensing and Geo-informatics

Addis Ababa University
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This is to certify that thesis prepared by EBISA TESFAYE DINADE, entitled: **"A *Fuzzy Approach for Modeling Potential Wind Farm Areas, A Case of HITOSA Woreda Oromia Region, Ethiopia*"** and submitted in partial fulfillment of the requirements for the degree of Masters of Science in Remote sensing and Geo-informatics complies with the regulations of the university and meets the accepted standards with respect to the originality and quality.

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Acronyms

a.m.s.l	Above Mean Sea Level
AHP	Analytical Hierarchy Process
AWEA	American Wind Energy Association
CSA	Central Statistical Authority
DEM	Digital Elevation Model
EEPCO	Ethiopian Electric Power Cooperation
EREDPC	Ethiopian Rural Energy Development and Promotion Centre
EMA	Ethiopian Map Authority
ERDAS	Earth Resources Data Analysis System
FAHP	Fuzzy Analytical Hierarchy Process
FCR	Fuzzy Consistency Ratio
FEA	Fuzzy Extent Analysis
GIS	Geographic Information Systems
GPS	Global Positioning Systems
GWR	Geographically Weighted Regression
IDW	Inverse Distance Weighted
LULC	Land use land cover
MCDM	Multi-Criteria Decision Making
MCE	Multi Criteria Evaluation
MLC	Maximum Likelihood Classification
MoWE	Ministry of Water and Energy of Ethiopian
NMSA	National Meteorological Service Agency
OLS	Ordinary Least Squares
PWFAM	Potential Wind Farm Areas Model
RMSE	Root Mean Square Error
SRTM	Shuttle Radar Topography Mission
TFN	Triangular Fuzzy Number
UTM	Universal Transverse Mercator
WLC	Weighed Linear Combination

Abstract

Being cleaner and climate friendly, wind energy has been increasingly utilized to meet the ever-growing global energy demands. In Ethiopia, a wide gap exists between wind resources and actual energy production, and it is imperative to expand the wind energy production. This study was conducted in Hitosa Woreda, which is located in East Showa Zone of Oromia Region, in the Rift valley area of the country. The main objective of this study was to identify potential wind farm sites in the study area using fuzzy approach. The development of new wind farm energy project requires studying of many parameters to achieve maximum benefits at the cost of minimum environmental impacts. While site selection, there is a problem comes with prioritizing criteria that determine the best location. Dealing with real life situation and experts' judgments involves uncertainty. To solve this problem, a model containing Multi-Criteria Decision Making (MCDM) technique that is Analytical Hierarchy Process (AHP) with fuzzy theory was designed to handle the uncertainty situations. Ten criteria were adopted in this method, including wind speed, distance to roads, to rivers, from towns, from faults, closeness to power line, slope, lithology, elevation, slope and exclusionary areas. The weights of the criteria of the site were obtained through application of developed FAHP idea. Geographic Information System (GIS) was used to overlay and generate criteria maps, and IDRISI 17.0 was used for fuzzy aggregation and development of suitability map. The study ends with an assessment of proposed sites to the generated suitability map. The results of the assessment showed that the northern zones of the investigated region have high wind energy potentials. Such zones are appropriate for setting up electricity generating wind turbines. From total investigated area of 1260sq. km. the amount of extremely suitable zone was 96.902 sq. km, highly suitable zones was 152.194 sq. km, moderately suitable zones is 179.11 sq. km, less suitable zones was 311.159 sq. km. The suggested model may serve as a useful decision making tool for the energy planners and decision makers, intending to develop wind farm energy in the present study area. This model is accepted to help to identify suitable wind farm locations in other areas with a similar geographic back ground.

Key words: Crisp, Fuzzy, FAHP, GIS, wind farm

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the study

Increasing use of fossil fuels as energy sources has exhausted due to population growth and has been damaging the environment. Nowadays, scientists have found renewable energy that are sustainable and safest options to prevent greenhouse gases spreading and the world population energy requests. According to Tester *et al.* (2005), the definition of sustainable energy is the combination of providing energy equally to all people and protecting the environment for next generations. The renewable energy systems have a common approval as a form of sustainable energy that keeps the attention recently (Omer, 2008). Exploitation of renewable energy resources such as wind energy reduces dependency on fossil fuels. Wind energy compared to fossil fuels causes less environmental damage. One of the major contributions of wind energy to environmental protection is through decreasing CO_2 emission (Caralis *et al.,* 2008).

In relation to other renewable energy resources, wind energy stands out because of several reasons (Balat, 2010). One of the main advantages is it global availability, as wind blows potentially everywhere around the world. The second advantage is that wind energy is relatively cheap in its production and implementation costs. For example, compared to biomass energy (Field *et al.,* 2008), wind energy has the advantage that it does not consume much agricultural space where is needed for solving other main world problems like food crops production.

In the past wind energy was considered to be a renewable energy source primarily for developed countries, because of its cost but this is slowly changing. Since 2001, wind energy production has risen significantly worldwide and the cumulative installed global capacity increased from 24 Giga Watt (GW) at the end of 2001 to 237 GW at the end of 2011 (The Wind Power, 2013). Currently, the largest share in wind energy production in Africa is held by Egypt and Morocco where most wind power installations are located with total capacities of 550 Mega Watt (MW) and 1300 MW, respectively, by the end of 2012 (Global Wind Energy Council, 2011).However, despite these positive trends and Africa's potential supply of wind energy, installed generation capacity of wind-based electricity located in Africa does not exceed 0.4 percent of global capacity (The Wind Power, 2013).

Wind speed generally decreases as one move from higher latitudes towards the equator. However, local effects like presence of geographic structures such as mountains, valleys and coastal areas might significantly enhance wind speed. As Ethiopia is located close to the equator, there might be a limited wind resource potential. But, the topography has a positive effect for having a good potential on this energy source.

According to the Ethiopian Rural Energy Development and Promotion Center (2007), the wind areas in Ethiopia located at the escarpment of the main East African Rift, the northeastern escarpment of the country near Tigray Regional State and the eastern part of the country (near northeast of the Somali Regional State).

In recent years, Ethiopian Government has formulated a series of policies for promoting national economic development, especially implemented "Sustainable Development and Poverty Reduction Program" (SDPRP). While Power industry is important basis of national economy, technical innovation and overall improvement of power industry can greatly push the development of other economic sectors. Powerful development of wind power generation projects can promote employment and increase national fiscal revenue.

According to current distribution of Ethiopian wind energy resources, many future power generation projects may be arranged in some under developed regions to promote local economic development, increase power supply and change the concept of life of local people. Undoubtedly, wind power generation can effectively strengthen the resource advantage and lay a firmer practical foundation for Ethiopian power export.

Many areas located in the Rift Valley of Ethiopia are identified as the high wind resource potential areas. One of these areas is Hitosa, located in the Rift (high wind resource potential) and significant geological structure (good for wind farm establishment) attracts stakeholders for the establishment of grid-based wind farm. But, selecting sites for wind farm is a complex process involving not only technical but also physical, economical, social and environmental requirements. Such complexities necessitate different influential factors consideration with several decision support tools such as GIS and multi-factor analysis system.

Hence in this research the fuzzy containing multi factor decision making techniques were used to solve this problem. This is because of the fuzzy approach allows decision makers to give interval judgments which can capture a human's appraisal of ambiguity when complex multi-attribute decision making problems are considered (Ibrahim *et al.,* 2011).

Therefore, Geographical Information System (GIS), IDRISI17.0, fuzzy logic with Analytical Hierarchy Process (AHP) and Weighed Linear Combination (WLC) were used to give weight for the factors and locate the most appropriate sites for Wind energy production in Hitosa woreda.

1.2. Statement of the Problem

According to the Master Plan Report of Wind and Solar Energy of Ethiopia (2012), the Federal Government of Ethiopia recently issued the National Energy Development Strategy to encourage the development of domestic renewable energy resources. This includes wind and solar energy, so as to realize the objective of "Energy Diversification" and guarantee energy security. In recent years, reservoirs cannot normally store water and generate power at full load, due to global warming and frequent appearance of extreme drought. This seriously affects Ethiopian Energy Supply such as power shortage at many places as the energy source of the nation is dominated by hydropower. This issue mainly affects the social and economic development of the country. On the other hand, wind energy resources are not seasonal, which is also constantly available during the dry season, unlike hydropower resources (Ethiopian Electric Power Corporation, 2006).

The government of Ethiopia with the collaboration of Chinese Government has prepared solar and wind master plan for Ethiopia in 2012. These encompass a capacity of 1350GW energy from wind farm and out of this, only 171MW is so far produced. However, this wind master plan does not include the specific potential area in the selected sites.

A 'Wind Farm' is created by a number of large wind turbines, which help to generate wind power. However, construction of wind turbine is greatly affected by location of a site, which can be carried out by multiple site selection criteria. Therefore, site selection for large wind farm requires consideration of a comprehensive set of factors and balancing of multiple objectives in determining the suitability of a particular area for a defined land use (Bennui *et al.,* 2007).

Wind farm site selection should be based on long term requirements. This requires reliable and up-to-date database about the natural resources and their distribution over space. With the conventional methods, data obtained are often time consuming and less accessible. Although

Ethiopia has potential of wind producing energy power, the tools and methods that have been applied to select the potential areas to install the wind turbines were time consuming and not appropriate.

Moreover, the criteria, which help to select the potential wind farm site are not properly seated and challenging. According to Saaty (1980), Analytical Hierarchy Process (AHP) of pairwise comparison method often applied for elicitation of criteria weights in weighed linear aggregation. It provides a hierarchical structure by systematically break down a problem into its smaller constituent parts and then guide decision makers through a series of pairwise comparison judgments to express the importance of the elements in the hierarchy. However, within the literature, it is felt that the conventional AHP technique of expressing decision maker‘s judgments in the form of single numbers does not fully reflect a style of human thinking in the real-world system. To handle this uncertainty, which is linked to the characteristics of the decision maker an integration of Fuzzy logic and the traditional AHP (FAHP) approach, which can tolerate this vagueness or ambiguity is required (Farajzadeh *et al.,* 2013; Talinli *et al.,* 2011).

Therefore, in this research, the fuzzy approach modeling method using satellite remote sensing data and GIS were used in order to investigate the potential area of wind farm in Ethiopia in general and particularly for the study area.

1.3. Objectives of the study

1.3.1. General objective

The general objective of this study is to develop a model to predict potential areas of wind farm in Hitosa district using fuzzy approach.

1.3.2. Specific objectives

- To assess and identify the factors that influence fuzzy approach potential for wind farm site selection.
- To develop a model for potential wind farm site in the study area using Fuzzy approach.
- To validate the suitability of fuzzy approach for potential wind farm site selection.

1.4. Research questions

The following questions have been formulated to achieve the above mentioned objectives.

- What are the main influencing factors for fuzzy potential wind farm modeling?

- How to develop a fuzzy approach potential wind farm conceptual model?
- What is the advantage of fuzzy approach comparing to the common crisp approach?

1.5. Significance of the study

The significance of the study could be i) for researchers, who are doing about wind energy by providing insights on the major factors that affect the wind farm, ii) it could be used as an input for government policy makers for their decision making processes related to selecting potential sites for wind energy, iii) it is also expected that with small modifications the method can be used for other areas of siting potential wind farm areas and iv) it could be used as an input for those who wants to invest on renewable energy.

1.6. Limitation of the study

The present study was attempted with all possible efforts in acquiring required inputs in the form of secondary and actual field data collection, analysis and technical interpretations. However, the study has encountered certain limitations, which are listed below:

- There is no full map of transmission line in EEPCO.
- Wind data were collected and documented by National Meteorological Service Agency (NMSA) primarily for a purpose of aviation. This data is not of much use for estimation of the resource as most of the stations do not qualify the required standard for wind speed measurements. Most of the station measurements for wind speed were taken at heights lower than the accepted standard of 10 m and over half were taken at just 2 m above the ground level.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. An overview of Renewable Energy

2.1.1. Introduction

Renewable energy development at the regional level can serve as a mechanism to reduce the environmental impacts of energy consumption, to improve the local economy, and to increase community participation in local environmental management (Cosmi and Macchiato, 2003). Planning for the integration of renewable energy source into existing electricity systems has been conducted through two main approaches: the use of geographic information systems (GIS) for discovery of resource potential, and mathematical programming for modeling and optimizing energy planning. The following sections provide detailed description regarding previous research in these areas and how they relate to the research presented in the following chapters.

2.1.2. Source and types of energy

Source of energy can be categorized as renewable and non- renewable. Sources of energy that are mostly biomass based and are available in unlimited amount in nature. Such energy sources are fuel wood, petro plants, agricultural waste like biogas, animal dung, wind energy, water energy, tidal energy, geothermal energy, solar energy. Energy sources such as petroleum, coal, natural gas, nuclear power and the like are categorized as non–renewable (EPA, 2003). The non-renewable or exhaustible energy sources are available in limited amount and develop over a longer period of time and as a result of unlimited use; such resources are likely to be exhausted any day (Aklilu Dalelo, 2005).

2.1.3. Importance of energy in the modern world

Development needs energy. The reliable and efficient provision of modern energy services is a central part of the global fight against poverty. Economic development of both rural and urban societies could be accelerated and achieved if energy is available. A quarter of the world population has no access for electricity; about 2.4 billion people have to rely on wood, charcoal or other plant material. Securing an energy supply is a necessary pre-condition for economic development whether in agriculture, manufacturing industry or in service sectors. This is shown by analyses of the trends in gross domestic product and energy use in many countries (GTZ, 2002).Hence, renewable energy such as hydro, including small scale geothermal, wind, solar and biomass energy in liquid and gaseous form, which are suitable for clean and sustainable development should be developed, exploited and promoted so as to bring fundamental and desired change on the living standard of the Ethiopian population, who the majority of them are subsistence farmers and live below poverty level (Asress Woldegiorgis, 2002).

2.1.4. Energy in Ethiopia

Ethiopia has substantial energy resources consisting mainly of biomass, hydropower and fossil fuels (especially natural gas and coal). Geothermal energy and other renewable energy sources such as wind and solar energy are also available in the country. Although currently dominated by traditional biomass consumption, other energy sources such as hydropower and natural gas can potentially offer the nation for major economic development opportunities (Ministry of Mines and Energy, 2009; Mulugeta Yacob, 2007). In 2007, average electricity generation mix of the country was composed of 86% hydro, 13% diesel and 1% geothermal (MoWE, 2008 as sited by Samuel Tesema and Getachew Bekele,2014) .Since hydro component is highly variable depending on the weather conditions, the increasing demand has to be met through imported diesel based generation. Energy consumption in Ethiopia from the national grid was 3894 GW during the 2009/2010 fiscal year (Embassy of Japan, 2008). Annual per capita consumption of electricity is 100 Kilowatt per hour (kWh), which is much lower than the Sub-Saharan Africa average of 510 kWh.

In recent years, due to economic growth, electricity consumption in the country has increased, and it is common to see small diesel generators running here and there to bridge the electrification gap in rural and pre-urban areas. Table 1 shows the country's energy potential and the major nine types of energy resources.

Table 1: Ethiopian Energy Resource Potential (Sources: MME, 2013)

Resource	Unit	Exploitable Reserve	Exploited Percent	
			Amount	Percent
Hydropower	MW	45,000	~ 2100	< 5%
Solar/day	KWh/m^2	4-6		~ 1%
Wind: power (at 6 m/s Speed)	GW	1350	171MW	≺ 1%
Geothermal	MW	7000	7.3MW	≺ 1%
Wood	Million tons	1120	560	50%
Agricultural Waste	Million tons	15-20	~ 6	30%
Natural gas	Billion m^3	113	-	0%
Coal	Million tons	>300	-	0%
Oil shale	Million tons	253	-	0%

2.1.5. Renewable energy resources in Ethiopia

The current use of traditional biomass fuels cannot meet the energy needs of Ethiopia's growing population without compromising the health of the environment (Karakezi and Kihyoma, 2003). For cooking and lighting needs, most Ethiopians rely on unsustainably sourced fuels such as charcoal and fuel wood. A 2010 report by Ethiopian non-governmental organization, Forum for Environment, found the Ethiopian population as a whole is almost exclusively reliant on traditional biomass sources, using charcoal and fuel wood to meet 94% of total energy requirements with petroleum and electricity representing the remaining 6%. Fuel wood consumption to this degree is a major issue, as it is associated with extensive deforestation and land degradation (Mulugetta Yacob, 2007; Karekezi and Kihyoma, 2003). While Ethiopia's urban population is currently increasing, following the global trend of the last half a century, the overwhelming majority of Ethiopians still live in rural areas and will remain there into the foreseeable future. Because of these demographic realities, it is rural energy consumption patterns that need to be addressed if the energy sector is to become sustainable.

Environmental problems resulting from Ethiopian energy consumption also extend beyond national borders. The burning of biomass and the resulting emissions are contributing to global climate change. In particular, the incomplete and inefficient combustion by traditional cook stoves releases greenhouse gases including carbon monoxide, nitrous oxide, and methane into the atmosphere (Kees and Lisa, 2011). Meanwhile, other organic compounds and particulate matter from biomass combustion contribute to local and regional air pollution.

Developing nations have sought to escape environmental ruin through the expanded use of energy efficient and renewable technologies. Ethiopia's renewable energy potential is considerable, with abundant biomass efficiency, biogas, solar, hydropower, wind, and geothermal possibilities available (Forum for Environment, 2010; Mulugetta Yacob, 2007). But to date, the potential in rural electrification through these renewable technologies, and the implementation of energy efficient technologies in biomass consumption have largely gone untapped.

Meeting the demand of a developing economy by hydropower plant alone causes some problems. As only medium or larger hydropower systems can be implemented economically, they cause something what the energy planners call '’the famine and feast'' phenomenon. That is during the planning and construction period of a medium sized hydropower plant; the demand is growing and starts to outgrow the supply. Power rationing is the unavoidable result; this will be aggravated when it happens at the time of draught ('famine'). Once the new hydropower plant is operational, suddenly more power will be available, but not needed. The plant is running far under its capacity with the result of generating relatively expensive electricity ('feast'). Under this situation, wind power can contribute to the smooth expansion of generating capacity and can help to avoid the worst effects of 'famine and feast' situation. Due to the wind plants' short lead time for planning and construction, smaller plants can be put into operation gradually; in doing so, the country can keep the pace with the growing electricity demand (Asres Woldegiorgis, 2002).

2.1.6. Importance of wind farm

Furthermore, in the world that has become increasingly concerned about climate change caused by the increase of carbon dioxide (CO_2) emissions from burning fossil fuels, a particular emphasis has been placed on renewable sources.

During the global move towards cleaner and greener electricity and to reduce the cost of electricity, developers are looking more favorably at renewable energy projects, especially wind energy. Modern electricity generating grid connected wind turbines constitute a promising technology, to supplement hydropower, especially because the correlation of wind resource and hydrology availability is very good (EREDPC, 2007).

2.2. Wind energy resource potential in Ethiopia

The total wind resource of Ethiopia is estimated to be 20.064 TJ/year; however, a significant amount of it had not been used yet throughout the country (Ramayya *et al.,* 2007). As the study of Woldeghiorgis Weldesenbet (1988) there are few promising windy areas in Ethiopian located alongside the main East African Rift Valley, the Northern Eastern escarpment of the country near Tigray regional state, the Southern part of Ethiopia near the Kenyan boarder, the central and eastern part of Ethiopian specially south east of the Somalia region. Areas estimated to have moderate and higher wind resources are primarily located in the highlands featuring a sudden change in altitude from the neighboring land masses. These areas are basically the escarpments along the Great Rift Valley extending to the Southern, Eastern, North Eastern parts of the country, and the central highlands. The strongest wind resources with energy density above 800 w/m^2 located on the ridge of the highlands in the central part of the rift valley.

Distribution of wind resource areas by regions are shown in Table 2.

Table 2: Regional distribution of wind resources under various wind categories

(Source: EREDPC, 2007)

Region	Wind Resource Category and Land Area Under Category(km^2)							
	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**	**Total**
Addis Ababa	--	42	277	207	--	--	--	526
Afar	67340	6331	1550	545	--	--	--	75,766
Amhara	88659	12578	2357	1687	328	--	--	105,609
Benshangul	4528	--	--	--	--	--	--	4,528
Dire Dawa	552	665	286	--	--	--	--	1503
Gambela	359	--	--	--	--	--	--	359
Harar	--	2	32	109	108	143	--	394
Oromia	131865	45257	26832	14794	3352	3492	1715	227,307
SNNPR	40857	6190	3305	2562	1,509	103	--	54,526
Ethio-Somali	196571	18946	3209	524	80	--	--	219,330
Tigray	33877	6790	5087	3547	1,152	77	--	50,530
Total	564,606	96,801	42,935	23,975	6,529	3,815	1,715	740,376

Information Regions under poor wind resources category (Class 1) are excluded as they are not technically and economically feasible with current technologies. Class 7 indicates the strongest wind regions. The majority of land area with good-excellent wind resources regions fall in Oromia followed by Tigray and SNNPR.

2.3. Application of GIS in potential wind farm site selection

The geospatial information technology contains the necessary tools to collect, develop, manage and analyze the required data at the appropriate scales for different suitability analysis (Baban, 2004).The use of GIS for renewable energy site selection has also been explored previously at the local, regional, and national levels (Voivontas *et al.,* 1998; Biberacher *et al.,* 2008; Short *et al.,* 2009). The suitability of renewable energy source deployment at specified locations is based on a variety of characteristics, which express the fitness of a certain renewable energy source. First and foremost, a wind farm location is constrained by the fact that this source is only exploitable where the resource is readily available and the development of a farm is permissible. While there may be good potential for wind at a certain location, if there are conservation restrictions on the area, or it is located close to a densely populated area, the ability to harness that resource is constrained and the potential resource cannot be utilized. It is not possible to move the availability of wind resources to other areas, which do not have such limitations or may be cheaper to access. The process of determining a suitable location for wind farm usage is a very specific form of the site selection problem, in which one or more sites are selected for use based on a series of characteristics such as cost and distance. In this case, GIS is the appropriate tool to utilize because it can synthesize geographic and regulatory parameters that are important in the site selection process.

2.4. Fuzzy approach for decision making

In reality, it is very hard to extract precise decision data related to measurement indicators by human judgments. Decision makers and policy makers also prefer natural language expressions rather than crisp numbers. Zadeh (1965) introduced the fuzzy theory and its first utilization for decision making problems. Fuzzy set theory has made a major contribution to represent vague and incomplete data when its capability to provide a methodology for computing directly with words is considered (Tolga *et al.,* 2005). Fuzzy theory is composed of three key factors, which are fuzzy set, membership function, and fuzzy number to change vague data into useful data efficiently (Zadeh, 1965).

Moreover, GIS-based Fuzzy Analytical Hierarchy process allows decision makers to give interval judgments, which can capture a human‘s appraisal of ambiguity when complex multi-attribute decision making problems such as wind farm siting are considered (Farajzadeh *et al.,* 2013; Talinli *et al.,* 2011).

2.5. Influential factors for potential wind farm areas

Site selection for large wind turbine requires consideration of a comprehensive set of factors and balancing of multiple objectives in determining the suitability of a particular area for a defined land use (Bennui *et al.,* 2007). Literature on the siting of wind power facilities generally incorporates the integration of many factors in order to determine a suitable location. Economic factors for the siting of wind power facilities include wind speed and/or wind power density and distance to transmission lines, roads, slopes and soil. Socially influenced factors includes distance from urban areas and historic sites. Environmental variables includes distance from wetlands, forests and water bodies (Baban and Perry, 2001; Mann *et al.,* 2012). Although the major factors affecting site selection for potential wind farm areas could be similar in different areas, the level at which they influence site selection for potential wind farm areas is different in different areas.

