Addis Ababa University

College of Natural and Computational sciences

School of Earth Sciences

FOREST FIRE RISK ZONE MODELING AND MAPPING IN BALE MOUNTAINS NATIONAL PARK (BMNP), OROMIA, ETHIOPIA.

A Thesis Submitted to the School of Graduate Studies of Addis Ababa University, in Partial fulfillment of the Requirements for the Degree of Master of Science in Remote Sensing and Geo-Informatics.

BY: MEGERSA TAFESSE

ADVISOR: Dr. GETACHEW BERHAN

Addis Ababa University

June, 2016

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This is to certify that the thesis prepared by Megersa Tafesse, entitled as "FOREST FIRE RISK ZONE MODELING AND MAPPING IN BALE MOUNTAINS NATIONAL PARK, OROMIA, ETHIOPIA" is submitted in partial fulfillment of the requirements for the Degree of Master of Science in Remote Sensing and Geo-Informatics compiles with the regulations of the university and meets the accepted standards with respect to originality and quality.

Signed by the examining committee:

Dr. Getachew Berhan	__________	___________
Advisor	**signature**	**Date**
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Chairman, Department Graduate Committee	**signature**	**Date**
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Examiner	**signature**	**Date**
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D E C L A R A T I O N

I hereby declare that, although I may have consulted with others in preparing for this assignment, and drawn upon a range of sources cited in this work, the thesis entitled" FOREST FIRE RISK ZONE MODELING AND MAPPING IN BALE MOUNTAINS NATIONAL PARK, OROMIA, ETHIOPIA" is my original work carried under the supervision of Dr. Getachew Berhan, Department of Earth Sciences, Addis Ababa University, Addis Ababa, during the year 2015-2016 as a part of Master of Science programme in Remote Sensing and Geo-Informatics. I further declare that this work has not been submitted to any other University or Institution for the award of any degree or diploma.

Megersa Tafesse

Signature__________________________ Date________________

Place: Addis Ababa

Date: June, 2016

CERTIFICATION

This is to certify that the thesis entitled as “FOREST FIRE RISK ZONE MODELING AND MAPPING IN BALE MOUNTAINS NATIONAL PARK, OROMIA, ETHIOPIA “is an authenticated work carried out by Megersa Tafesse under my guidance and supervision. This is the actual work done for the partial fulfillment of the award of the Degree of Master of Science in Remote Sensing and Geo-Informatics from Addis Ababa University. Addis Ababa.

Dr. Getachew Berhan

Signature__________________________

Department of Earth Science

Addis Ababa University

Addis Ababa

Date: June 2016

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List of Acronyms

AIC	Akaki Information criteria
ArcGIS	Aeronautical Reconnaissance Coverage Geographic Information System
ASTER	Advanced Space born Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Radiometric Resolution
BMNP	Bale Mountains National Park
BMNP GMP	Bale Mountains National Park General Management Plan
CFFDRIS	Canadian Forest Fire Danger Index
CIFOR	Center for international Forestry Research
DEM	Digital Elevation Model
DMSP	Defense Meteorological Satellite Program
EMA	Ethiopian Mapping Agency
ERDAS	Earth Resource Data Analysis System
ETM	Enhanced Thematic Mapper
FAO	Food and Agricultural organization
GOES	Geostationary Operational Environmental Satellite
GIS	Geographic Information System
GPS	Global Positioning System
GWR	Geographically Weighted Regression
JRC	Joint Research Center
IAWF	International Journal of Wild land Fire
MgC/ha	Carbon milligram per hectare
MOA	Ministry of Agriculture
MODIS	Moderate Resolution Imaging Spectrometer
NASA	National Aeronautics and Space Administration
NFDRS	National Fire Danger Rating System
NDVI	Normalized Difference vegetation Indices
NOAA	National Oceanic and Atmospheric Administration
OLI	Operational Land Imager
OLS	Ordinary Least Square
SPOT	Satellite Pour l'Observation de la Terre (French)
SRTM	Shuttle Radar Topography Mission
TIFF	Tagged Image File Format
TM	Thematic Mapper
USGS	United States geological Survey
UTM	Universal Transverse Mercator
VIF	Variance inflation factor

Abstract

Although BMNP is playing a vital role in environmental protection, it is suffering from a frequent forest fire in the past two decades. Despite the observed increasing forest fire incidence in the BMNP, there are limitations of detailed forest fire risk modeling and mapping and identification of factors influencing forest fire. The aim of this study was to identify the key explanatory attributes of forest fire, model and map forest fire risk zones and to validate the model. Landsat 8 OLI of 2015, SRTM 30m DEM, and Topographic map of scale 1:50,000 was used to produce the explanatory attributes. Six explanatory attributes: lulc, elevation, slope, aspect, proximity to settlements and distance from roads were identified using correlation analysis and OLS and GWR regression analysis. The factors were grouped into two sub-models consisting of Biophysical and Ignition sub-models. Pairwise