Evaluating suitable locations for wind energy is a difficult undertaking for planners and decision-makers. For instance, variations of opinions of decision-makers exist in the choice of important criteria and their relative importance for solving the problem. Different decision-makers will likely place different values on the criteria and use information in different ways (Dye and Shaw, 2007). While there are clear challenges with the choice and relative importance of conflicting criteria, improvements of Spatial Decision Support System (SDSS) frameworks that can support conflict resolution and promote consensus among planners are necessary for the decision making process.

CHAPTER THREE

3. MATERIALS AND METHODS

3.1. Description of the Study Area

3.1.1. Location

Hitosa Woreda (currently Lude Hitosa and Hitosa) is one of the Woredas in Arsi zone of the Oromia Regional State of Ethiopia. The administrative center of the Woreda is Iteya town, which is located south east of Addis Ababa at about 160 km and 25 km from northeast of Asella, the capital of Arsi Zone.

This Woreda has a total area of 1260 km^2 and located geographically between 7^{o}54'45"–8^{o}17'56" N latitude and 39^{o}07'09"– 39^{o}33'08"E longitude. It shares boundaries with Dodota in the North, Digeluna Tijo in the South, Ziway Dugda in the West, Misrak Shewa Zone in the northwest and Tena Woredas in the East. It is located completely within the Ethiopian Rift Valley.

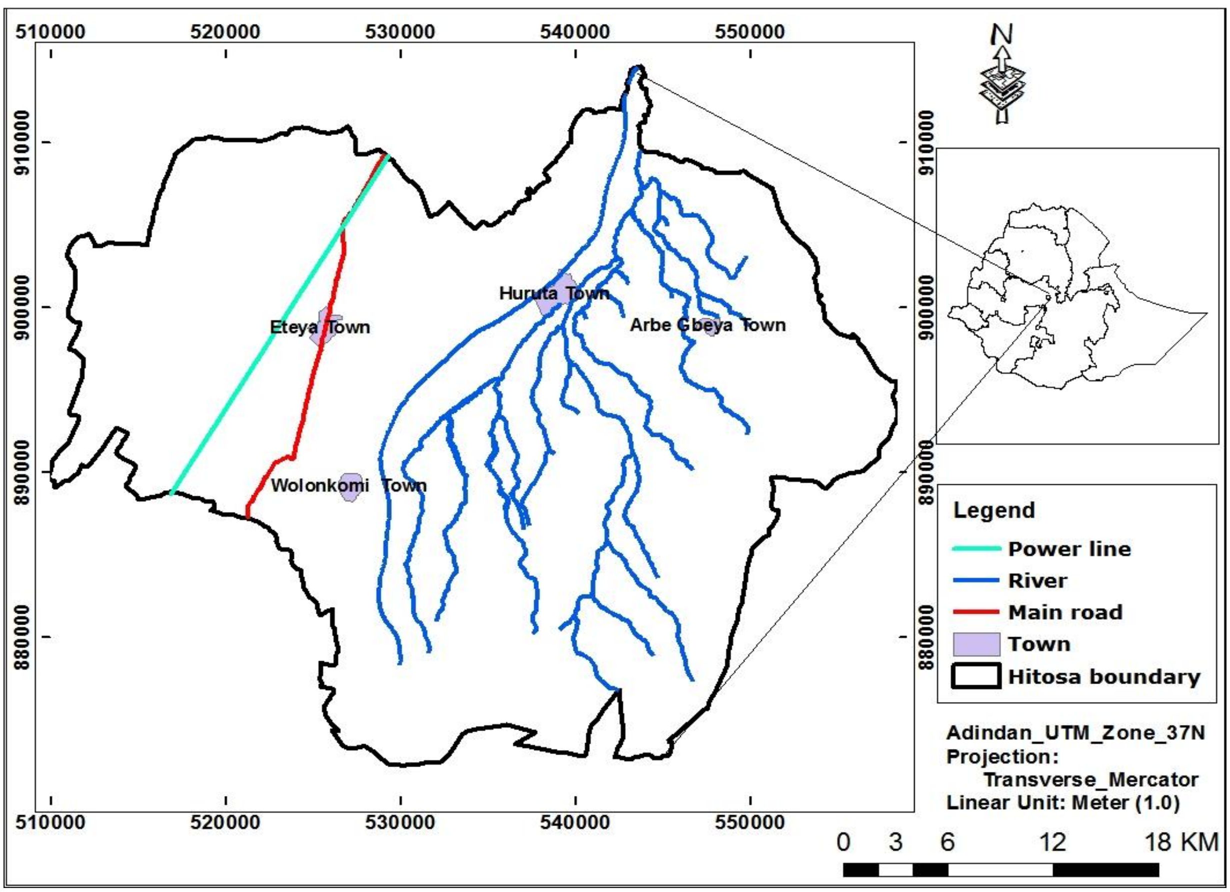


Figure 1: Location map of the study area

3.1.2. Climate and Topography

Hitosa Woreda has three climatic zones. The topography of the area comprises 27 % highland (dega), 31% midland (weyena dega) and the rest (41percent) is lowland (kola). The altitude of the Woreda ranges from 1590m a.m.s.l. to 4185m a.m.s.l.. The average temperature of the Woreda varies between 20.50^0C and 270^0C with minimum annual rainfall of 800mm.

3.1.3. Population and Economic Activity

Total population of Hitosa Woreda is about 124,179. Out of this, 62,335 are men and 61,734 are women, most of them (about 85 %) live in rural areas (CSA, 2008). Agriculture is the dominant livelihood strategy of the majority of the population and it is one of the most agriculturally productive Woredas in the Oromia Region.

3.1.4. Wind Speed

The monthly average wind speed measured at Iteya (MoWE, 72m height) shows that the monthly average wind speed and monthly wind power density change greatly from January to March and from October to December; and lower in April and September; and the seasonal change is obvious (Fig.2). According to this, 72m height mast the wind speed at Iteya gets minimum in August (4.03 m/s) and maximum in December, January and February (10.25 m/s, 9.66 m/s, 9.94 m/s), respectively.

Moreover, the value of wind speed interpolated from six metrological stations (Kulumsa, Robe, Nazareth, Golelcha, Nurera and Methara) shows that the minimum wind speed occurs in August (1.34 m/s), while the maximum wind speed occurs in December, January and February (2.28 m/s, 2.12 m/s, and 2.31m/s), respectively (Table 3).

Table 3: Wind speed value at 2m, 10m, 70m and wind power density at 70m height.

Month	Wind Speed(m/s) at 2m	Wind Speed(m/s) at 10m	Wind Speed(m/s) at 70m	Wind-power density(w/m²)at70m
January	2.12	8.1	9.66	508.2
February	2.31	8.2	9.94	595.1
March	2.13	7.5	8.60	435.9
April	1.77	5.21	5.35	146.9
May	1.78	6.62	6.83	287.8
June	1.83	5.21	5.58	109.2
July	1.99	5.53	5.58	107.3
August	1.34	3.61	4.03	62.6
September	1.66	3.96	4.15	65.4
October	2.05	7.5	9.87	531.2
November	2.14	8.1	9.54	502.1
December	2.28	8.2	10.25	609.2
Average	2.10	6.456	7.50	331.8

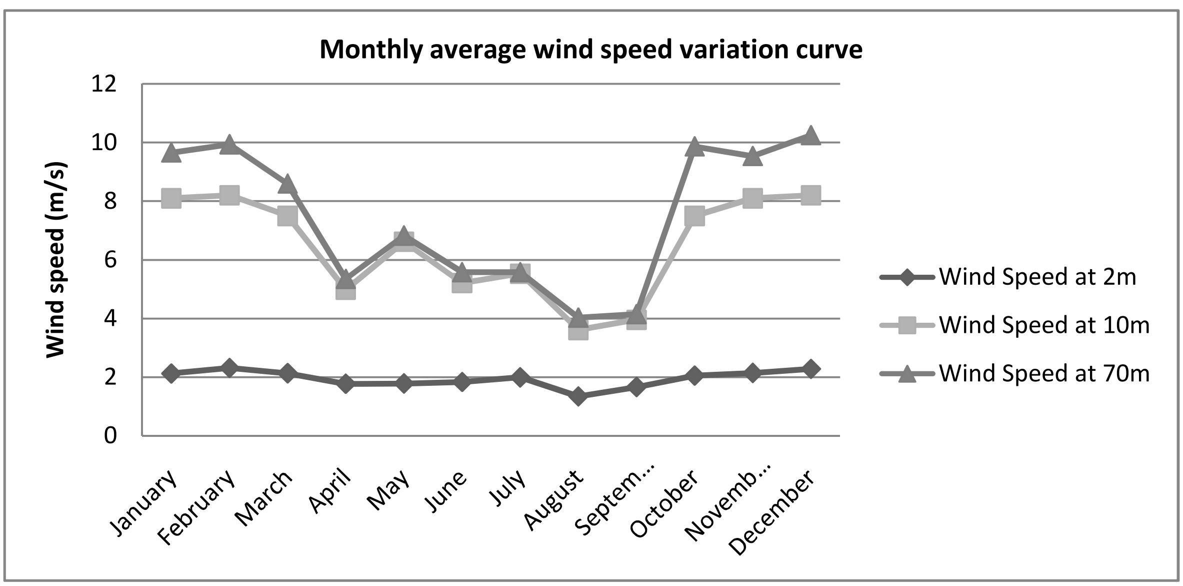


Figure 2: Mean monthly wind speed of Hitosa at 2m, 10m and 70m

3.1.5. Land Use Land Cover

The total land size of the Woreda is 126,000 hectare. The land use types in the study area are classified into five classes (Fig. 3). These are agriculture, bare-land, forest, grass land and settlements. Of this, agricultural sector takes the lion's share (69,438 hectare), bare-land (19,188 ha), forest (4,676 ha), grass land (29,003 ha) and settlements (3,695 ha) as shown in Table 4.

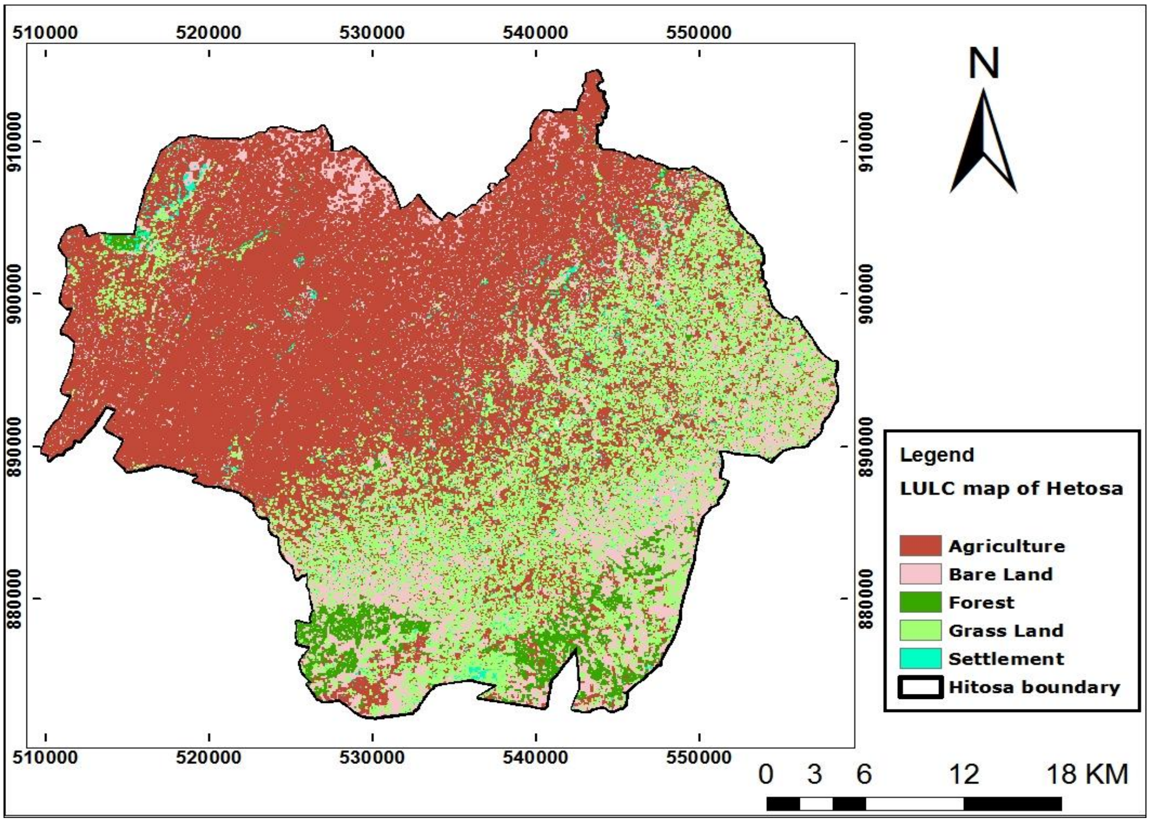


Figure 3: Land use Land cover map of Hitosa

Table 4: Land use Land cover classification and area coverage of Hitosa

Land Use	Area in hectare	Percentage
Agricultural land	69438	55.109
Bare-land	19188	15.228
Forest	4676	3.712
Settlement	3695	2.933
Grass Land	29003	23.018
Total	126,000	100

3.1.6. Geology

According to Ethiopian 1:50,000 geological map (Nazareth, Assela sheet) and its instructions, the stratum lithology of the study area includes Basalt flow, Old basalt, Alkaline basalt, Rayolite dome and tuffs, and Lacustrine sediments (Fig.4). From all types of stratum Basalt flow has higher bearing capacity, which can be used as natural foundation support layer for wind turbines and different infrastructures of wind farm. The bearing capacity of the rest stratum lithology decreasing towards the areas covered by Old basalt, Alkaline basalt, Rayolite dome and tuffs, Lacustrine sediments.

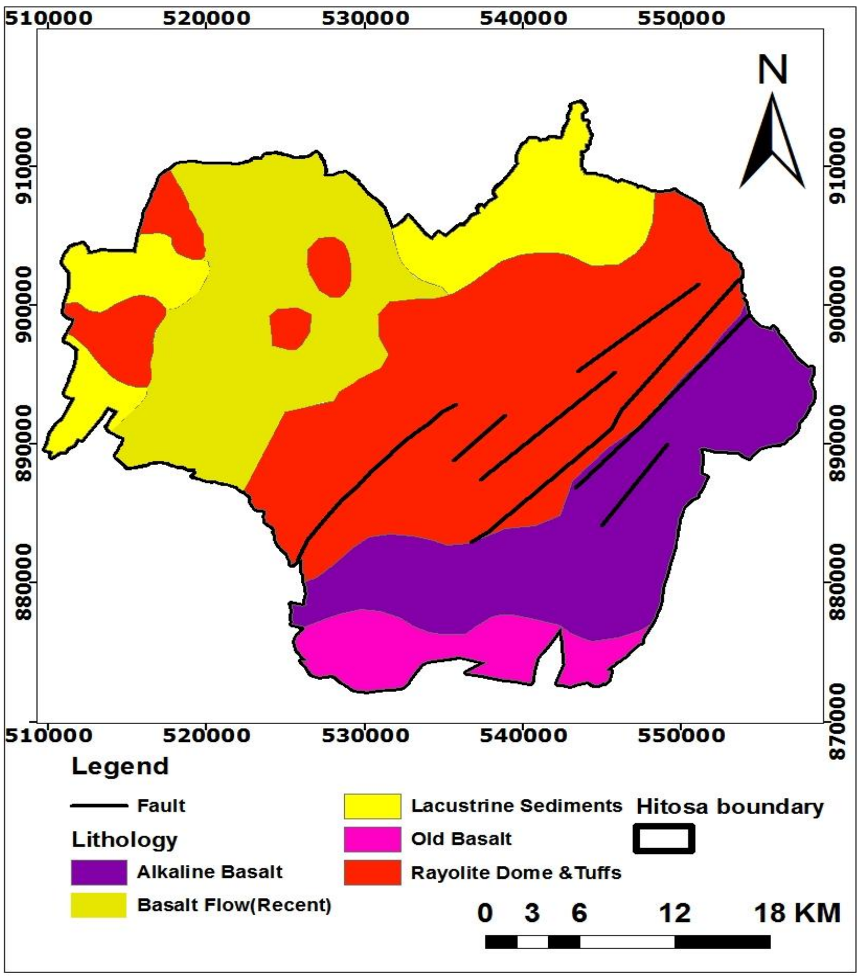


Figure 4: Digitized geologic map of the study area (Source: Geological survey of Ethiopia, 1978)

3.2. Data Description and Software

3.2.1. Data Description

To achieve the above stated objective, data were collected and organized from primary and secondary sources. The primary data includes Global Positioning System (GPS) data for verification of Land Use Land Cover (LULC) map that was produced from image of Landsat 8. This landsat image was also the primary data, which was downloaded from U.S. Geological Survey Global Visualization Viewer Website (glovis.usgs.gov) without the presence of cloud cover. In addition to Land sat 8 Operational Land Imager (OLI), Shuttle Radar Topography Mission (SRTM), Digital Elevation Model (DEM) data with resolution of 30*30m was used for Elevation and slope analysis.

The secondary data used were those published and unpublished documents from various organizations. National Meteorological Agency was the main source to identify wind speed for potential wind farm. Demographic characteristics as well as related data were gathered from Central Statistical Agency, geological data from Geological Survey of Ethiopia, topographic map from Ethiopian Map Authority (EMA) and different data related with wind energy from Ethiopian Electric Power Corporation (EEPCO).

3.2.2. Software Packages used

The software packages used for this study were ERDAS (Earth Resources Data Analysis System) Imagine 2014 for remote sensing application in order to process satellite images including LULC classification, ArcGIS 10.3 for data storage, visual exploration and map preparation and IDRISI 17.0 software is appropriate for fuzzifying to give weight with FAHP (Fuzzy Analytical Hierarchy Process) and to make aggregation using WLC (Weighted Linear Combination) for dependent factors to develop the final model.

3.3. Methods

The method for this research includes the following stages: i) identification and evaluation of criteria; ii) data collection; iii) preprocessing; iv) input dataset; v) explanatory variables autocorrelation; vi) protected areas (Constraints); vii) reclassified input layers; viii) standardizing criteria with fuzzy approach; ix) Pair wise comparison of criteria and give weight with FAHP; x) Fuzzy aggregation with multi criteria evaluation and validation (Fig. 5).

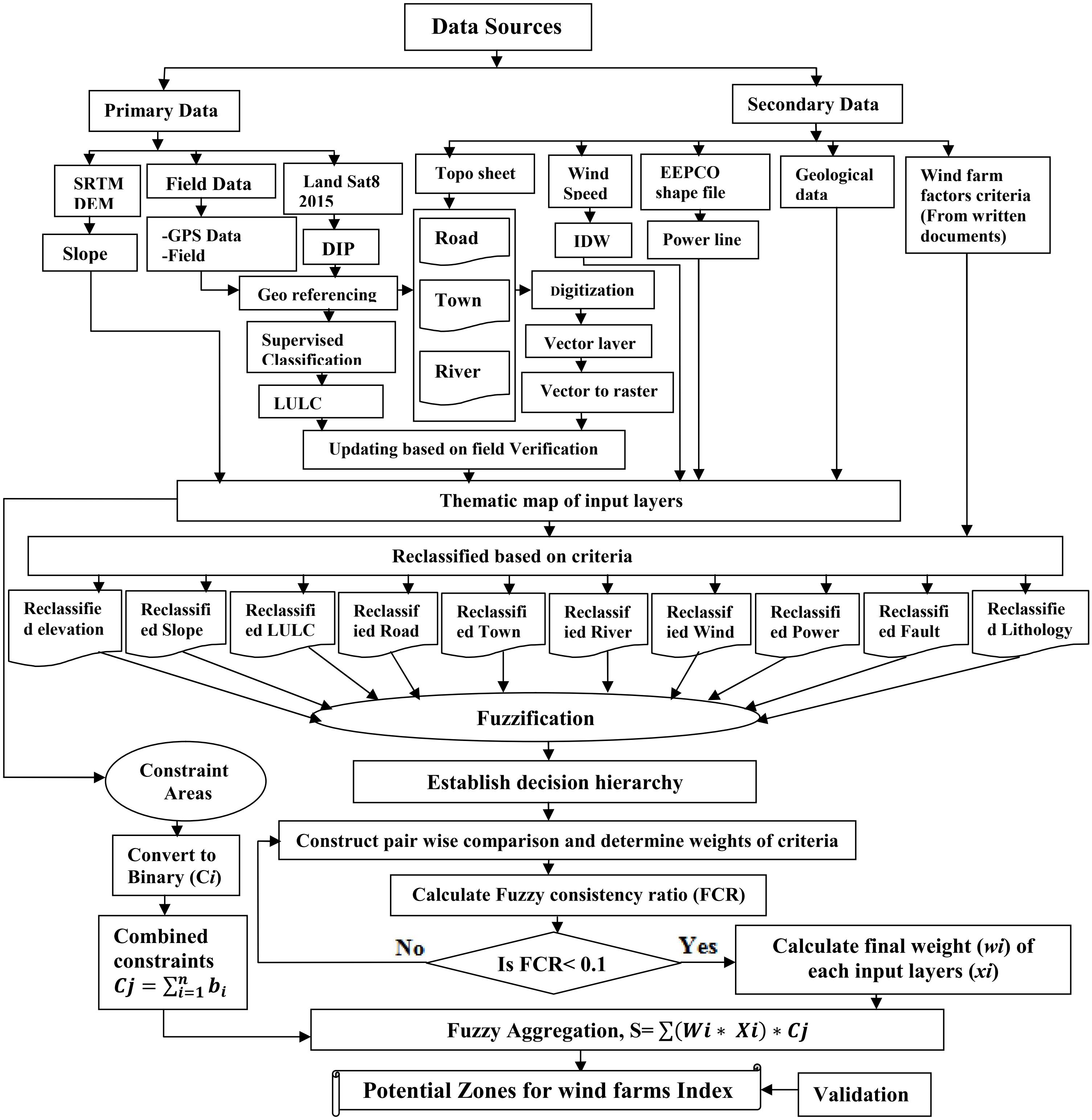


Figure 5: Flow chart of the methodology

3.3.1. Identification and Evaluation of Criteria

Different modeling approaches were followed to identify the most appropriate sites for wind farm. It is dependent on different factors such as economical, social and environmental. Economic factors for the site of wind power facilities include wind speed and/or wind power density and distance to transmission lines, road and slope. Socially influenced factors include distance from urban areas and historic sites. Environmental variables generally include distance from wetlands, rivers, forests, water bodies, elevation and geology (Baban and Perry, 2001; Mann *et al.,* 2012).

The environmental and associated criteria of the wind farm site selection was obtained by reviewing different literature of the wind turbine site selection . Since there are many related studies using different attributes or criteria for wind turbine site selection, the widely used criterion are applied in the present study. The recognized criterion is economical factors such as wind speed, distance to transmission lines, roads and slopes; social variable such as distance from urban areas; and environmental variables such as distance from rivers, elevation, LULC and geology were reviewed as follows:

Wind Speed

According to Vanek and Albright (2008), the wind power in a given site depends on having sufficient wind speed available at the height at which the turbine is to be installed. Wind power density is a most important factor because it provides information on the most feasible and profitable areas in the region for siting a wind power project (Baban and Perry, 2001).

Moreover wind turbines at locations with an average wind speed below 5.1 m/s at 10m of height cannot generate wind electricity at economically viable levels (Grubb and Meyer, 1993; World Energy Council, 1994).

Proximity to Major Road

The proximity to major transportation infrastructure is essential step in the planning process because transportation of oversized turbines can be complex and costly. For instance, tower sections for the common 80 m turbine can weigh more than 70 tons, be 36 m long, have a diameter of 4.5 m, and have blades that can range between 33 to 44 meters in length (AWEA, 2009). Often, these components must be transported as single pieces, thus requiring large equipment for shipment. Small residential roads cannot easily support the size and weight of such components and may have inadequate turning radii for bringing the turbine components to the site. The distance from the potential wind farm site to major roads should be minimized to lower construction costs by making the transportation of wind turbines as efficient as possible (Bartniki and Williamson, 2012). The criterion for major road was shown in Table 5.

Table 5: Criteria for Major road (Source: Pandian and Iyappan, 2015).

Factors	Criteria value	Classification
Main road	150 -2500m	Extremely suitable
	2500-5000m	Very suitable
	5000-7500m	Suitable
	7500-10000m	Less suitable
	< 150m and > 10000 m	Not suitable

Proximity to Power Line

A suitable location will need to be in close proximity to existing roads and hydro lines to minimize production costs (Bartnicki and Williamson, 2012). Siting a wind farm where transmission lines are lacking will require new transmission lines to be installed, which will increase the costs associated with wind farm development. Based on this, Table 6 was shows as the suitability decreases with increasing distance from transmission line.

One of the major costs of setting up new wind farm is the expense associated with construction of new transmission lines that must be built from the location of the facility to existing grid structures. The lack of transmission capacity for new projects has been one of the major hurdles that projects have needed to overcome and siting of new transmission lines can be a costly and contentious process (Vajjhala and Fischbeck, 2007).

Table 6: Criteria for Power line (Source: Pandian and Iyappan, 2015).

Factors	Criteria value	Classification
Transmission line	200-5,000m	Extremely suitable
	5,000-10,000m	Very Suitable
	10,000-15,000m	Suitable
	15,000 -20,000m	Less Suitable
	< 200m and > 20,000 m	Not Suitable

Slope

Bartnicki and Williamson (2012) explain that at the summit of steep slopes wind may not hit the turbine rotor at a perpendicular angle. This will result in an increased level of fatigue for the turbine (Table 7). Building on higher slopes also increases project costs. Ideally, the terrain should be rounded or flat because they will be exposed to higher, more constant wind speeds (Baban and Parry, 2001).

Table 7: Criteria for slope (Source: Farajzadeh *et al.,* 2013).

Factors	Criteria value	Classification
slope	< 12%	Extremely suitable
	12 - 15%	Very Suitable
	15 - 30%	Suitable
	30 - 45%	Less Suitable
	> 45%	Not Suitable

Urban areas, Settlement and Historic sites

Highly urbanized or otherwise densely populated regions are severely constrained as is evident in potential assessment and planning studies at national level (Hoogwijk *et al,* 2004). As shown in Table 8, due to the noise and vibration generated from wind turbines it is important to ensure that wind farms are located outside the residential area (Al-Yahyai *et al,* 2012).

Table 8: Criteria for Urban areas (Source Bennui *et al.,* 2007).

Factors	Criteria value	Classification
Urban areas	>5500m	Extremely suitable
	4500-5500m	Very suitable
	3500-4500m	Suitable
	2500-3500m	Less suitable
	0.0-2500m	Not suitable

Water bodies, Distance from wetlands

Any type of water bodies, lakes, sea, rivers, wetlands and flood plains are to be protected to preserve the natural wealth (Baban *et al,* 2001). Moreover, it was shown in Table 9.

Table 9: Criteria for rivers (Source: Bennui *et al.,* 2007)

Factors	Criteria value	Classification
River, Stream	>800m	Extremely suitable
	600-800m	Very Suitable
	400-600m	Suitable
	200-400m	Less Suitable
	0.0-200m	Not Suitable

Land use Land Cover

Although individual wind turbines have a relatively small footprint on the land, a concern surrounding wind farms is the impact on land related to the construction and operation of the turbines. According to Denholm *et al.* (2009), different amount of land cover future was impacted by utility-scale wind farms on different types of land uses (Table 10). The study showed that wind farms located on the same land use are often associated with the same layout configurations, and the layout of the turbines correlates with how much land is permanently impacted. The study suggested that wind farms located on agriculture, pasture, and shrub impact less amount of land than grassland and forestland. For instance, installation patterns such as parallel string configuration are often used in grassland and that is not the case in forested areas where clearing for access roads, turbine pads, and set back areas around each turbine is required.

Table 10: Criteria for Land use Land cover (Source: Farajzadeh *et al.,* 2013).

Factors	Criteria value	Classification
Land use	Bare land	Extremely suitable
	Agricultural land	Very suitable
	Grass land	Suitable
	Forest land	Less suitable
	Wet land	Not suitable

Surface Faulting

The offset or tearing of the earth surface by differential movements across a fault is an obvious hazard to structures built across active faults. A variety of structures have been damaged by surface faulting, including buildings, railways, roads, tunnels, bridges, canals, water wells and water mains, wind turbines, electricity lines and sewers. Particularly severe to structures partly embedded in the ground and for underground pipelines or tunnels. Surface faulting generally affects a long and narrow zone ranging from few meters to more than 100 m (Table 11). Subsidiary branch faults have extended as much as 10 km from the main fault and secondary faulting has been observed more than 25 km away from the main fault (Studer, 2000).

Table 11: Criteria for fault (Source: Farajzadeh *et al.,* 2013).

Factors	Criteria value	Classification
Fault	> 5000m	Extremely suitable
	4000-5000m	Very suitable
	3000-4000m	Suitable
	2000-3000m	Less suitable
	< 2000m	Not suitable

3.3.2. Data collection

The primary and secondary data that identified as criteria factors for analysis were collected from different sources as shown in Table 12.

Table 12: Description of GIS data layers used in the current study.

GIS data layer	Description	Data Source
Vector (polygon)	Woreda Boundary	CSA(2008)
Raster	Wind speed	NMSA (2004-2014)
Raster	Elevation	Shuttle Radar Topography Mission (SRTM)
Raster	Slope	Shuttle Radar Topography Mission (SRTM)
Vector (line)	Power lines	EEPCO
Vector (line)	Main road	Topographic map, scale 1:50,000 (EMA)
Vector	Town	Topographic map, scale 1:50,000 (EMA)
Vector (line)	River	Topographic map, scale 1:50,000 (EMA)
Raster	Land use land cover Classification	Land sat 8 (OLI) (glovis.usgs.gov)
Vector (polygon)	Litholgy	Geological survey of Ethiopia (1978)
Vector (line)	Fault	Geological survey of Ethiopia (1978)

3.3.3. Preprocessing

The third stage is preprocessing, that includes i) importing, layer stacking, sub-setting of satellite image based on the boundary of the Hitosa Woreda and ii) radiometric and geometric correction in order to reduce distortion of image data in ERDAS Imagine 2014 software. In addition, the image was geo-referenced using topographic Sheet provided by EMA. This data was further re-projected to make the accessible input image for further analysis. During geo-referencing and re-projecting process, Adindan _ UTM _ Zone_37N coordinate system was followed for raster data as well as vector data in the research to maintain uniformity.

3.3.4. Input Dataset

In the fourth stage, thematic map of input layers were prepared for multiple variables such as social, economical and environmental factors, which included in the geographical modeling. The thematic maps of road, town, and river prepared by digitizing from geo-referenced topographic map of 1:50,000 scale in GIS environment. Then, the processed data were stored in Esri-shape file.

Slope map generated from DEM data of SRTM in the GIS environment. Thematic map for fault and lithology was also prepared by digitizing from 1:50,000 geological maps of Assela and Nazareth sheet for the modeling.

Thematic map of wind speed for the study area was interpolated in Arc GIS 10.3 from available annual average 2m height metrological data of ten years (2005-2014) of six stations which are Kulumsa, Robe, Nazareth, Golelcha, Nurera and Methara by using an Inverse Distance Weighted (IDW) technique.

Thematic map for land use was obtained from LULC classification of the study areas. In this study one of the types of supervised classification which is Maximum Likelihood Classification (MLC) was used in order to classify and produce a LULC map. This kind of classification is important as the analyst can have clues in editing and creating the signatures or training areas. This is a merit used to segregate features with nearby reflectance values and that cannot overcome by unsupervised classification (Campbell and Wynne, 2011). This LULC map from Land sat 8 (OLI) of 2015 was prepared and validated based on field data with over all accuracy of 82.22% by using ERDAS Imagine 2014.

Each factor map was prepared in a manner that can support to the overall goal of wind potential site modeling. The digitized vector layers and prepared input layers were changed to raster layers of 30m cell size in order to make appropriate for the analysis. Because of raster layers are a simple data structure and a powerful format for intense statistical and spatial analysis.

3.3.5. Explanatory Variables Autocorrelation.

After the layer map of the factor was prepared, the correlation analysis was carried out on CORREL work sheet function by extracting 2000 sample value data of each of the factors. This correlation analysis tool examined each pair of measurement variables tend to move together, that is, weather large values of one variable tend to be associated with large values of the other (positive correlation(+1)), weather small values of one variable tend to be associated with large values of the other (negative correlation(-1)), or values of both variables tend to be unrelated (correlation near zero(0)).The value of any correlation coefficient must be between -1 and +1 inclusive. This autocorrelation removes redundancy of factors for the modeling.

Equation of correlation coefficient:

$$Correl(x, y) = \frac{\sum(x-\bar{x})\,(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}} \quad \text{.......} \quad (1)$$

Where x and y are the sample value of the two variables.

3.3.6. Protected Areas

This stage involved utilizing exclusionary criteria (also known as constraints) in preliminary screening to exclude unacceptable areas for siting a wind farm. It is excluded for protecting effects on environment, communities, visualization, eco-conservation, and engineering frontier (Bennui *et al.,* 2007). A threshold was assigned for constraint criteria. Such threshold classifies a criteria raster into suitable and unsuitable pixels using a binary classification (Effat, 2014). Suitable pixels were assigned a value of "one" while unsuitable pixels were assigned a "zero" value. In the last stage of data analysis, inappropriate zones were combined in a single constraints binary map and excluded. Constraints of the present study explained as follows:

Power Line Setback

Moiloa (2009) suggested that for wind farm a minimum distance of 250 meters should be kept apart from high voltage lines. The Same distance was considered for the current study. To put this into practice, as shown in Fig. 6, areas in 250m of power line were assigned an index value of "0" to represent their unsuitability whilst the other areas considered to be suitable for locating a wind farm were assigned the index value "1".

Town Setback

According Bartnicki and Willamson (2012), from wind farm areas, a minimum distance of 550m setback should be used for urban, recreational and historic areas. For the current study, a setback of 2500 m was used for towns to account for growth expansion. As shown in Fig.6, an index value of "1" was assigned to areas, greater than 2500m from towns, were suitable for constructing a wind farm, whilst the other areas, considered to be unsuitable, were assigned an index value of "0".

Main Roads Setback

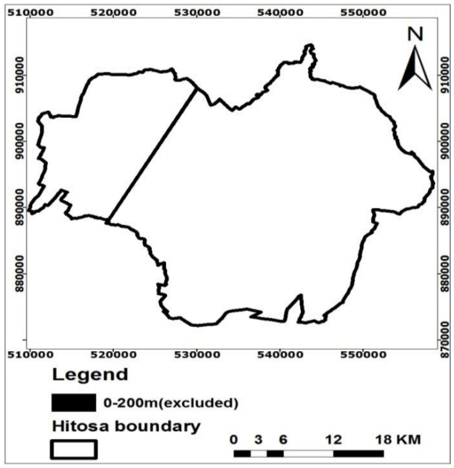
A distance of 2500m from main roads and railroads and a distance of 250 meter from secondary roads were suggested for wind farm site selection (Moiloa, 2009). A distance function was used to classify the region, where the areas closer to the roads setback buffers were given high suitability while areas further to the buffer were given low suitability. For the present study, as shown in Fig.6, a setback of 150 meter was used. To put this into practice, areas in 150m from roads were assigned an index value of “0” to represent their unsuitability whilst the other areas considered to be suitable for locating a wind farm were assigned the index value “1”.

Rivers Setback

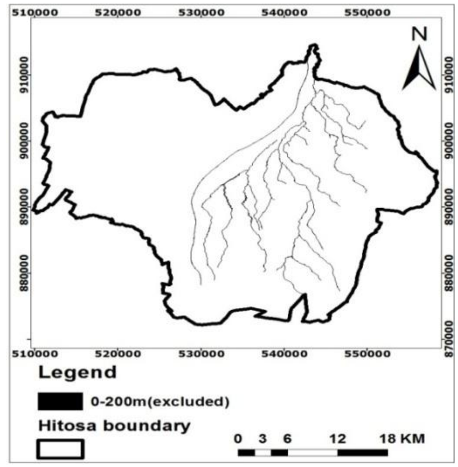
According to Baban and Parry (2001), any type of water bodies and rivers are to be protected to preserve the natural wealth. For the current study, a setback of 200 meters was used for rivers to account for natural wealth. An index value of “1” was assigned to areas which greater than 200m from river, suitable for constructing a wind farm, whilst the other areas, considered to be unsuitable, were assigned an index value of “0”(Fig.6).

Faults Setback

Fault is an obvious hazard to building structures such as wind turbine especially active faults. Faults generally are a long and narrow zone ranging from few meters to more than 100 m (Studer, 2000). For the current study, a setback of 2000 meters was used for fault to account for safety. To put this into practice as shown in Fig.6, areas in 2000m of fault were assigned an index value of “0” to represent unsuitability while the areas considered to be suitable for locating a wind farm were assigned the index value “1”.



a)



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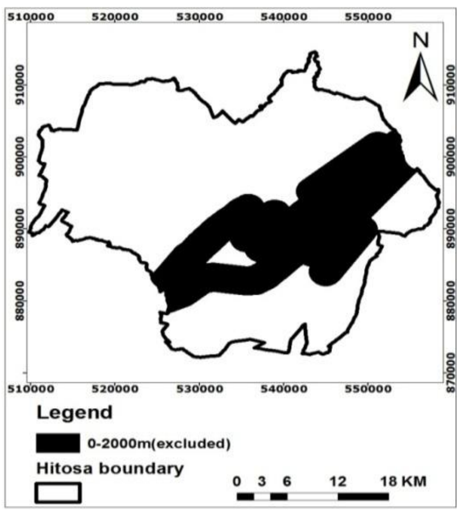

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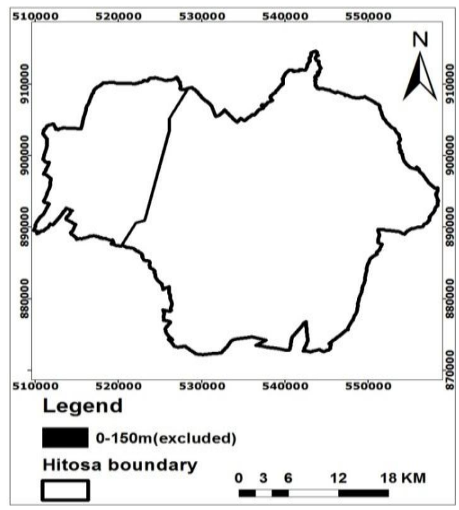

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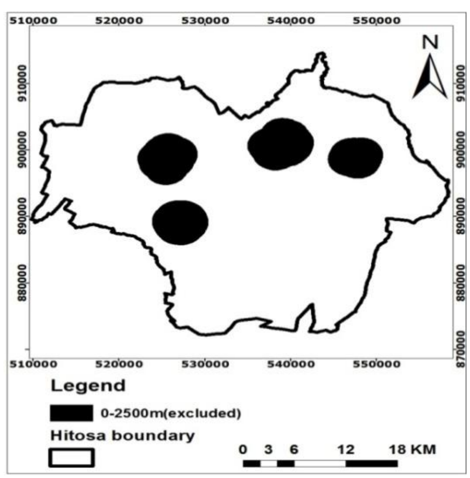


e)

Figure 6: Constraints maps, (a) power line; (b) rivers; (c) fault; (d) road; (e) towns

Creating an Overall Constraint Map

After reducing the constraint maps to Boolean images (images with 1 and 0 values), all the layers were assigned an equal weight as they were considered to be equally important. The Boolean images were subsequently over laid consecutively; by using the Boolean Intersection or Logical AND technique available in the Multi-criteria Evaluation (MCE) module of the IDRISI 17 software package. This technique was considered to be a very extreme form of decision making in which a location must meet every criterion for it to be included in the decision set. According to Eastman (2006), Boolean Intersection overlay selects locations based on the most cautious strategy possible and hence considered a risk-averse technique. It can be represented mathematically by Equation 2.

$$SI = \sum_{i=1}^{n} b_i \quad \text{.........} \quad (2)$$

Where, SI is the overall suitability index value (0 or 1), b is the suitability index value for each constraint criterion (0 or 1) and n is the number of constraint criteria.

3.3.7. Creating Reclassified Factor Maps

In determining the value given to each criteria and in establishing the level of desirability of each attribute, different measurements and ranges was used where most applicable to existing national norms and standards.

Data processing and analysis of all factor maps were done in the ArcGIS and IDRISI software. Distance maps were generated by using the spatial analyst straight line distance function in ArcGIS, which created such maps by calculating the straight line (Euclidian) distance from the identified criteria. The “RECLASS” function was used to classifying in to different classes.

Based on the reviewed concepts of different authors, the criteria used in this study are presented in the following section:

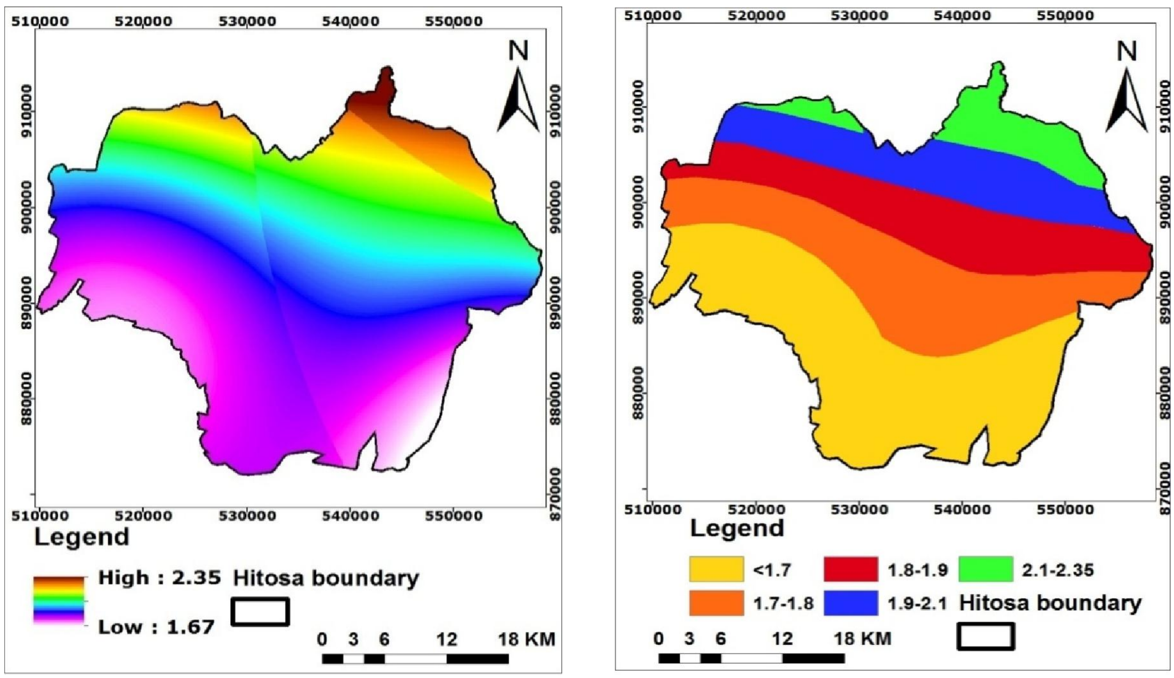
Wind Speed

The wind speed value is the essential criteria used in determining the potential wind farm areas.

As shown in Fig.7, depending on the experience and reality of national existing wind farm, the wind speed at 2m height of the study area is reclassified in to five classes (Table 13).

Table 13: Reclassification of wind speed factor

Factor	Speed in m/s	Suitability value	Classification
Wind	2.1-2.35	5	Extremely suitable
	1.9-2.1	4	Very suitable
	1.8-1.9	3	Suitable
	1.7-1.8	2	Less suitable
	<1.7	1	Not suitable



a) b)

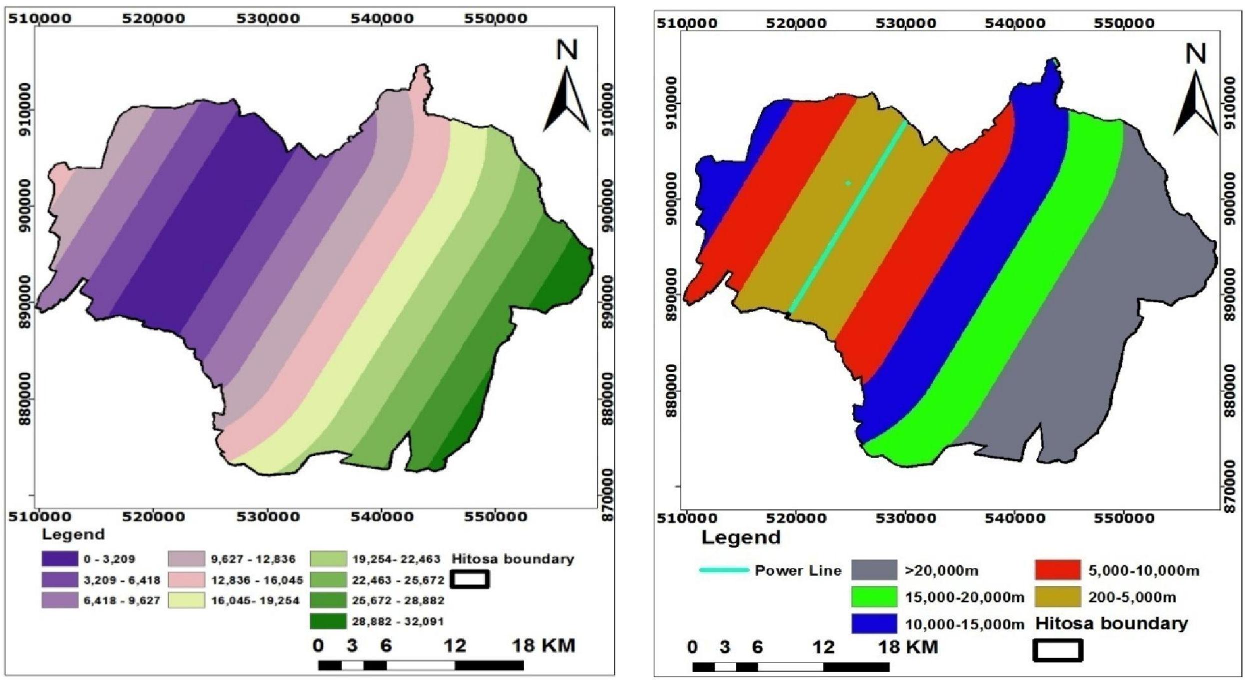
Figure 7: Wind speed factor map a) Interpolated input wind speed map b) Reclassified map of wind speed (m/s)

Proximity to Power Line

The distance to transmission lines is a necessity in order to transport the energy created by the wind turbines and reduce costs. Land that is connected to an electrical grid therefore provides a more suitable site. As shown in Fig.8, proximity to transmission line was reclassified in to five classes (Table 14).

Table 14: Reclassification of power line factor

Factors	Distance in m	Suitability value	Classification
Power line	200-5000	5	Extremely suitable
	5000-10000	4	Very suitable
	10000-15000	3	Suitable
	15000-20000	2	Less suitable
	> 20000	1	Not suitable



a) b)

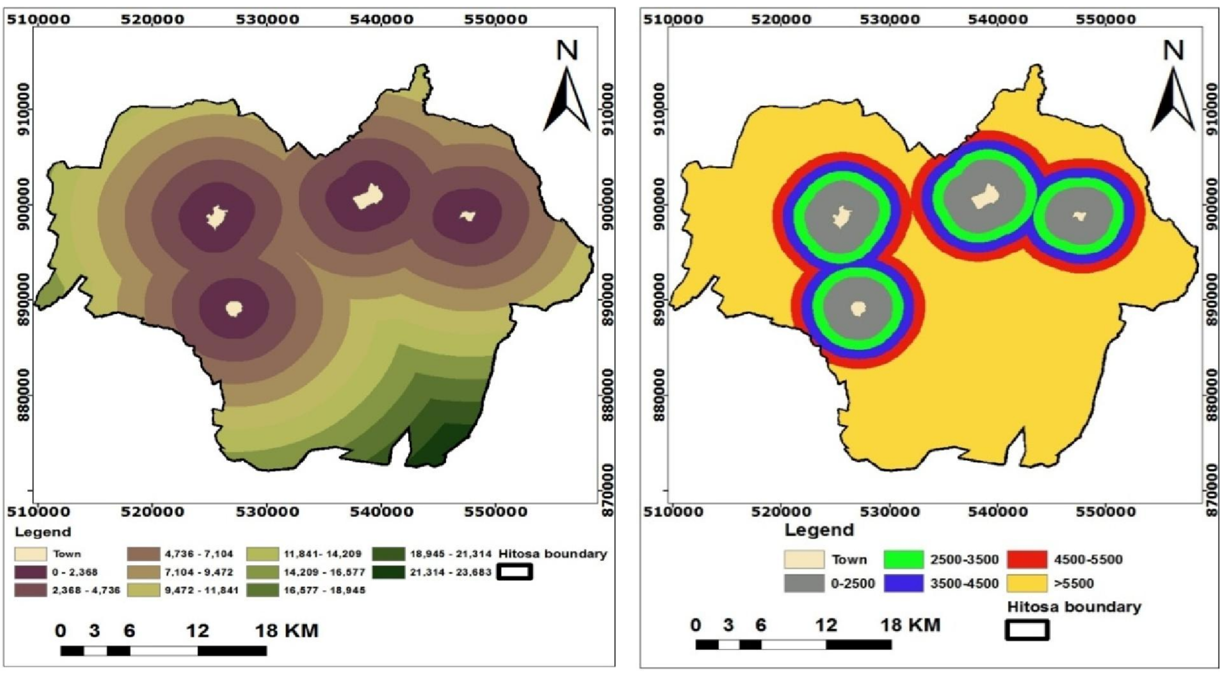
Figure 8: Power line factor map, a) Euclidian distance from power line b) Reclassified map of power line (m)

Proximity to Town

Due to the noise, vibration generated from wind turbines and considering growth expansion of town it was important to ensure that wind farms were located outside the residential area. As shown in Fig. 9, proximity to town was reclassified in to five classes (Table 15).

Table 15: Reclassification of town factor

Factors	Distance in m	Suitability value	Classification
Town	>5500	5	Extremely suitable
	4500-5500	4	Very suitable
	3500-4500	3	Suitable
	2500-3500	2	Less suitable
	0-2500	1	Not suitable



a) b)

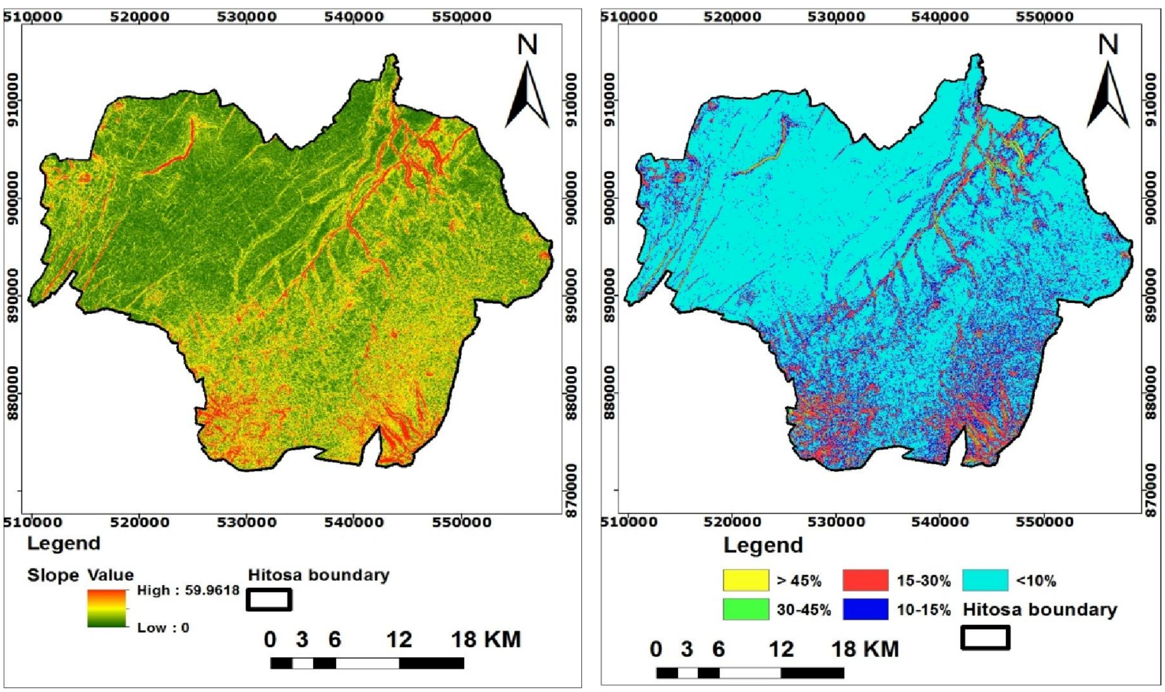
Figure 9: Town factor map, a) Euclidian distance from town b) Reclassified map of town (m)

Slope

It is obvious that constructing on higher slopes increase project cost. This is because steep slope will require more grading and earth movement than gentle slope. Steep slope may also limit the size of turbines that can be installed due to limitations in the ability to transport the turbines and cranes to the site. As much as possible, the terrain should be flat because it will be exposed to higher and more constant wind speeds. In this study, according to its significance for wind farm establishment, the slope was reclassified in to five categories as shown in Fig.10, ranked between most suitable for flat to 10 degrees and unsuitable for slopes greater than 45 degrees (Table 16).

Table 16: Reclassification of slope factor

Factors	Slope in %	Suitability value	Classification
Slope	<10	5	Extremely suitable
	10-15	4	Very suitable
	15-30	3	Suitable
	30-45	2	Less suitable
	>45	1	Not suitable



a) b)

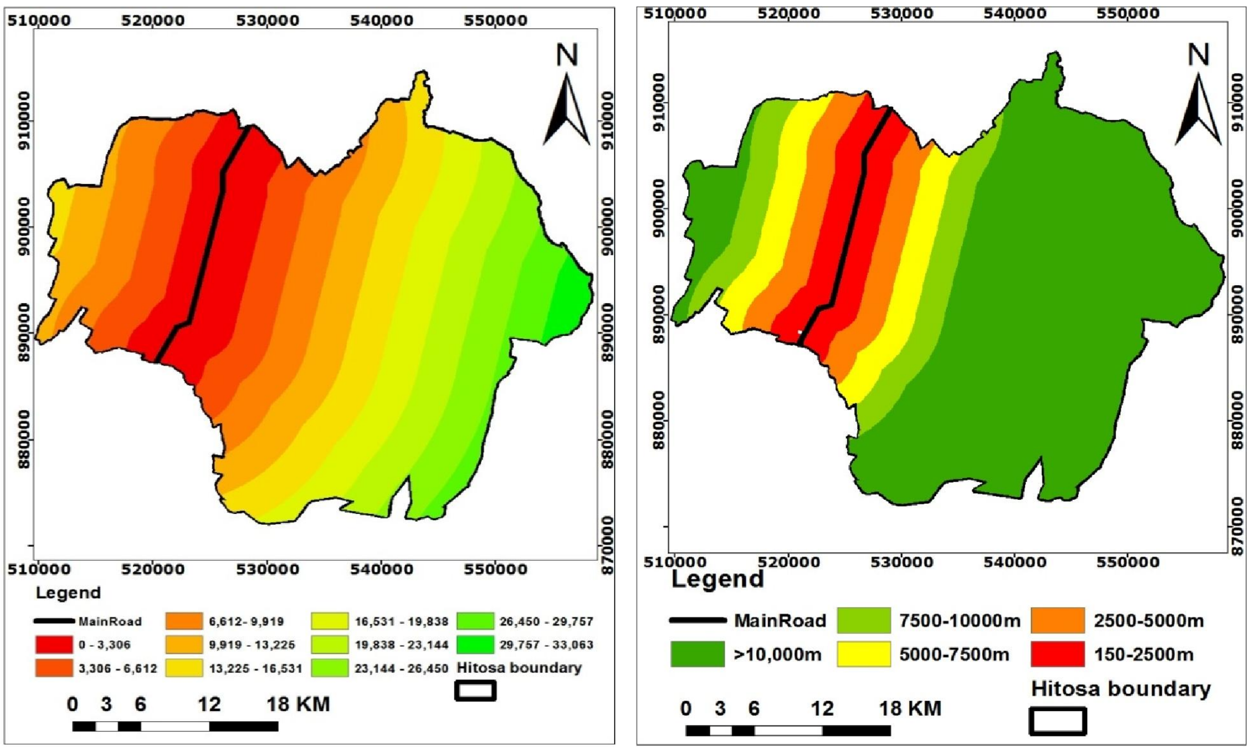
Figure 10: Slope Factor map a) Slope map b) Reclassified map of Slope (%)

Proximity to Main Road

The distance from the potential wind farm site to main roads should be minimized to lower costs by making the transportation of wind turbines as efficient as possible. In this study, distance from main road was reclassified in to five categories as shown in Table 17 and Fig.11.

Table 17: Reclassification of main road factor

Factors	Distance in m	Suitability value	Classification
Main road	150-2500	5	Extremely suitable
	2500-5000	4	Very suitable
	5000-7500	3	Suitable
	7500-10000	2	Less suitable
	>10000	1	Not suitable



a) b)

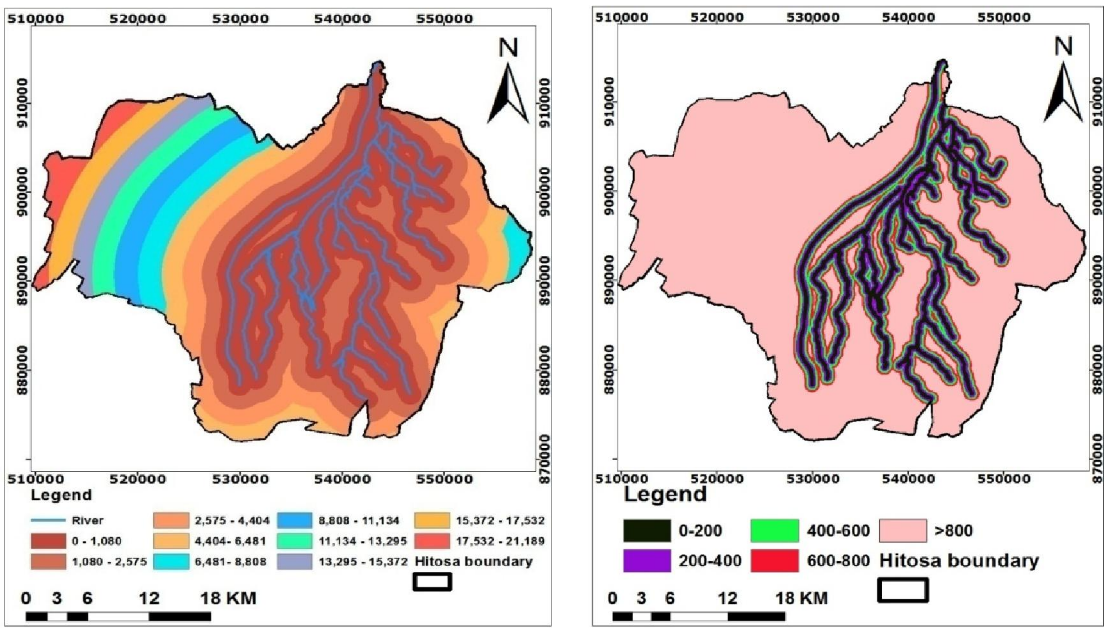
Figure 11: Road Factor map a) Euclidian distance from road b) Reclassified map of road (m)

Proximity to River

Any type of water bodies, rivers are to be protected to conserve the natural wealth. In this study distance from river was reclassified in to five categories as shown in Table 18 and Fig.12.

Table 18: Reclassification of river factor

Factors	Distance in m	Suitability value	Classification
River	> 800	5	Extremely suitable
	600-800	4	Very suitable
	400-600	3	Suitable
	200-400	2	Less suitable
	0-200	1	Not suitable



a) **b)**

Figure 12: River Factor map (m) a) Euclidian distance from river b) Reclassified map of river

Lithology

From all type of stratum lithology, Basalt flow has higher bearing capacity, which can be used as natural foundation support layer for wind turbines and different infrastructures of wind farm.

The stratum bedrock type was reclassified in to five categories as shown in Table 19 and Fig.13, ranked between higher bearing capacity for Basalt flow and lower bearing capacity for Lacustrine sediments (Peck *et al.*, 1974).

Table 19: Reclassification of Lithology

Factors	Type	Suitability value	Classification
Lithology	Basalt flow(recent)	5	Extremely suitable
	Old basalt	4	Very suitable
	Alkaline basalt	3	Suitable
	Rayolite dome and tuffs	2	Less suitable
	Lacustrine sediments	1	Not suitable

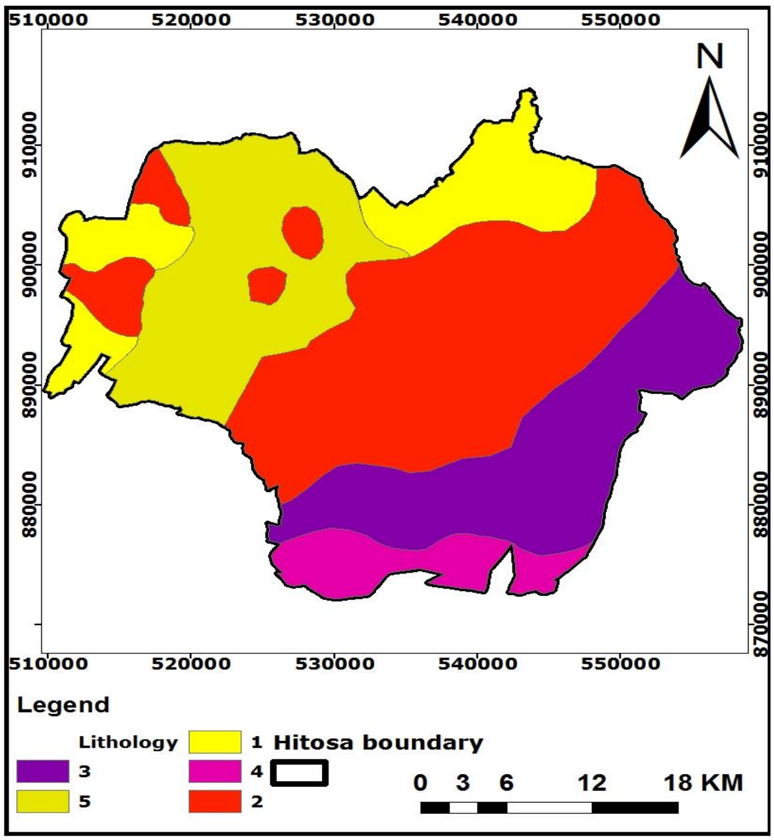


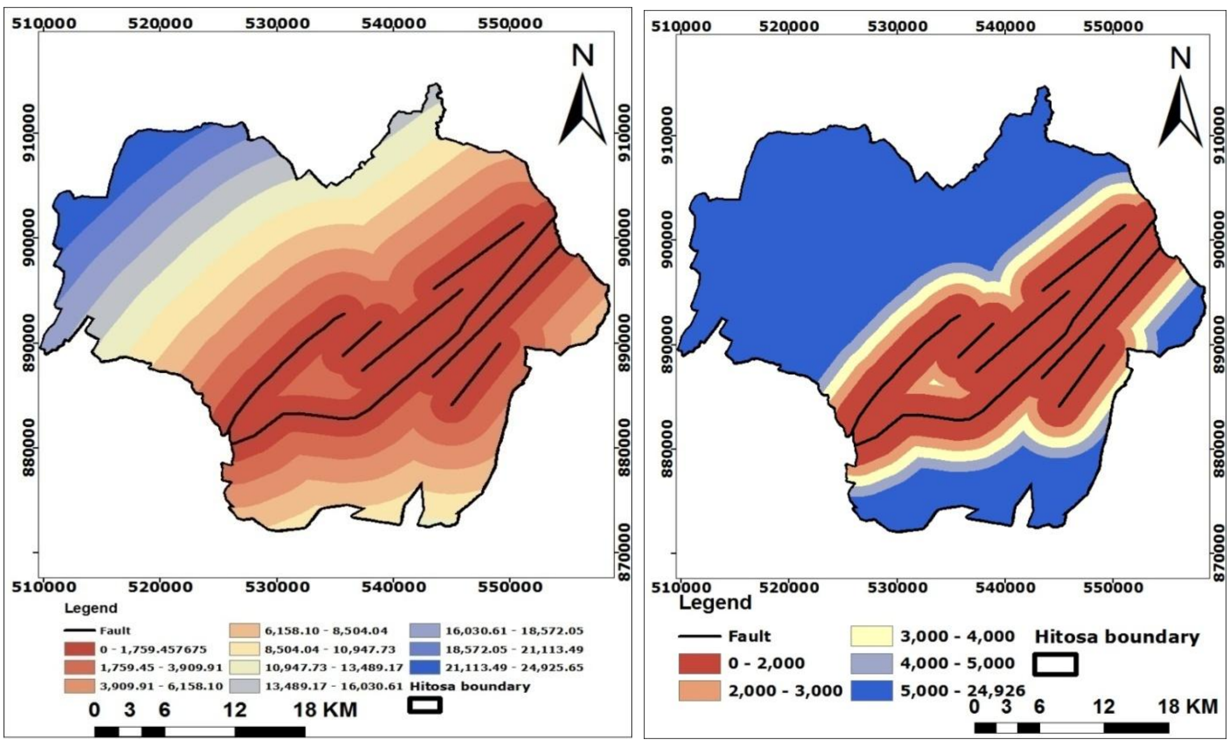
Figure 13: Reclassified map of Lithology

Fault

For the reason that faulting can be particularly severe to structures partly embedded in the ground it is important to ensure that wind farms are located outside the fault area. Surface faulting generally affects a long and narrow zone. As shown in Fig.14, proximity to fault was reclassified in to different five classes (Table 20).

Table 20: Reclassification of fault factor

Factors	Distance in m	Suitability value	Classification
Fault	> 5000	5	Extremely suitable
	4000-5000	4	Very suitable
	3000-4000	3	Suitable
	2000-3000	2	Less suitable
	0-2000	1	Not suitable



a) b)

Figure 14: Fault Factor map (m) a) Euclidian distance from fault b) Reclassified map of fault

LULC

Different studies suggested that wind farms located in agriculture, bare land, and shrub impact less amount of land than grassland and forest land. As shown in Table 21 and Fig.15, LULC was reclassified in to different five classes.

Table 21: Reclassification of LULC factor

Factors	classification	Suitability value	Classification value
LULC	Bare land	5	Extremely suitable
	Agricultural land	4	Very suitable
	Grass land	3	Suitable
	Forest	2	Less suitable
	Settlement	1	Not suitable

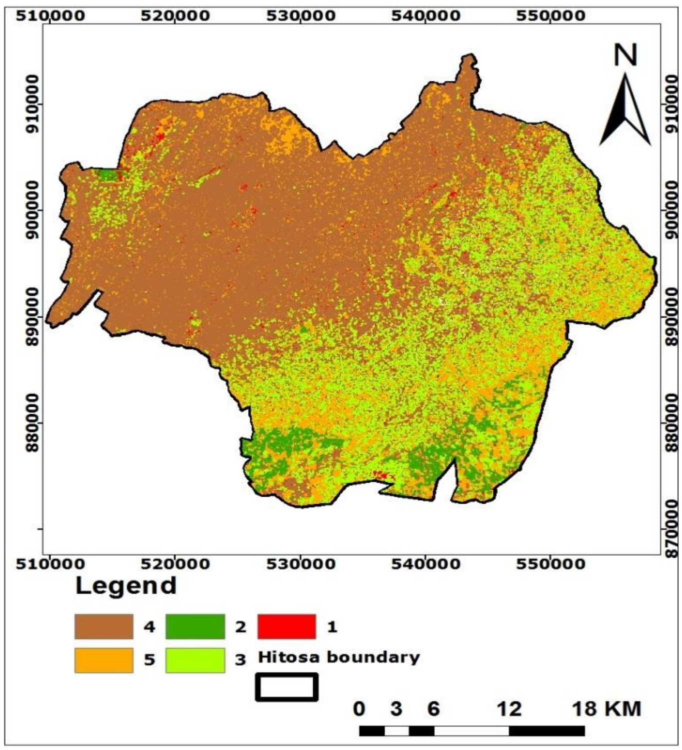


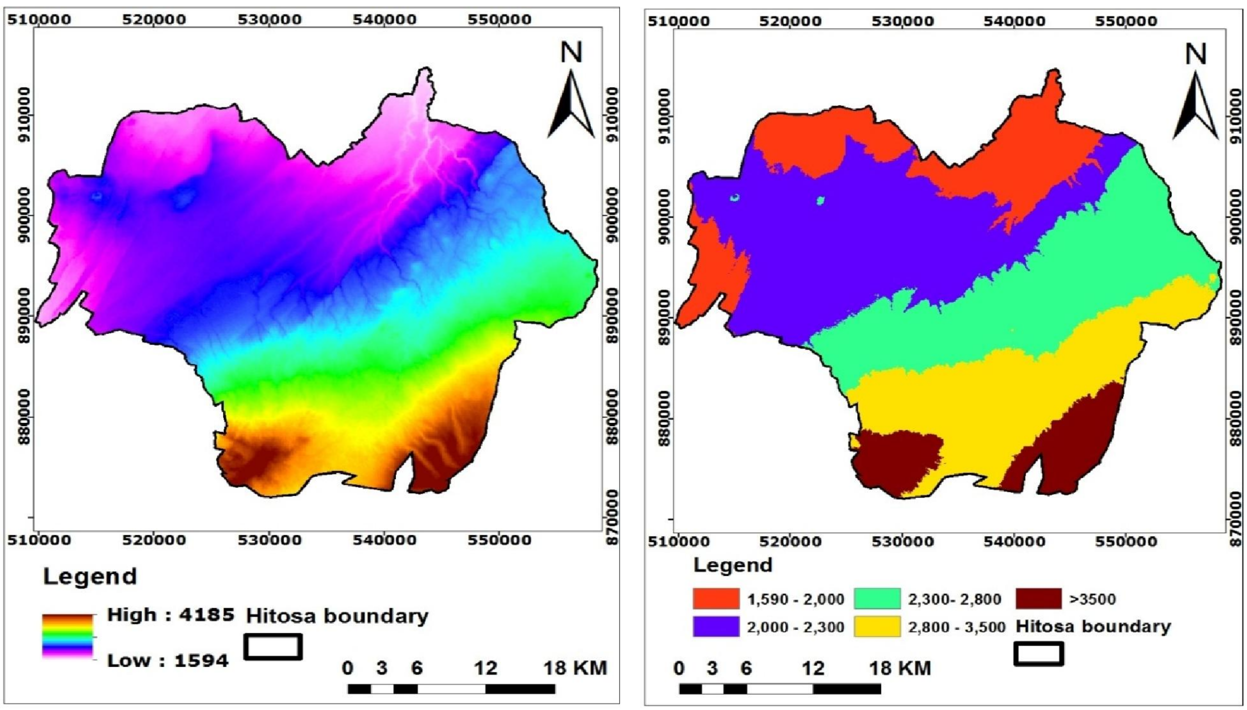
Figure 15: Reclassified map of LULC

Elevation

For a given wind speed, the wind energy also depends on the elevation of the wind turbine above sea level. This is because the density of the air decreases with increase in altitude and the wind energy is proportional to the air density. In this study elevation was reclassified in to five categories as shown in Table 22 and Fig.16.

Table 22: Reclassification of elevation factor

Factors	Altitude in m a.m.s.l	Suitability value	Classification
Elevation	1590-2000	5	Extremely suitable
	2000-2300	4	Very suitable
	2300-2800	3	Suitable
	2800-3500	2	Less suitable
	>3500	1	Not suitable



a) b)

Figure 16: Elevation Factor map (m) a) Elevation map b) Reclassified map of elevation

3.3.8. Fuzzy sets theory and Crisp set theory

In general, set theory an element is either a member of a set or not. We can express this fact with the characteristic function for the elements of a given universe to belong to a certain subset of this universe. We call such a set a crisp set.

Definition 1 (Characteristic function). Let A be a subset of a universe X.

The characteristic function X_A of A is defined as $XA: X \rightarrow \{0,1\}$ with

$$\text{XA}\ (x) = \begin{cases} 1\ iff\ \ x \in A \\ 0\ iff\ \ x \notin= A \end{cases} \quad \ldots\ldots\ldots\ldots \text{(3)}$$

In this way we always can clearly indicate whether an element belongs to a set or not. If, however, we allow some degree of uncertainty as to whether an element belongs to a set, we can express the membership of an element to a set by its membership function.

Definition2.(Fuzzy Set). A fuzzy set A of a universe X is defined by membership function μA such that $\mu A\colon X \rightarrow [0,1]$ where $\mu A(X)$ is the membership value of x in A. The universe X is always crisp set.

If the universe is a finite set X= $\{x_1, x_2, \ldots\ldots X_n\}$, then a fuzzy set A on X is expressed as A= $\mu A(X_1)/X_1 + \mu A(X_2)/X_2 + \ldots\ldots\ldots + \mu A(X_n)/X_n = \sum_{i=1}^{n} \mu A(Xi)/Xi$. ………………………… (4)

The term $\mu A(Xi)/Xi$ indicates the member sheet value to fuzzy set *A* for *Xi.* The symbol "/" is called separator, £ and "+" function as aggregation and connection of terms.

According to the above definition a membership function assigns to every element of the universe a degree of membership (or membership value) to a fuzzy set. This membership value must be between zero (no membership) and one (definite membership).

3.3.9. Modeling Fuzzy Membership

The seventh stage was standardizing input layers using fuzzy membership function on IDIRISI 17.0 Software. Before aggregating the input layers in a model they must be on the same scale. This process is known as standardization and involves assigning the same dimensionless continuous scale, either 0-255 or 0-1, to all the input layers (Rodney *et al.,* 2011). Fuzzy Membership Functions were used to standardize the criterion scores. Among the known functions from the Sigmoidal, Linear, J-Shaped and user defined in this study the user defined was used. This process indicates the unit of measurement of each factor map as belonging to a set ranging from 0.0 to 1.0 or 1 to 255, indicating a variation from non-belonging to complete-belonging or least valuable to most valuable. In this study, continuous scale (0.0 to 1.0) was used.

3.3.10. Modeling Fuzzy AHP

Fuzzy AHP

AHP is one of the well-known multi-criteria decision making (MCDM) method invented by

Saaty (1980). It is a powerful and useful MCDM approach tool. Saaty suggested the AHP as a decision making tool to resolve unstructured problems. AHP is based on pairwise comparisons. In this method, decision-maker forms a hierarchical decision tree and determines its indices and options. Although the AHP method is to capture the expert's knowledge by perception or preference, AHP still cannot reflect the human thoughts totally with crisp numbers as compared to fuzzy AHP method due to its interval values instead of simple crisp numbers. Therefore, the fuzzy AHP, which is a fuzzy extension of AHP, which is developed based on triangular fuzzy numbers, was applied in this research to solve the hierarchical fuzzy MCDM problems.

Triangular Fuzzy Numbers

Fuzzy numbers are in fact natural generalizations of ordinary numbers. Triangular and trapezoidal fuzzy numbers are usually used to capture the vagueness of the parameters which are related to selecting the alternatives (Lee *et al,* 2013). In this research, triangular fuzzy number was used to prioritize suitability of land for wind sites based on the reclassified value of map. Triangular fuzzy numbers are expressed with boundaries instead of crisp numbers for reflecting the fuzziness as decision makers select the alternatives or pairwise comparisons matrix.

A fuzzy number M on R is called a triangular fuzzy number (TFN), as it is membership function is given by (Chang, 1996),

$$\mu ä(x) = R \rightarrow [0,1]$$

$$\mu ä(x) = \begin{cases} \frac{x}{m-l} - \frac{l}{m-l} & x \in [l, m] \\ \frac{x}{m-u} - \frac{u}{m-u} & x \in [m, u] \\ 0 & otherwise \end{cases} \quad \text{......} \quad (5)$$

Where *l* is the lowest possible value, *m* is the middle possible value and *u* is the highest possible value in judgment interval of decision makers.

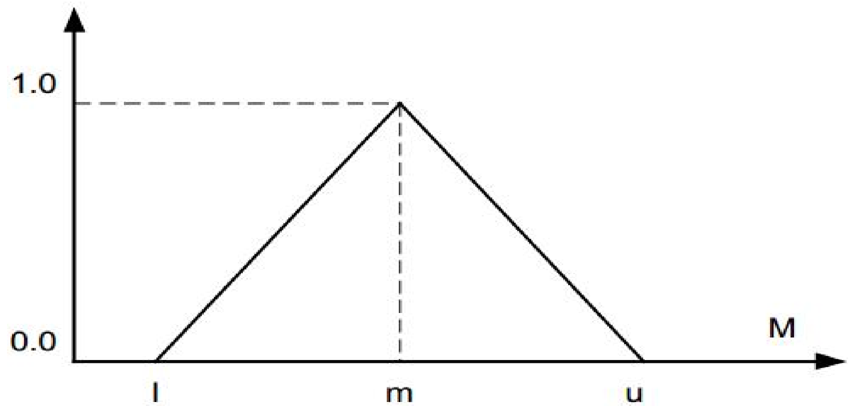


Figure 17: Fuzzy triangular numbers

Consider two triangular fuzzy numbers (TFNs) M1 and M2, M1= ($l1$, $m1$, $u1$) and M2= ($l2$, $m2$, $u2$). Their operations laws are as follows (Lee et al, 2013):

($l1$, $m1$, $u1$) + ($l2$, $m2$, $u2$) = ($l1$+$l2$, $m1$+$m2$, $u1$+$u2$)

($l1$, $m1$, $u1$) x ($l2$, $m2$, $u2$) = ($l1$x$l2$, $m1$x$m2$, $u1$x$u2$)

$(l1, \mathrm{m1}, \mathrm{u1})^{-1} = (\frac{1}{u1}, \frac{1}{m1}, \frac{1}{l1})$

Table 23: Proposed Triangular Fuzzy Numbers (TFNs), linguistic variables used in this study

Crisp-Saaty's-scale-of relative-importance (Saaty, 1980)	Preference-expressed-in linguistic-variables by (Saaty, 1980)	TFNs.scale (l,m,u)	Reciprocal-of Triangular-Fuzzy numbers
1	Equally strong	(1,1,1)	(1,1,1)
3	Moderate strong	(1,3,5)	(1/5,1/3,1)
5	Strong	(3,5,7)	(1/7,1/5,1/3)
7	Very strong	(5,7,9)	(1/9,1/7,1/5)
9	Extreme strong	(7,9,9)	(1/9,1/9,1/7)
2,4,6,8	Intermediate		

Determining weights of criteria

This research used Fuzzy Extent Analysis method proposed by Chang (1996). According to Chang (1996) to construct pair wise comparison of alternatives under each criterion, like that was said for traditional AHP, a triangular fuzzy comparison matrix is defined as follows:

$$\tilde{A} = (\tilde{a}_{ij})_{nxn} \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) \ldots.. & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & (1,1,1) \quad \ldots.. & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & (1,1,1) \end{bmatrix}$$

Where $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) = \tilde{a}_{ij}{}^{-1} = (1/l_{ji},\ 1/m_{ji},\ 1/u_{ji})$ for *i, j= 1……,n and i ≠ j.*

The steps of Chang's fuzzy extent analysis are as follows:

Step 1: Normalized values of row sums, also known as values of fuzzy synthetic extent where computed for each of the fuzzy judgment matrices, by making use of fuzzy arithmetic operations of equation 6.

$$\tilde{s}_i = \sum_{j=1}^{n} \tilde{a}_{ij} * \left[\sum_{k=1}^{n} \sum_{j=1}^{n} \tilde{a}_{kj}\right]^{-1} \ldots\ldots\ldots\ldots\ldots\ldots \text{(6)}$$

Where *denotes the extended multiplication of two fuzzy numbers. To obtain $\sum_{j=1}^{n} \tilde{a}_{ij}$, the fuzzy addition operation was applied to the fuzzy numbers in the fuzzy judgment matrices, such that,

$$\sum_{j=1}^{n} \tilde{a}_{ij} = (\sum_{j=1}^{n} l_j, \sum_{j=1}^{n} m_j, \sum_{j=1}^{n} u_j) \ldots\ldots\ldots\ldots\ldots\ldots \text{(7)}$$

To obtain $\left[\sum_{k=1}^{n} \sum_{j=1}^{n} \tilde{a}_{kj}\right]^{-1}$, the fuzzy addition operation was applied to column values in the matrix obtained from Equation 7, followed by computation of the inverse of the resulting vector such that,

$$\left[\sum_{k=1}^{n} \sum_{j=1}^{n} \tilde{a}_{kj}\right]^{-1} = \left(\frac{1}{\sum_{k=1}^{n} u_k}, \quad \frac{1}{\sum_{k=1}^{n} m_k}, \quad \frac{1}{\sum_{k=1}^{n} l_k}\right) \ldots\ldots\ldots\ldots \text{(8)}$$

Step 2: This step involved taking two criteria at a time and then using their normalized TFN's obtained from Equation 6, to determine the degree of possibility of one criterion fuzzy number's being greater than or equal to the other criteria fuzzy number's ($\tilde{s}_i \geq \tilde{s}_j$). This can be represented by Equation 9 as follows:

$$V(\tilde{s}_i \geq \tilde{s}_j) = \sup_{y \geq x} \left[\min\left(\tilde{s}_i(x), \tilde{s}_j(y)\right)\right] \ldots\ldots\ldots\ldots\ldots\ldots \text{(9)}$$

This can be equivalently expressed as,

$$V(\tilde{s}_i \geq \tilde{s}_j) = \begin{cases} 1 & if \quad m_i \geq m_j \\ \frac{l_j - u_i}{(m_i - u_i) - (m_j - l_j)} & if \quad l_j \leq u_i \\ 0 & otherwise \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots \text{(10)}$$

Where $\tilde{s}_i = (l_i, m_i, u_i)$ and $\tilde{s}_j = (l_j, m_j, u_j)$

In order to compare, $\tilde{s}_i$ and $\tilde{s}_j$, both the values of $V(\tilde{s}_i \geq \tilde{s}_j)$ and $V(\tilde{s}_j \geq \tilde{s}_i)$ were computed.

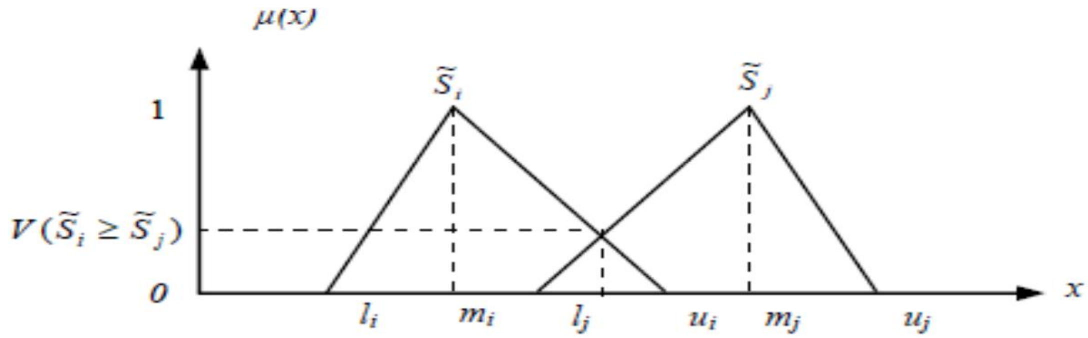


Figure 18: The degree of possibility $\boldsymbol{V(\tilde{s}_i \geq \tilde{s}_j)}$

The degree of possibility for a fuzzy number to be greater than n fuzzy numbers $\tilde{s}_i = (i = 1,2, \dots j)$ Can be defined by:

$V(s \geq \tilde{s}_1, \tilde{s}_2, \dots, \tilde{s}_j)$= $V[(S \geq S_1) and (S \geq S_2) and \dots . and (S \geq S_j)]$

$= minV((S \geq S_i), i = 1,2, \dots, j)$... (11)

Assume that $d(\tilde{A}_i) = minV(S_i \geq S_j), j = 1,2, \dots, n; j \neq i$

then the weight vector is given by:

$w' = (d'(A_1), d'(A_2), \dots, d'(A_n))^T$.. (12)

Where $\tilde{A}_i$ are n elements

Via normalization, the normalized weight vectors are

$$w = (d(A_1), d(A_2), \dots, d(A_n))^T$$

Where w is a non–fuzzy number

Step 3 : The normalized weight vectors for each fuzzy comparison matrix, $\tilde{A}$, at each level of the hierarchy were then determined by normalizing the weight vector, w. In other literature‘s this process is known as de–fuzzification and involves dividing each value in the weight vector, w, by their total sum as follows:

$w_i = \frac{V(\tilde{s}_i \geq \tilde{s}_j \mid j=1,\dots,n; j \neq i)}{\sum_{k=1}^{n} V(\tilde{s}_k \geq \tilde{s}_j \mid j=1,\dots,n; j \neq k)}, i = 1,$.. (13)

According to reviewed literatures and the expert’s opinions by perception or preference, Table 24-28 shows the pair comparison matrix of factors.

Table 24: The TFNs pair wise comparison matrix of D—C1-C3

D	C_1	C_2	C_3	W
C_1	(1,1,1)	(1,3,5)	(3,5,7)	0.5736
C_2	(0.20,0.333,1)	(1,1,1)	(1,3,5)	0.3754
C_3	(0.143,0.2,0.333)	(0.20,0.333,1)	(1,1,1)	0.051

D= potential wind farm areas, C_1= Economic factor, C_2= Environmental factor, C_3= Social factor, W is the weight of C_1, C_2, C_3 to D $FCR = 0.012$

After obtaining SC_1, SC_2, SC_3 from equation 6, these fuzzy values are compared by using equation 10 and the following are obtained.

$V(SC_1 \geq SC_2, SC_3) = 1$; $V(SC_2 \geq SC_1, SC_3) = 0.6546$; $V(SC_3 \geq SC_1, SC_2) = 0.0889$

The priority weights respect to main goal are calculated using equation 3.13 as:

W= (0.5736, 0.3754, 0.051)

Table 25: The TFNs pair wise comparison matrix of C1—F1-F4

C_1	F_1	F_2	F_3	F_4	W
F_1	(1,1,1)	(1,3,5)	(3,5,7)	(5,7,9)	0.475603
F_2	(0.2,0.333,1)	(1,1,1)	(1,3,5)	(3,5,7)	0.337951
F_3	(0.143,0.2,0.333)	(0.2,0.333,1)	(1,1,1)	(1,3,5)	0.150307
F_4	(0.111,0.143,0.2)	(0.143,0.2,0.333)	(0.2,0.333,1)	(1,1,1)	0.036139

C_1= Economic factor, F_1= Wind speed, F_2= Slope, F_3= distance from power line, F_4= Distance from roads, W is the weight of F_1, F_2, F_3, F_4 to C_1 $FCR = 0.016$

$V(SF_1 \geq SF_2, SF_3, SF_4) = 1$; $V(SF_2 \geq SF_1, SF_3, SF_4) = 0.710573$; $V(SF_3 \geq SF_1, SF_2, SF_4) = 0.316035$; $V(SF_4 \geq SF_1, SF_2, SF_3) = 0.075986$

Table 26: The TFNs pair wise comparison matrix of C2—F5-F8

C_2	F_5	F_6	F_7	F_8	W
F_5	(1,1,1)	(1,3,5)	(3,5,7)	(5,7,9)	0.475603
F_6	(0.2,0.333,1)	(1,1,1)	(1,3,5)	(3,5,7)	0.337951
F_7	(0.143,0.2,0.333)	(0.2,0.333,1)	(1,1,1)	(1,3,5)	0.150307
F_8	(0.111,0.143,0.2)	(0.143,0.2,0.333)	(0.2,0.333,1)	(1,1,1)	0.036139

C_2= Environmental factor, F_5= Geology, F_6= Elevation, F_7= LULC, F_8= River W is the weight of F_5, F_6, F_7, F_8 to C_2 $FCR = 0.016$

V ($SF_5 \geq SF_6$, SF_7, SF_8) =1;V($SF_6 \geq SF_5$, SF_7, SF_8)=0.710573;V ($SF_7 \geq SF_5$, SF_6, SF_8) =0.316035; V($SF_8 \geq SF_5$, SF_6, SF_7)= 0.075986

Table 27: The TFNs pair wise comparison matrix of C3—F8-F9

C_3	F_9	W
F_9	(1,1,1)	1

C_3= Social factor, F_9= Town, W is the weight of F_9 to C_3 *FCR* = 0.000

Table 28: The TFNs pair wise comparison matrix of F_5—G1-G2

F_5	G_1	G_2	W
G_1	(1,1,1)	(1,3,5)	0.700023
G_2	(0.2,0.333,1)	(1,1,1)	0.299977

F_5= Geology, G_1= Lithology, G_2= Fault, W is the weight of G_1, G_2 to F_5

V ($SG_1 \geq SG_2$) =1; V ($SG_2 \geq SG_1$) = 0.428525 *FCR* = 0.000

Calculating the Fuzzy Consistency Ratio

To determine if the comparisons are consistent or not in assigning the weights a Consistency Ratio which is known as Fuzzy Consistency Ratio (FCR) was calculated using equation 18 proposed by Modarres *et al.* (2010). The steps of the algorithm are as follows:

Step 1: A fuzzy matrix $\widetilde{H}$ was defined such that:

$$\tilde{h}_{ij} = w_j . \tilde{a}_{ij} \quad \text{.......... (14)}$$

Where w_j is the weight for the j[th] criteria or attribute, for j=1,….., n, and are the TFN's in the fuzzy judgment matrix.

Step 2: $\tilde{S}_i$ values in each i^{th} row were summed, as follows,

$$\widetilde{S}_i = \sum_{j=1}^{n} \tilde{h}_{ij} \quad \text{.......... (15)}$$

Step 3: $\tilde{\lambda}_i$ (*for i*= 1 *to n)* values were then calculated as:

$$\tilde{\lambda}_i = \frac{\tilde{s}_i}{w_i} \quad \text{.......... (16)}$$

Step 4: The Fuzzy Consistency Index (FCI) was then calculated as follows:

$FC\tilde{\iota} = \frac{\frac{1}{n}\sum(\tilde{\lambda_{\iota}}-n)}{n-1}$, n is the dimension of the fuzzy judgment matrix. .... (17)

Step 5: Then, find the Fuzzy Consistency Ratio number ($F\tilde{C}R$) such that:

$F\tilde{C}R = \frac{F\tilde{C}_i}{RC}$ ……………………………………………………………………….… (18)

Where, RI is the random consistency index, which was obtained from Table 29.

Table 29: Random Indices for Consistency Check (Saaty, 1980)

n	2	3	4	5	6	7	8	9	10
RI	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.51

n = dimension of judgment matrix

In this study, the numbers of criteria are 10 and have the corresponding RI used for this study was 1.51.

Step 6: Because TFN's were used to represent the vagueness in the judgment matrix, the FCR values obtained from Equation 18 were in the form of a set with 3 values. According to Modarres and Sadi-Nezhad (2001), FCR is determined as a preference ratio, which is defined as the percentage of the i^{th} fuzzy number within a set being the most preferred one. This ratio is expressed by Equation 19 as follows:

$R(i) = \frac{|\Omega_i|}{|\Omega|}$... (19)

Where Ω_i and Ω are values in the FCR set obtained from equation 18

The FCR was designed in such a way that if FCR < 0.10, the ratio indicates a reasonable level of consistency. However, if FCR > 0.10 the value of the ratio is indicate inconsistent judgments (Shariff and Wan, 2008). In this study, the value of all comparisons made for the criteria at each hierarchical level (Tables 24 to 28) were lower than 0.10, which indicated that the weights were acceptable.

Calculating the final weights of each input layer

The final weights (w_f) of each influential factor were calculated by normalizing the weight (w) of each factor as shown in Tables 24-28. This was done by multiplying the weight of a factor in the lower level by that of the element/s in the upper level as long as they were directly related as in the hierarchical structure. For example, to get the final weight of the Lithology input layer (represented by G_1 in the hierarchy), the following formulae was used:

*Final weight of G_1= weight of G_1 to F_5 * weight of $F_5$to C_2 * weight of C_2 to objective D*

This was done for all the input layers and the results are shown in Table 30.

Table 30: Final criteria weights for all factors

Objective	Hierarchy C	Hierarchy F	Hierarchy G	W_f
D	C_1	F_1		0.272805
		F_2		0.193848
		F_3		0.086216
		F_4		0.020728
	C_2	F_5	G_1	0.124980
			G_2	0.053562
		F_6		0.126860
		F_7		0.056435
		F_8		0.013566
	C_3	F_9		0.05100
				Total=1

3.3.11. Fuzzy Aggregation

Once the criteria maps (factors and constraints) were developed and the associated weights were assigned to each of the input layers, an evaluation (or aggregation) stage was undertaken to combine the information from the various factors and constraints. The MCE module in the IDRISI 17software package offers three methods for the aggregation of multiple criteria, such as Boolean Intersection, Weighted Linear Combination (WLC), and the Ordered Weighted Average (OWA).WLC chosen as the method of aggregation. According to Baban and Wan-Yusof (2003), this technique is a much better representation of the way major decisions are made in reality and it avoids the hard decisions of defining any particular area as absolutely suitable or not, but rather uses a continuous scale to represent suitability. As shown in Equation 20, this method multiplies each standardized factor map by its factor weight and then sums the results as:

$S = \sum(Wi * Xi)$ ………………………………………………………………...… (20)

Where

S = suitability,

Wi= weights of factor i, and

X_i = factor i

This process was done on a pixel by pixel basis and yielded a suitability map with the same range of values as the standardized factor maps that were used. Factor maps were converted to byte binary format used in Equation 20 was then multiplied by the constraint map to "mask out" the areas unsuitable for siting a potential wind farm. The constraint map was a binary coded image showing all areas were siting of a wind farm was simply not possible due to environmental and economical factors as zero (0) values whilst the other areas were shown as one (1). Thus, Equation 20 was modified as follows:

$S = \sum(Wi * Xi) * Cj$ ……………………………………………………………… (21)

S=([windspeed]*0.272805+[slope]*0.193848+[Elevation]*0.12686+[Lithology]*0.12498+[Powerline]*0.086216+[LULC]*0.056435+[Fault]*0.05356+[Town]*0.051+[Road]*0.0207+[River]*0.013566)*Cj

Where

Cj = Constraint j,

The final output of equation 21 was a map showing a number of suitable sites for locating potential wind farm in classes 1 to 5.

3.3.12. Modeling spatial relationships of factors on final model

The potential wind farm areas model (PWFAM) as the dependent variable; independent variables were slope, wind speed, fault, bedrock type, LULC, road, town, power line, river and elevation values. First OLS regression applied in an attempt to explain the global relations between dependent and independent variables. The model was set as:

PWFAM = $\beta_0 + \beta_1$ slope+ β_2 wind speed + β_3 fault+ β_4 bedrock + β_5 LULC+ β_6 road + β_7 town+ β_8 power line + β_9 river+ β_{10} elevation + ε. β_0 to β_{10} ………………………………………….…. (22)

Where, β is the regression coefficients whereas ε is the model random error.

The diagnoses of an OLS model were approached by assessing multicollinearity and the residuals. The multicollinearity is assessed through variance inflation factor (VIF) values, and if VIFs were greater than 10, this indicated multicollinearity existed (Menard, 2002). The spatial independency of residuals was evaluated by the spatial autocorrelation coefficient, Moran's *I*.
The values of Moran's *I* would be approximately between +1 (positive autocorrelation) and −1 (negative autocorrelation), and the expected value in the absence of autocorrelation is (−1)/(n−1). Positive spatial autocorrelation meant similar values tended to occur in adjacent areas, while negative autocorrelation implied nearby locations tended to have dissimilar values. If no spatial autocorrelation was found, then the spatial arrangement would be completely random (Moran, 1950).

A GWR local model was applied to analyze how the relationships of dependent variable (PWFAM) and independent variables changed from one location to another in the study area. It was a localized multivariate regression that allowed the parameters of a regression estimation to change locally. Unlike conventional regression, which produced a single regression equation to summarize global relationships among the independent and dependent variables, GWR detected spatial variation of relationships in a model and produced maps for exploring and interpreting spatial non-stationarity (Fotheringham *et al.,* 2002).

The spatial variability of an estimated local regression coefficient was examined to determine whether the underlying process exhibited spatial heterogeneity (Fotheringham *et al.,* 2002). The regression model can be rewritten as:

$$PWFAM_i(g) = \beta_{0i}(g) + \beta_1\ slope_i(g) + \beta_2\ wind\ speed_i(g) + \beta_3\ fault_i(g) + \beta_4\ bedrock_i(g) + \beta_5\ LULC_i(g) + \beta_6\ road_i(g) + \beta_7\ town_i(g) + \beta_8\ power\ line_i(g) + \beta_9\ river_i(g) + \beta_{10}\ elevation_i(g) + \varepsilon_I \quad \ldots\ldots (23)$$

Where (g) indicated the parameters that were estimated at each sample point in which the coordinates were given by vector g; *i* represented each sample point. By applying GWR modeling, the spatial influences among neighborhoods could be assessed, which was not able to be achieved through traditional OLS methods (Fotheringham *et al.,* 2000).

Additionally, the local collinearity as well as the independency and normality of residuals of GWR model examined to evaluate the fit of the model. The adjusted coefficient of determination

(Adjusted R^2) and ANOVA were used for comparing OLS and GWR models. Akaike Information Criterion (AIC) generated for OLS and corrected Akaike Information Criterion (AIC) calculated for GWR were also used for model comparison (Fotheringham *et al.,* 2002). The concept here is to determine which model could interpret data better.

3.3.13. Validation of the final model

According to Pindyck and Rubinfeld (1976), the mean square error (MSE) is the most common measures of forecast error, thus the appropriate measures of fit, to validate any predicted model.

MSE is defined as:

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(S_t - A_t)^2 \quad \ldots\ldots (24)$$

Where

n= number of observations (t=1,…, n)

S_t = Simulated value at time t.

A_t= Actual value at time t.

The MSE has the advantage that large errors are weighted more heavily than small ones, and that errors of opposite sign do not cancel each other out. Often the square root of the mean square error is taken, yielding the root mean square error (RMSE). The RMS error provides a measure of error with the same units as the variable under consideration. It is often more convenient to compute a normalized measure of error.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}[S_t - A_t]^2} \quad \ldots\ldots (25)$$

In this research, the fitness/validity of the predicted model to the actual one was measured by RMSE, which was forecast error of appropriate measures of fit.

Based on the master plan of Solar and wind farm of Ethiopia which was prepared by Ethiopian government with collaboration of Chinese government in 2012, the center point co-ordinate of Iteya phase I wind farm (in Hitosa Woreda) is located at longitude 520186.2m and latitude of 903043.6m. The maximum distance from this point in the direction of east-west is about 9.6km and north–south is 13.74km (Ethiopian Rural Energy Development and Promotion Center). Accordingly the result of the model was validated using the given center point of the master plan and incorporating the respective distances. Therefore, additional 59 sample points were extracted for validation. ArcGIS10.3 of geo processing tool were used to offset 4.8km to east and west; 6.87km to north and south from center as shown in Fig. 19 in order to create sample points.

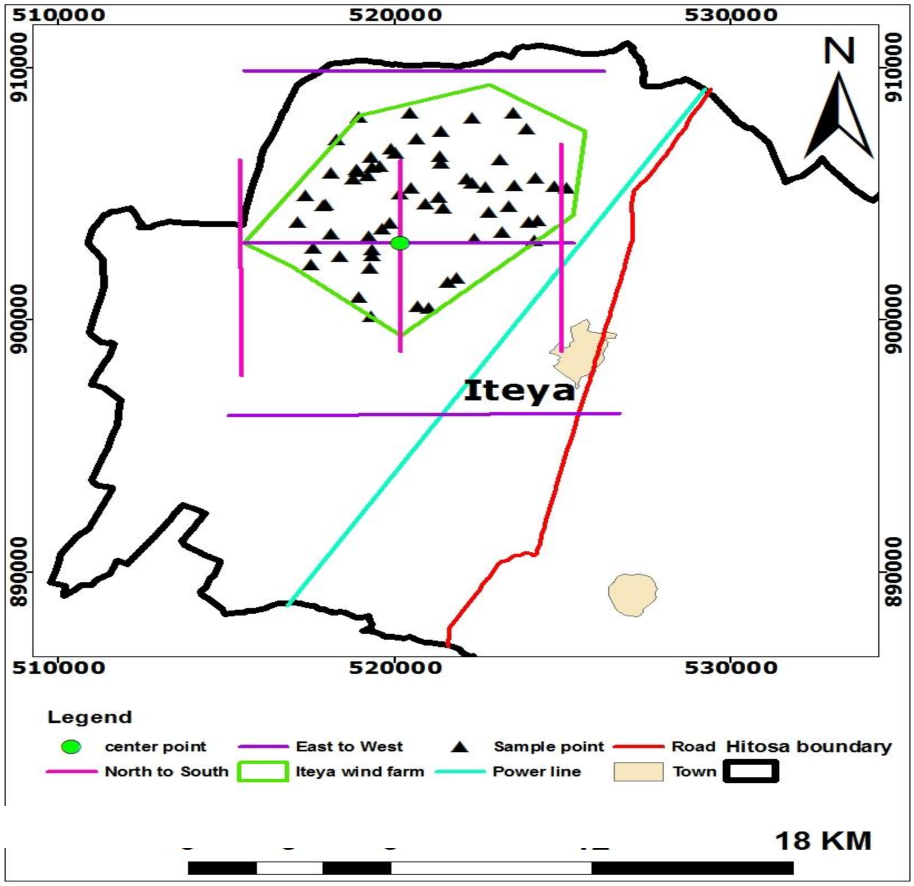


Figure 19: Extracted Sample Points for Validation

CHAPTER FOUR

4. RESULTS

The study was conducted using different data's which mentioned in Table 12 with geographic information systems (GIS) for mapping and IDRISI 17.00 for the analysis to select potential wind farm sites for the study area. Results revealed that the northern zones of the investigated region have high wind energy potentials. Such zones are appropriate for setting up electricity generating wind turbines. The total investigated area is equivalent to 1260sq. km. extremely suitable zones amount to 96.902 sq. km with percent of 7.69% and highly suitable zones amounting to 152.194 sq. km having percent of 12.08%. Results can be explained as follows:

4.1. Explanatory Variables Autocorrelation

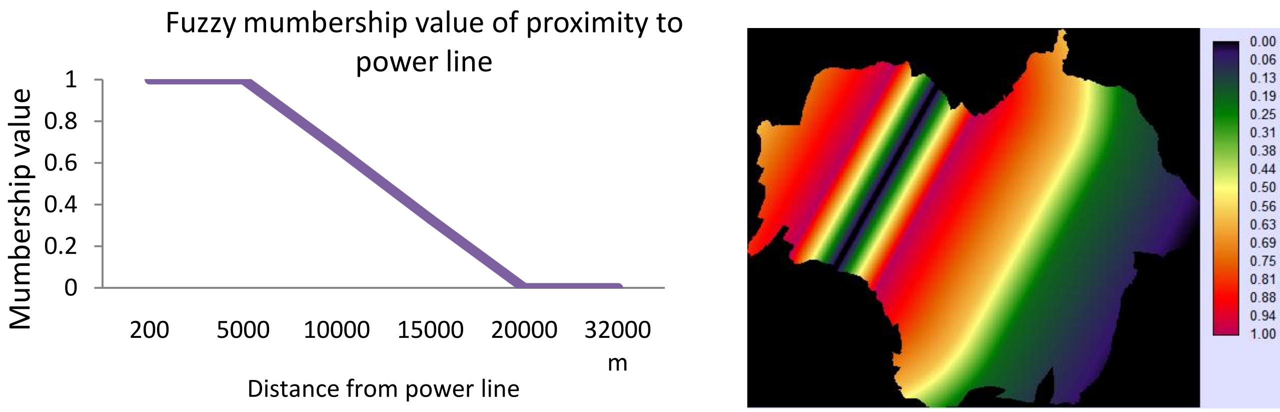
As shown on Table 31, the correlation coefficient value between each factor is near to zero this indicated that all factors are not correlated and appropriate for the modeling.

Table 31: The CORREL coefficient value of the factors.

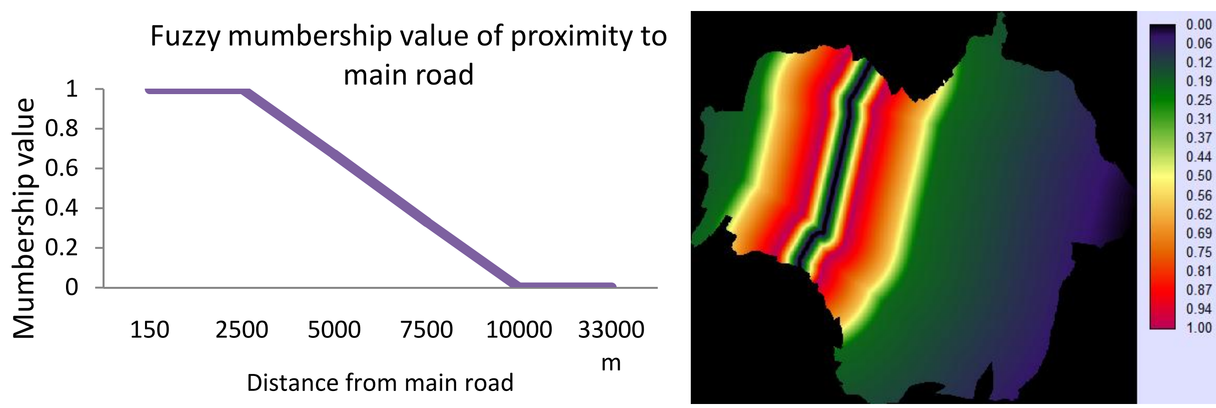
	Fault	River	Power line	Bedrock	Elivation	Town	Wind	Slope	Road	LULC
Fault	1									
River	-0.001	1								
Power line	-0.001	-0.001	1							
Bedrock	0.009	0.006	0.035	1						
Elivation	0.023	-0.011	-0.011	0.029	1					
Town	-0.003	-0.002	-0.002	-0.093	-0.018	1				
Wind	-0.001	-0.016	0.039	-0.179	-0.156	0.047	1			
Slope	0.032	0.027	-0.003	0.028	-0.097	-0.023	-0.045	1		
Road	0.012	0.131	0.012	0.001	0.034	-0.021	0.014	0.012	1	
LULC	-0.069	0.042	0.003	-0.003	-0.085	0.031	0.015	0.053	0.036	1

4.2. Modeling Fuzzy Membership

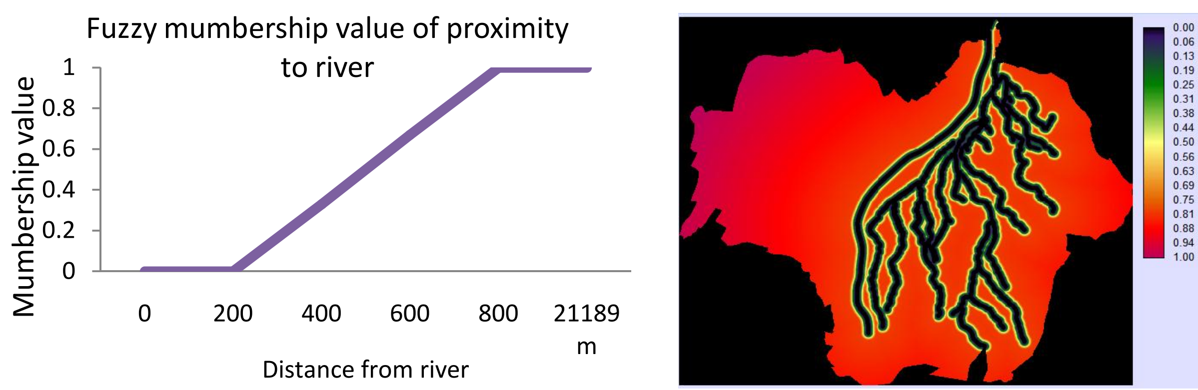
The standardized input layers maps using user defined fuzzy membership function of IDIRISI 17.00 Software for distance to power lines, distance to main roads, distance to river, distance to town and distance to fault are depicted in Fig. 20 (a-e). The suitability attribute maps of slope, elevation, Wind, Lithology, LULC are shown in Fig. 21 (a-e). The standardized attribute values based on suitability for siting wind energy zones are presented in Table 32.


Fuzzy mumbership value of proximity to power line
Mumbership value
1
0.8
0.6
0.4
0.2
0
200 5000 10000 15000 20000 32000 m
Distance from power line
0.00 0.06 0.13 0.19 0.25 0.31 0.38 0.44 0.50 0.56 0.63 0.69 0.75 0.81 0.88 0.94 1.00

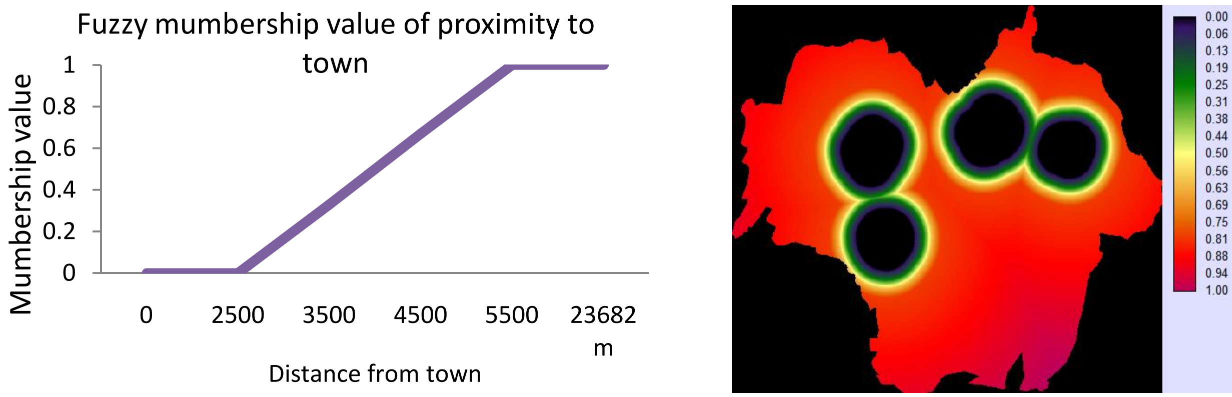
a)


Fuzzy mumbership value of proximity to main road
Mumbership value
1
0.8
0.6
0.4
0.2
0
150 2500 5000 7500 10000 33000 m
Distance from main road
0.00 0.06 0.12 0.19 0.25 0.31 0.37 0.44 0.50 0.56 0.62 0.69 0.75 0.81 0.87 0.94 1.00

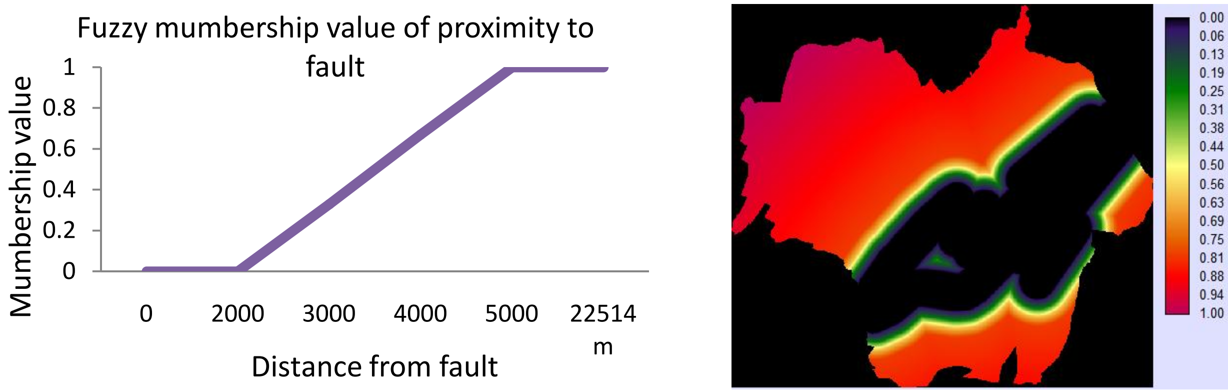
b)


Fuzzy mumbership value of proximity to river
Mumbership value
1
0.8
0.6
0.4
0.2
0
0 200 400 600 800 21189 m
Distance from river

c)

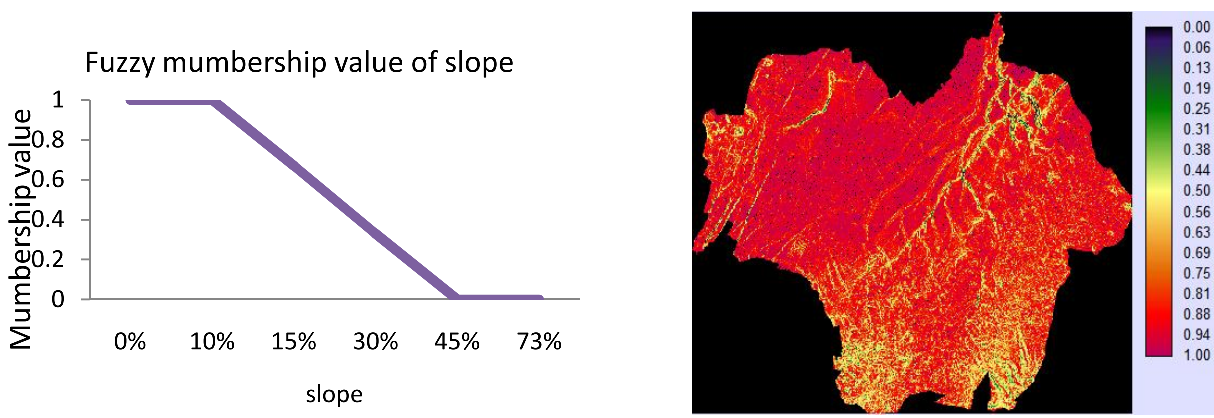


d)

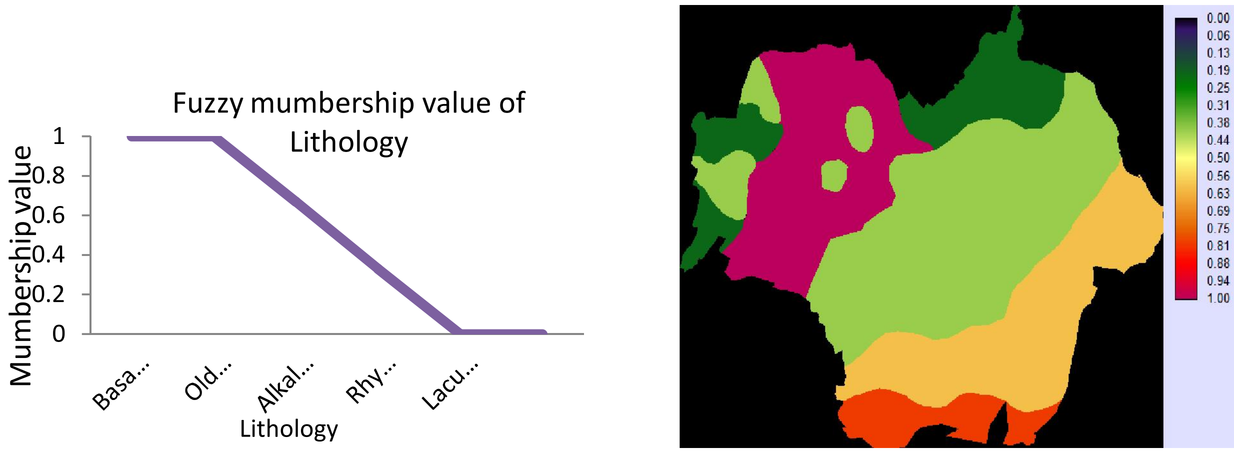


e)

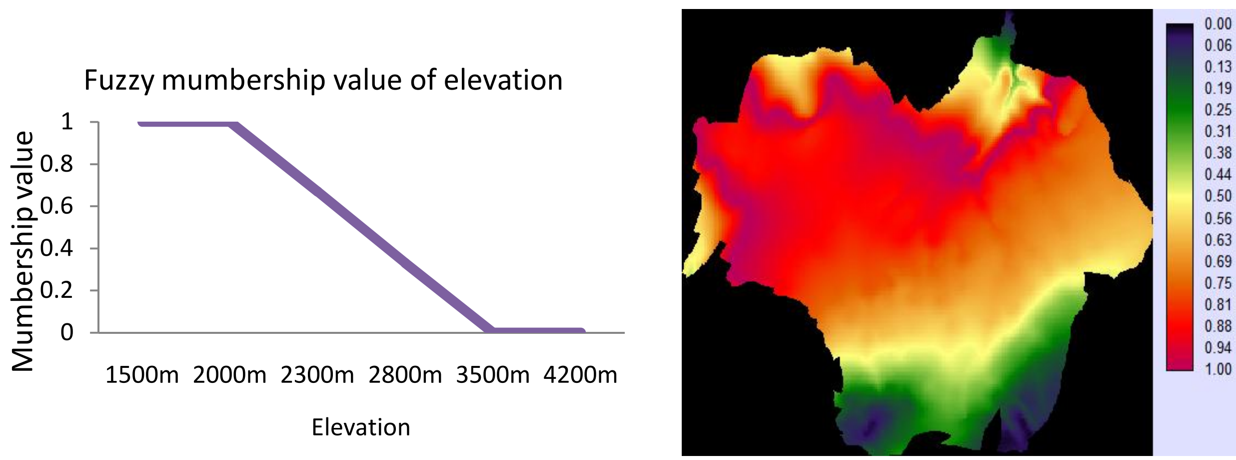
Figure 20: Fuzzy membership of Reclassified factors a) Power line; b) Main road; c) River; d) Town and e) Fault



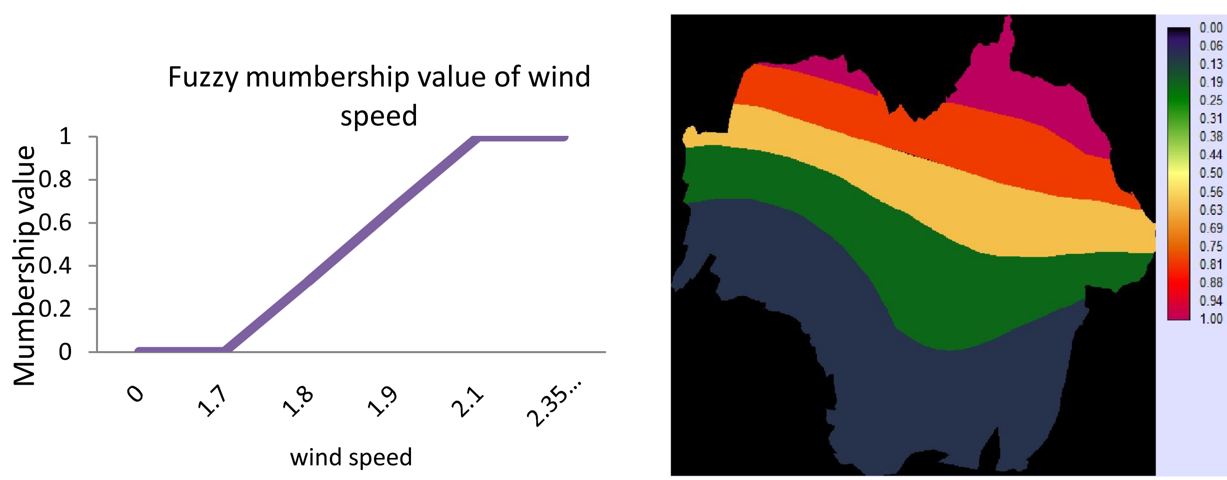
a)


Fuzzy mumbership value of Lithology
Mumbership value
1
0.8
0.6
0.4
0.2
0
Basa…
Old…
Alkal…
Rhy…
Lacu…
Lithology
0.00
0.06
0.13
0.19
0.25
0.31
0.38
0.44
0.50
0.56
0.63
0.69
0.75
0.81
0.88
0.94
1.00

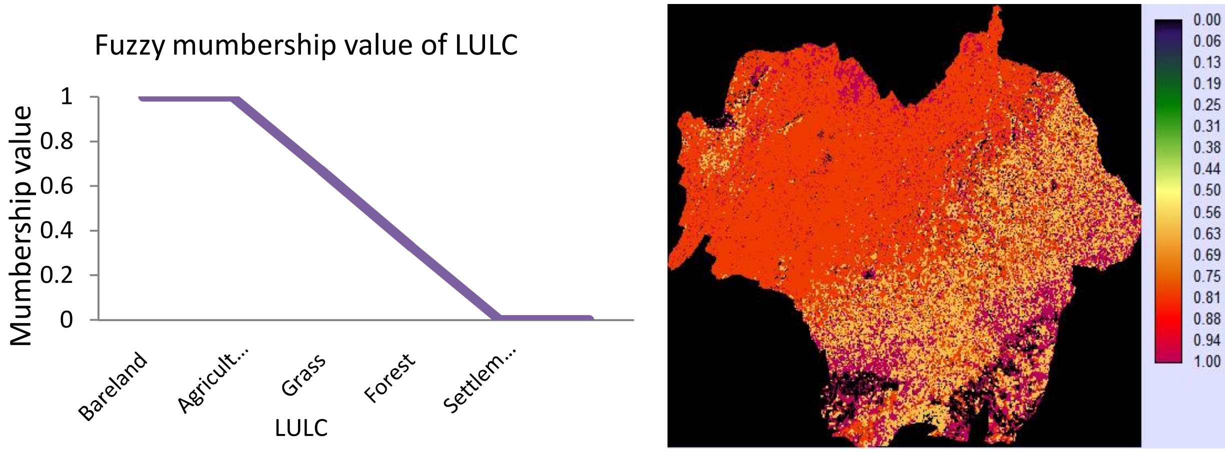
b)


Fuzzy mumbership value of elevation
Mumbership value
1
0.8
0.6
0.4
0.2
0
1500m 2000m 2300m 2800m 3500m 4200m
Elevation
0.00
0.06
0.13
0.19
0.25
0.31
0.38
0.44
0.50
0.56
0.63
0.69
0.75
0.81
0.88
0.94
1.00

c)


Fuzzy mumbership value of wind speed
Mumbership value
1
0.8
0.6
0.4
0.2
0
0
1.7
1.8
1.9
2.1
2.35…
wind speed
0.00
0.06
0.13
0.19
0.25
0.31
0.38
0.44
0.50
0.56
0.63
0.69
0.75
0.81
0.88
0.94
1.00

d)



e)

Figure 21: The suitability fuzzy membership attribute maps of a) slope; b) lithology; c) elevation; d) Wind speed; e) LULC

Table 32: Fuzzy standardized attribute values based on suitability for the wind farm site.

	Extremely Suitable	**Very Suitable**	**Suitable**	**Least Suitable**	**Not Suitable**
Fuzzy Score	1	0.8	0.5	0.2	0
Wind Speed	2.1-2.35m/s	1.9-2.1m/s	1.8-1.9m/s	1.7-1.8m/s	0-1.7m/s
Fault	>5000m	4000-5000m	3000-4000m	2000-3000	0-2000m
Lithology	Basalt Flow	Old Basalt	Alkaline Basalt	Rhyolite dome and tuffs	Lacustrine Sediments
Main Road	150-2500m	2500-5000m	5000-7500m	7500-10000m	>10000
Slope	<10%	10-15%	15-30%	30-45%	>45%
LULC	Bare Land	Agricultural Land	Grass Land	Forest Land	Settlement
Power Line	200-5000m	5000-10000m	10000-15000m	15000-20000m	>20000m
Town	>5500m	4500-5500m	3500-4500m	2500-3500m	0-2500m
River	>800m	600-800m	400-600m	200-400m	0-200m
Elevation	1590-2000	2000-2300	2300-2800	2800-3500	>3500

4.3. Modeling Fuzzy AHP of influential factors

Weights were assigned to the factors using a series of pair wise comparison judgments to express the relative strength of each of the factor maps. Pair wise comparison allows one to consider two factors at a time, which reduces the complexity of the decision making process. Assigning weights using pairwise comparison is more suitable than direct assignment of the weights, because one can check the consistency of the weights by calculating the consistency ratio. This study used a pairwise comparison of FAHP to determine the factors weights from judgment set of decision making experts. The FCI was used in this research to calculate the Fuzzy Consistency Ratio (FCR) and the result was < 0.1. The assigned weights from applying FAHP were presented in Table 33.

Table 33: Weight of factors resulting from FAHP

Factors	Wind speed	Lithology	Fault	Elevation	Slope	LULC	Power line	Road	Town	River	Total
Weight	0.2728	0.12498	0.05356	0.12686	0.193848	0.056435	0.086216	0.0207	0.051	0.013566	1

4.4. Overall constraint map

The constraint values criteria map are binary maps. Such map was presented in Fig. 22 in the constraint map, the excluded zones are presented in black color with the value of zero (0) while the rest of the study area was presented in white color with the value of one (1). Fig. 22 depicts the combination of excluded zones for the power lines, rivers, towns, main roads and faults sites. The set back buffer zones are described in Table 34.

Table 34: Excluded zones (Constraints) threshold.

Excluded zones (Criteria)	Buffer around excluded zones in m
Power lines	200 around power lines
Main roads	150 around main roads
Towns	2500 around towns
Rivers	200 around rivers
Faults	2000 around faults

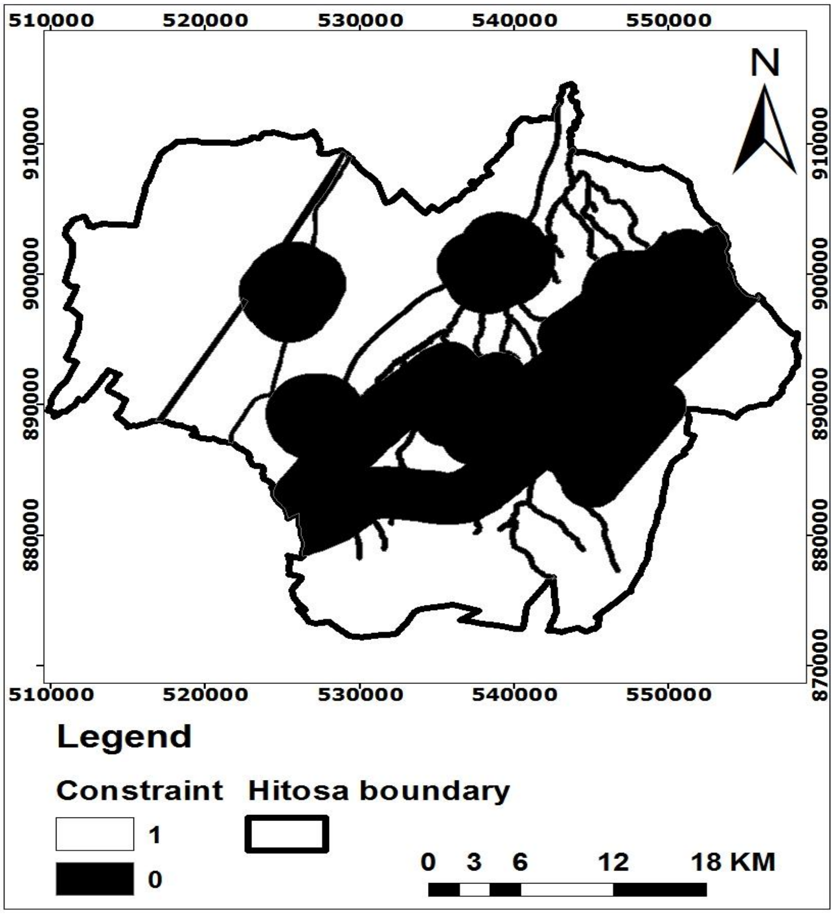


Figure 22: Combined constraint map of the study area

4.5. Potential wind farm site

4.5.1. Fuzzy aggregation

Once the factors and constraints maps had been developed and the associated weights assigned to each input layer, an aggregation stage was undertaken to combine the information from the various factors and constraints. From the three methods of MCE module in the IDRISI17 software package WLC was chosen as the method of aggregation at this research. This method multiplies each standardized factor map by its factor weight then sums the results.

4.5.2. Suitability map

The suitability index values resulting from the fuzzy aggregation of WLC was classified into five suitability classes. Each class representing suitability ranges (Table 35).

Most suitable zones of class 5 have wind speed that range between 1.95 to 2.35 m/sec and flat lands. Geologically it is sited on basalt and far from faults and rivers. This class exists near to power line and road on the north south-part of the study area which suited on bare land and agricultural land. Suitable net areas for class 5 are equivalent to 96.902 sq. km, which is 7.690 percent (Fig. 23).

Highly suitable zones of class 4 have wind speed ranging between 1.7 to 2.35 m/sec and a land area equivalent to 152.194 sq. km, which is 12.08 percent after subtraction of setback buffers and constraints. This class exists almost near to transmission line and main road and far from faults , mostly flat lands to gentle slopes (less than 10 degrees), which suited on agricultural land and are in close proximity to class 5 (Fig. 23).

Moderately suitable zones in class 3 have wind speed range of 1.71 to 2.1 m/sec, which is acceptable to good, but the slopes are quite steep. Due to minimized wind speed reduces the suitability values. Net area of such class is 179.11 sq. km, which is 12.08 percent after subtraction of setback buffers and constraints (Fig. 23).

Less suitable zones in class 2 have wind speed range of 1.7 – 1.8 m/sec., which is marginally acceptable, but the slopes are steep (15-30 degrees) and it is near to surface fault. The slope constraint cause more turbulent wind patterns and may cause disruptions in turbine stability and lead to low suitability values. Total area of such class is equivalent to 311.159 sq. km, which is 24.69 percent after subtraction of setback buffers and constraints (Fig. 23).

Unsuitable zones in class 1 are excluded zones (zones treated as constraints). Total area of such class was equivalent to 520.635 sq. km, which was 41.32 percent of the study area. Regardless of the wind farm, such zones excluded for environmental, social and economic reasons (Fig. 23).

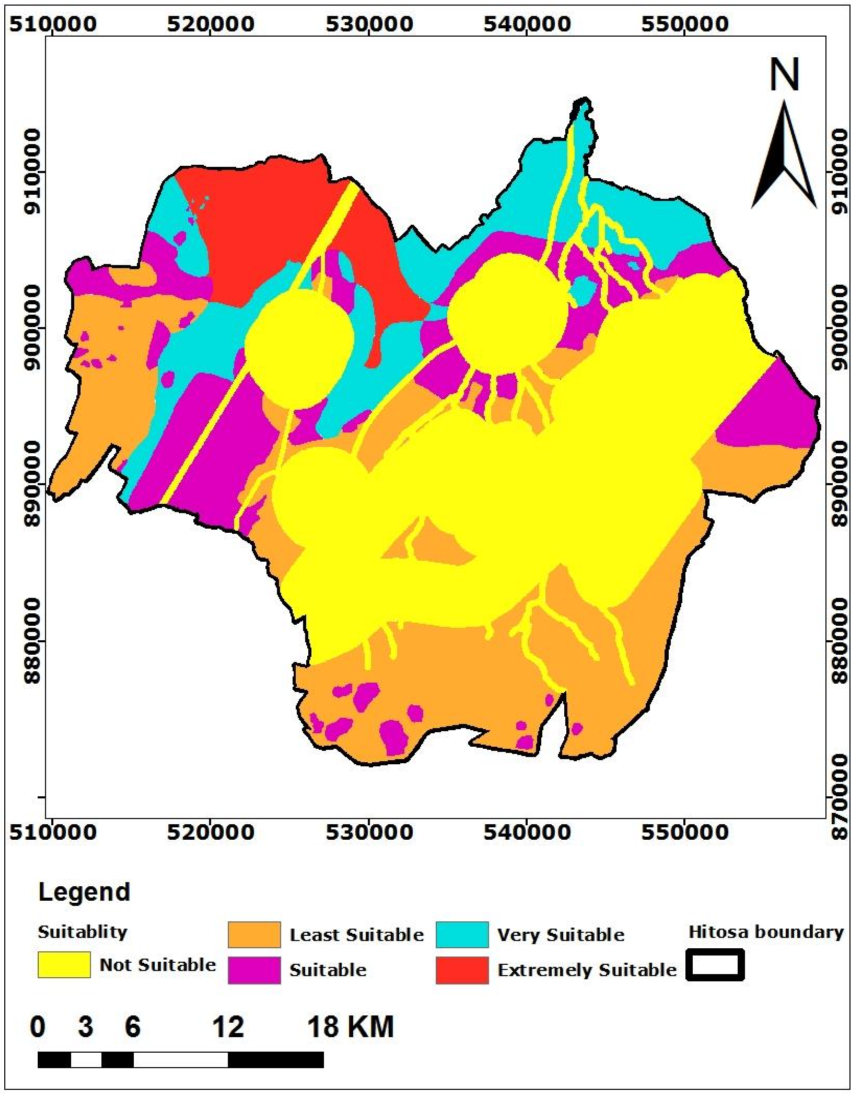


Figure 23: Suitability index map for most appropriate zoning of wind farms

Table 35: Suitability classes and land areas for wind power energy farm

Class	Class describtion	Area(sq.km)	Percentage of total area
1	Not suitable	520.635	41.32
2	Less suitable	311.159	24.69
3	Suitable(Moderate)	179.11	14.22
4	Very suitable	152.194	12.08
5	Extremly suitable(ideally)	96.902	7.690
Total		**1260**	**100%**

4.6. Suitability of fuzzy approach comparing to crisp for modeling potential wind farm areas

As shown in Fig. 24 and Fig. 25, in order to illustrate the difference between a Boolean approach and fuzzy logic two maps were produced. In the first Fig. 24 all the factor layer maps were created with crisp approach are combined using an OR operator. In the second Fig. 25 all the factor maps were standardized with fuzzy membership are combined by using WLC operator. According to the result, in the Boolean Suitability index map the high class boundaries of the Fuzzy Suitability index map disappear and replace by a gradual decrease of potential wind farm areas as a distance increases from each feature. The result shows that the fuzzy approach is more reasonable and reflects the human perception in better way. As indicate in Fig. 25 potential wind farm area by fuzzy method increased and improved some land classes. This indicates that flexibility is another characteristic of fuzzy logic.

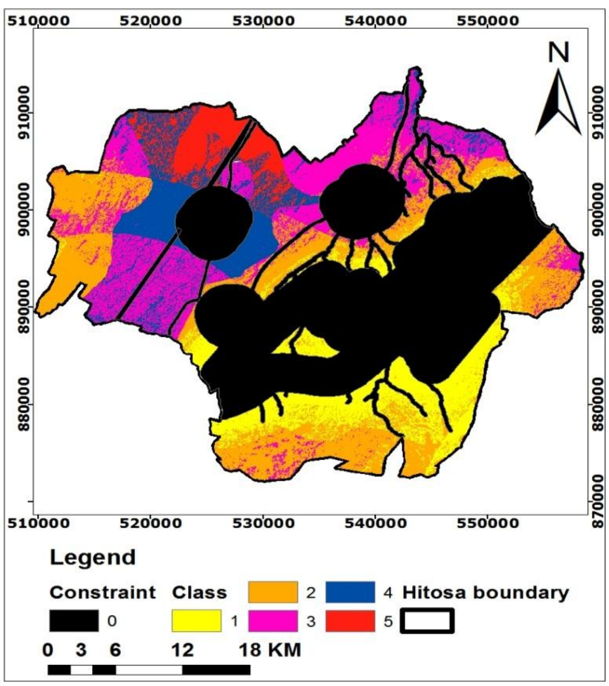


Figure 24: Boolean Suitability map

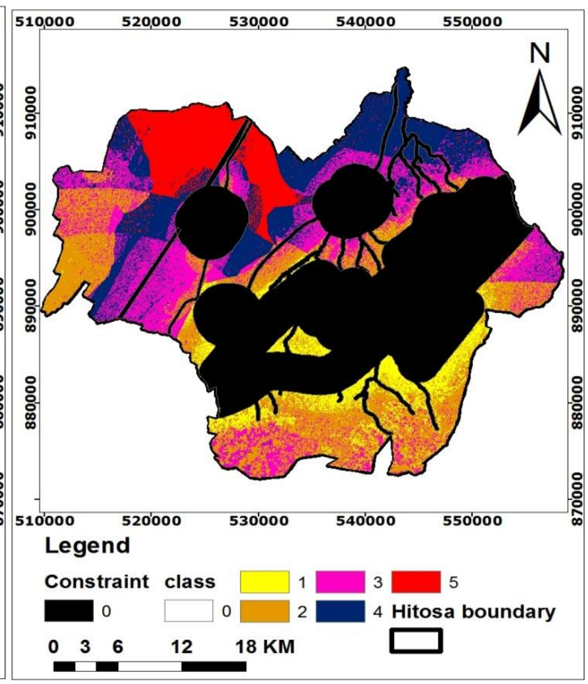


Figure 25: Fuzzy Suitability map

4.7. Modeling spatial relationships of factors on final model

OLS and GWR tools have been executed with GIS raster data on GIS 10.3, by considering PWFAM as dependent variable and slope, wind speed, fault, lithology, LULC, road, town, power line, rivers and elevation values as explanatory variables. They were tested to try to checking

Multicollinearity between factors, model bias and explain if all explanatory variables have influence on PWFAM.

4.7.1. Checking Multicollinearity

The Variance Inflation Factor (VIF) result of OLS regression indicated in Table 36 is less than 7. This shows that there was no Multicollinearity among explanatory variables. Further, the residuals of the OLS model were examined, and found the residuals had no spatial autocorrelation (Moran's I = -0.055083, p < 0.01).

Table 36: Ordinary Least Squares (OLS) results.

Variables	Estimated Value	Standard Error	*P*-value	VIF
Intercept		0.089250	0.000031*	
Fault		0.008340	0.000000*	1.698347
River		0.009248	0.000144*	1.211655
Power line		0.018780	0.000003*	5.489117
Road		0.017776	0.0010520*	4.282031
Town		0.009058	0.001010*	1.369904
Slope		0.008115	0.000000*	1.033094
Elevation		0.020223	0.00000*	4.12539
Wind speed		0.018809	0.00000*	2.23689
Bedrock		0.012268	0.00000*	1.90121
LULC		0.013872	0.00021*	1.06568
Adjusted R^2	0.924811			
AIC	775.267443			
Jarque-Bera Statistic			0.024092*	

*An asterisk next to a number indicates a statistically significant p-value (p< 0.01).

The GWR and OLS model results were compared to interpret the better results. It is shown on the Table37 that the GWR model is suitable than the OLS model since its R^2 result indicates 95.599 percent of the total model with decreased AIC.

Table 37: The GWR and OLS result.

Regression	Adjusted R^2	AICc
GWR	95.5993	772.882
OLS	92.4811	775.267443

4.7.2. Checking the model

The Jarque-Bera test was used to check model bias. When this test is statistically significant ($p < 0.01$), model predictions are biased (the residuals are not normally distributed). But, here in this model as shown in Table 36, the Jarque-Bera Statistic were not significant which the result was $p = 0.024092^* > 0.01$. This result indicates that the model is reliable and not biased and the residuals were normally distributed.

4.7.3. Relationship between PWFAM and explanatory variables values

The results of OLS which shown in Fig. 26 indicates that there was strong relationship between PWFAM and explanatory variable values that should be taken into consideration for future researches.

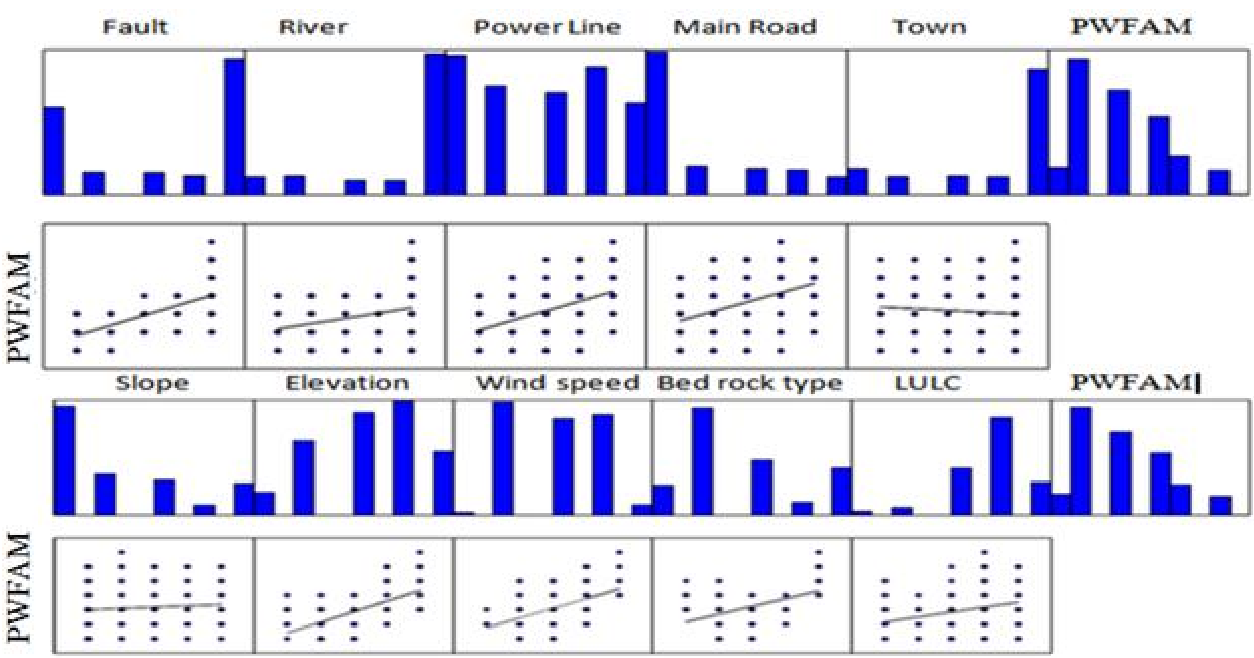


Figure 26: Variable distributions and relationships

4.8. Validation of the model

Based on the methodologies which described under section 3.3.13, the RMSE for both Fuzzy and Boolean model were obtained by comparing with Iteya phase I wind farm. As a result, the RMSE for the final suitable Fuzzy model and Boolean was 0.13 and 0.39 respectively. This shows that the fitness of fuzzy model map to the proposed Iteya phase I wind farm is greater than Boolean model map.

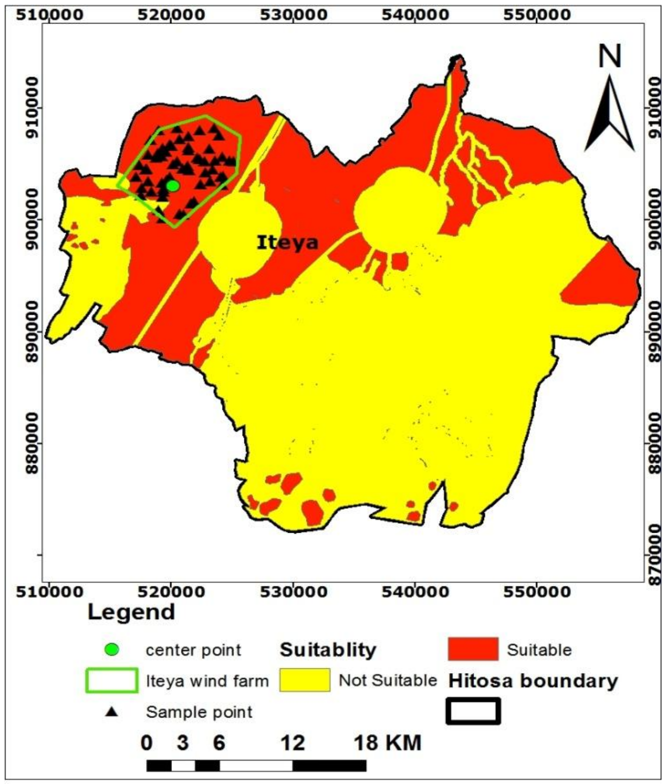


Figure 27: Suitable and unsuitable map of wind farm

CHAPTER FIVE

5. DISCUSSION

In this study, the final output of potential wind farm model of fuzzy approach developed through identification and selection of influential factors of wind farm which are the key determinant for selection of potential wind farm areas. In this research, these different influential factors that identified for the analysis were examined by calculating correlation coefficient value between each to removes redundancy of factors. Based on different researchers, if the result of correlation coefficient between each factor is near to zero the factors are unrelated and it can be used for further analysis (Glass and Hopkins, 1996; Nunnally and Bernstein, 1994). As the result in Table 31 shows, the correlation coefficient between each factor was near to zero all considered factors were accepted for the analysis.

Besides managing decisional uncertainty, Fuzzy set theory (Zadeh, 1965) is often used for criteria standardization before it is coupled with the Weighed linear aggregation methods (Gorsevski *et al.,* 2006; Jiang and Eastman, 2000). Different researchers used a fuzzy membership functions for the standardization of raster GIS-based criteria to assign a value between zero and one to each grid cell (Burrough and McDonnell, 1998; Eastman, 1999; Gorsevski *et al.,* 2006). According to Rodney *et al.*(2011), this process expresses the unit of measurement of each factor map as belonging to a set ranging from 0.0 to 1.0 or 1 to 255, indicating a variation from non-belonging to complete-belonging (or least suitable to most suitable).This is important to transforms and rescales the original criteria in to comparable units. In this paper as shown in Fig. 20 and Fig. 21 of section 4.2, all value of input layers were scored by fuzzy standardization between 1.0 which is most suitable and 0.0, which is unsuitable.

Moreover, the different influential factors identified for the analysis are not equally important to select potential wind farm areas. This difference can be managed by multi factor evaluation of weighted linear aggregation method for Weight calculation to give weight to each criterion to reflect their relative importance. This can be effective because it forces the decision maker/s to give thorough consideration to all elements of a decision problem and also by assigning quantitative weights it is possible to make important criteria have a greater impact on the outcome than other criteria.

In this research, the method that integrates Fuzzy logic and AHP (FAHP) (equation 5-13) was adopted to obtain weights to each factor for locating potential wind farm areas. GIS-based FAHP schemes for potential wind farm area analysis have been reported by number of studies (Farajzadeh *et al.,* 2013; Talinli *et al.,* 2011).This approach allows decision makers to give interval judgments, which can capture a human‘s appraisal of ambiguity when complex multi-attribute decision making problems such as wind farm siting are considered. Different researchers uses FAHP, according to Akbari *et al.*(2008) and Ocalir *et al.* (2010), integrating fuzzy logic into the AHP process give a much better and more exact representation between criteria and alternatives. In this research the calculated FCR from Equation 18 was less than 0.1 which indicates that a reasonable level of consistency in the pairwise comparisons and the weights were accepted.

According to Vanek and Albright (2008), the wind power in a given site depends on having sufficient wind speed available at the height at which the turbine is to be installed. From all factors, wind speed is the most important factor because it provides information on the most feasible and profitable areas in the region for siting a wind power project (Baban and Perry, 2001; Ucar and Balo, 2009). Hence, in this research the weight obtained from FAHP shows that weight of wind speed 27.2805 % is greater than the weight of slope 19.3848%, elevation 12.686%, lithology 12.498 %, distance from power line 8.6216%, LULC 5.6435% ,distance from fault 5.356%, distance from town 5.1% , distance from road 2.07 %, and distance from river 1.3566% as presented in Table 33.

However, analyzing data for appropriate zones for the wind turbine installation in this study had higher weights for the effectiveness of wind speed, slope, elevation and lithology than other factors. This shows that the extremely suitable, class 5, and the high suitable, class 4, areas were found in high wind speed zones and flat areas. This is corresponding to the wind power map of Ethiopia.

Moreover, utilizing exclusionary criteria in preliminary screening is important to exclude unacceptable areas for siting a wind farm. In this research as shown in Fig. 22, different areas were identified as exclusionary to prevent effects on environment, communities and engineering frontier. For instance, surface faulting can be particularly severe to structures partly embedded in the ground, the distance from fault at less than 2000m was considered as ‘exclusion zones’.

Further, areas were in 200m from river to be protected to conserve the natural wealth and areas in 150m from road, 200m from transmission line and 2000m from towns are become 'exclusion zones' due to growth expansion and noise. Different researchers stated that, during selecting potential wind farm areas there is unacceptable areas which is to be excluded for protecting effects on environment, communities, visualization, eco-conservation, and engineering frontier (Bennui *et al.,* 2007; Effat, 2014).

Once the factors and constraints maps were developed and the associated weights assigned to each input layer, an aggregation stage was undertaken to combine the information from the various factors and constraints. The candidate sites identified and shown in Fig. 23 are on a continuous dimensionless scale ranging from 1 to 5, indicating a variation from least suitable to most suitable site. This is one of the characteristics of the Weighted Linear Combination (WLC) technique, which was used to aggregate the constraints and factor maps used in this study. According to Baban and Wan-Yusof (2003), this technique is a much better representation of the way major decisions are made in reality and it avoids the hard decisions of defining any particular area as absolutely suitable or not, but rather uses a continuous scale to represent suitability. This is also aided by the fact that the WLC method allows weights to be assigned to factors. The WLC of MCE schemes for potential wind farm area analysis have been reported by number of studies (Talinli *et al.,* 2011; Ucar and Balo, 2009).

In this study the fuzzy set approach can provide an alternative approach to cope with logical constraints in the crisp approach in the understanding and evaluation of environmental phenomena. According to researcher's comparison of the results obtained by Boolean and fuzzy methods, Burrough and McDonnell (1998) argued that fuzzy methods produce contiguous areas and reject less information at all stages of analyses and are, therefore, much better than Boolean methods for the classification of continuous variation. In comparison with Boolean logic, fuzzy logic is a more appropriate foundation for spatial classification with and without GIS (Leung and Leung, 1993b).

The result of fuzzy analysis in Fig. 25 shows a gradual suitability for a potential wind farm site. The results of the Boolean (Fig. 24) and the fuzzy analysis (Fig. 25) also compared. Flexibility is another characteristic of fuzzy logic. By using a fuzzy map, decision-makers, regarding the social, economic and environmental aspects, may first select areas with a high suitability membership value and then to field investigations. If for any reason the site deemed inappropriate they can proceed either to another site with the same membership value or to another membership value of lower suitability. The benefit is that they do not need to conduct a new analysis, or change the rules, or the criteria, saving time and effort.

To check the model is not biased and the independent variables impact on the dependent model the OLS and GWR tools were used. Menard (2002) stated that the multicollinearity is assessed through variance inflation factor (VIF) values, and if VIFs is greater than 10, the multicollinearity is existed. The Variance Inflation Factor result (VIF < 7) of OLS regression which indicated in Table 36 shows that the residuals had no spatial autocorrelation.

In the field of geosciences, many researchers present the Root Mean Square Error (RMSE) as a standard metric for model errors. According to Pindyck and Rubinfeld (1976), the RMSE is the most common measures of forecast error to validate any predicted model. When the RMSE value is less than 0.5 it is acceptable error and shows the good fitness of the model to the actual one. Result in section 4.8. Show that the RMSE of the final suitable Fuzzy model was 0.13 which was acceptable and valid.

CHAPTER SIX

6. CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

In this study, the GIS-based spatial multi-criteria evaluation approach, in terms of the Fuzzy AHP module were used to assess the land suitability for wind farm implementation in Hitosa Woreda of East Showa Zone. The method was quite flexible in creation of the evaluation criteria, assigning importance weights, standardization and map overlay. It provides visual intermediate and final results in the form of thematic maps that are comprehensive and useful for planning purposes. The method succeeds in mapping potential zones for wind farm and avoiding constraint sites, while considering some factors such as slopes, accessibility, wind speed, fault, town, lithology, river, LULC, elevation and power network. The identified factors cannot be generalized for all areas where potential wind farm assessment will be carried out. Since the areas under investigation are in different environment in addition to the factors used for this study different factors will be considered such as historic sites, Air ports, Rail way, Birds site etc.

By excluding the land constraints, the developed model identified the ideal zones with all suitability conditions for siting potential wind energy farms. These ideal zones amount to 96.9 sq. km and 152.194 sq. km of the total land area demonstrate extreme and very high suitability level, respectively. The results of the current study highlights the need of adopting a holistic integrated approach that integrates land resources, potentials and constraints in the land-use decision strategies for achieving sustainable planning at a regional scale. Thus, providing indicator maps; as a guide for zoning and land-use strategies. The methodology is applicable and can be conducted for creating zoning maps of wind farm areas in other regions.

Based on the output of this study, it was found that the Woreda has a potential for implementing wind farms to generate power. This will bring major advantages by alleviating incidents related to indoor pollution, and reducing burden on the country’s economy by replacing imported fuel.

6.2. Recommendations

Based on the result of the present study, the following recommendations are suggested for decision makers and future researchers:

- The government has to give high attention for wind farm site selection and encourage investors who need to invest on renewable energy.
- Field investigation should be carried out for further assessment of environmental impact of each potential zone.
- The land use decision makers of wind farm should adopt the methodology of Fuzzy approach with multi criteria evaluation analysis of this study as a template for other regions of the country by adding other factors not included in the model that add value to the analysis.
- In addition to selecting potential wind farm, in future research, the Fuzzy statistical approach must further investigated to use in different suitability assessment.

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Appendices

Annex 1: Kulumsa monthly average wind speed at 2 meters height (m/s)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2005	1.9	2.3	1.5	1.6	1.2	1.3	1.4	1.0	0.9	2.3	2.6	2.6
2006	1.8	2.4	1.6	1.3	1.4	1.5	1.4	1.5	1.1	2.6	2.1	2.2
2007	2.1	1.9	1.6	1.8	1.7	1.7	1.3	1.4	1.2	2.4	2.8	2.7
2008	1.9	2.6	1.5	1.3	1.4	1.3	1.5	1.8	0.9	2.1	2.4	2.4
2009	1.9	2.3	1.7	1.9	1.6	1.6	1.2	1.5	0.8	2.8	2.6	2.1
2010	2.4	1.0	1.5	0.8	0.7	0.8	1.2	1.1	0.6	2.0	1.6	1.6
2011	1.2	3.1	1.8	1.3	1.2	0.8	1.1	0.9	0.6	3.1	2.2	2.6
2012	2.3	2.5	1.9	1.1	1.6	1.0	1.1	0.7	0.5	2.2	1.9	2.0
2013	2.0	1.9	1.3	1.6	0.7	0.8	1.1	0.7	0.5	1.3	2.0	2.2
2014	2.0	2.1	1.9	1.8	1.9	1.5	1.5	1.2	1.1	2.2	2.4	2.6

Annex 2: Golelcha monthly wind speed at 2 meters height (m/s)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2005	2.4	1.7	1.1	1.5	0.8	1.5	1.6	0.8	1.1	1.4	0.8	1.1
2006	2.1	1.2	1.6	1.4	1.2	1.1	1.3	1.4	1.4	0.9	1.1	1.5
2007	2.1	1.6	1.5	1.4	0.9	0.9	0.9	1.1	1.3	1.1	1.4	1.8
2008	1.9	1.8	1.4	1.2	1.2	0.7	1.8	1.4	0.9	1.3	1.2	0.9
2009	1.4	1.1	1.8	1.3	1.6	1.2	0.7	0.8	1.2	0.8	1.5	1.5
2010	2.4	1.3	1.2	0.9	1.1	1.1	1.2	0.9	1.5	1.2	1.3	1.1
2011	2.1	1.9	1.6	1.1	1.5	1.8	1.6	1.2	1.3	1.5	0.7	1.6
2012	1.8	1.4	1.1	0.7	1.0	0.8	1.5	1.4	1.5	0.7	0.9	1.8
2013	1.6	1.5	1.1	0.9	0.9	0.8	0.6	0.8	1.1	1.3	0.9	1.4
2014	1.3	1.2	1.4	1.2	1.4	1.6	1.5	1.0	1.2	1.2	1.3	1.7

Annex 3: Metehara monthly wind speed at 2 meters height (m/s)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2005	2.6	2.9	3.1	2.3	2.8	2.5	2.1	2.1	2.5	2.1	2.4	2.5
2006	2.8	3.1	2.4	2.4	2.1	2.6	2.4	1.8	2.1	2.3	2.1	2.4
2007	2.1	2.8	2.8	2.4	2.5	2.4	2.1	2.1	2.4	1.9	2.5	2.5
2008	2.9	3.0	2.6	1.9	2.4	2.6	2.4	2.5	2.6	2.4	2.2	2.1
2009	2.8	2.9	2.6	2.6	2.6	2.8	2.2	2.4	2.4	2.1	2.3	1.9
2010	3.1	2.7	3.1	2.5	2.1	2.3	2.6	2.5	2.5	2.3	2.5	2.5
2011	2.7	2.8	2.5	2.2	2.2	2.8	2.5	2.6	2.5	1.8	1.9	2.8
2012	2.7	2.6	3.0	2.1	2.4	2.6	2.9	2.5	2.4	2.1	2.0	2.0
2013	2.2	2.8	2.0	2.0	2.1	2.7	3.2	2.0	1.7	1.6	1.8	2.1
2014	2.5	2.9	2.1	1.8	2.4	2.6	2.9	2.2	2.0	1.8	2.1	2.1

Annex 4: Adama monthly wind speed at 2 meters height (m/s)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2005	2.2	2.7	2.2	2.3	1.6	3.0	3.1	2.5	1.9	2.5	2.6	2.8
2006	2.8	2.3	1.9	1.9	2.2	2.9	3.0	2.7	1.8	2.1	2.5	2.7
2007	2.8	2.2	2.3	1.9	2.1	2.8	2.6	2.3	1.7	1.9	2.8	2.6
2008	2.4	2.5	2.1	2.0	1.9	2.9	2.9	2.5	1.7	2.1	2.6	2.7
2009	2.6	2.4	2.2	2.1	1.8	2.8	2.8	2.7	1.8	1.9	2.8	2.9
2010	2.8	2.6	2.1	1.9	1.7	2.7	2.9	2.8	1.6	2.2	2.8	3.1
2011	2.6	2.6	2.1	2.2	2.1	2.9	2.9	2.7	1.4	2.1	2.9	2.9
2012	2.6	2.7	2.3	1.9	1.9	2.8	3.0	2.6	1.6	2.4	3.1	2.9
2013	3.0	2.5	2.3	2.3	2.0	3.0	2.7	2.6	1.6	2.5	2.9	2.8
2014	2.8	2.5	2.2	2.1	1.9	2.9	2.6	2.3	1.7	3.0	2.7	2.7

Annex 5: Nurera monthly wind speed at 2 meters height (m/s)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2005	2.8	2.6	2.4	2.1	2.4	3.4	3.1	2.8	2.6	2.4	2.8	2.4
2006	2.4	2.4	2.6	2.6	2.1	3.5	2.8	2.8	2.1	2.9	2.4	2.6
2007	2.6	2.5	2.1	2.1	2.7	2.8	3.0	2.7	3.0	2.7	2.7	2.4
2008	2.9	2.6	2.5	2.5	2.5	2.7	2.4	3.0	2.8	2.5	2.5	2.8
2009	2.3	2.1	2.6	2.7	2.2	2.9	2.4	2.6	2.1	2.2	2.3	2.7
2010	2.6	2.3	2.7	2.8	2.7	3.8	3.8	3.1	2.6	2.6	2.5	2.3
2011	2.5	2.5	2.3	2.6	2.2	3.3	3.1	2.5	2.4	2.3	2.7	2.8
2012	2.5	2.6	2.8	2.8	2.8	3.1	2.9	2.3	2.8	2.6	2.5	2.6
2013	2.2	2.3	2.1	2.2	2.8	4.2	4.2	2.9	2.7	2.3	2.2	2.1
2014	2.4	2.2	1.9	2.3	2.6	4.0	4.7	4.1	3.0	2.5	2.5	2.4

Annex 6: Robe monthly wind speed at 2 meters height (m/s)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2005	1.2	1.4	1.4	1.4	1.4	1.2	1.2	1.1	1.1	1.1	1.2	1.2
2006	1.3	1.3	1.6	1.2	1.5	0.9	1.4	1.3	1.2	1.3	0.8	1.3
2007	0.9	1.5	1.3	1.6	1.3	1.2	1.3	1.1	0.9	1.1	0.6	1.8
2008	1.4	1.3	1.5	1.6	1.9	1.1	1.5	0.8	1.3	0.9	1.4	1.4
2009	1.2	1.6	1.4	1.9	1.1	1.4	1.2	1.4	1.1	0.8	1.6	1.5
2010	1.1	0.8	1.1	0.9	0.9	1.4	0.9	0.9	0.9	1.1	0.9	1.0
2011	1.2	1.3	1.5	2.0	1.1	1.2	1.0	1.3	0.9	0.9	0.9	1.1
2012	1.2	1.5	1.4	1.1	1.3	1.1	1.2	1.1	0.8	0.9	0.7	0.9
2013	1.0	1.1	1.0	0.9	1.1	1.0	0.9	0.7	0.7	0.7	0.8	1.0
2014	1.3	1.4	1.6	1.7	0.9	1.3	1.2	1.7	1.6	1.2	1.4	1.8

Annex 7: LULC classification accuracy assessment report

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ACCURACY TOTALS
----------------
          Class  Reference       Classified       Number  Producers        Users
           Name     Totals           Totals      Correct   Accuracy     Accuracy
     ---------- ----------       ----------      ------- ----------        -----
     Settlement          8                9            7     87.50%       77.78%
     Grass land          9                9            9    100.00%      100.00%
       Bareland         10                9            7     70.00%       77.78%
         Forest          8                9            7     87.50%       77.78%
Agricultural la         10                9            7     70.00%       77.78%

         Totals         45               45           37

Overall Classification Accuracy =     82.22%

                ----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS
---------------------

Overall Kappa Statistics = 0.7778

Conditional Kappa for each Category.
------------------------------------

         Class Name               Kappa
         ----------               -----
         Settlement               0.7297
         Grass land               1.0000
           Bareland               0.7143
             Forest               0.7297
  Agricultural land               0.7143

                ----- End of Kappa Statistics -----
```

Annex 8: Summary of OLS Results - Model Variables

Variables	Cooffecient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-0.388685	0.089250	-4.355024	0.000018*	0.092041	-4.222928	0.000031*	---------
Fault	0.289734	0.008340	34.738625	0.000000*	0.008415	34.431304	0.000000*	1.698347
River	0.033838	0.009248	3.659117	0.000280*	0.008824	3.834664	0.000144*	1.211655
Power line	0.093653	0.018780	4.986936	0.000001*	0.019533	4.794616	0.000003*	5.489117
Road	0.027187	0.017776	1.529453	0.0010520*	0.017495	1.554023	0.001020*	4.282031
Town	0.028627	0.009058	3.160449	0.001638*	0.008669	3.302162	0.001010*	1.369904
Slope	0.058382	0.008115	7.193943	0.000000*	0.007938	7.354797	0.000000*	1.033094
Elevation	0.221797	0.020223	10.96744	0.000000*	0.02101	10.55828	0.00000*	4.12539
Wind speed	0.556085	0.018809	29.56431	0.000000*	0.01888	29.44821	0.00000*	2.23689
Bedrock	0.434631	0.012268	35.42733	0.000000*	0.01221	35.60286	0.00000*	1.90121
LULC	0.054110	0.013872	3.900630	0.000112*	0.01452	3.726788	0.00021*	1.06568

Declaration

I the undersigned declare that this thesis is my original work and has not been presented for a Degree in any other university and that all sources of materials used for the thesis have been duly acknowledged.

Ebisa Tesfaye Dinade

Signature ________________________ Date_______________________

School of Earth Science

June, 2016

This thesis has been submitted for examination with my approval as university advisor.

Dr. Binyam Tesfaw

Signature ______________________ Date________________________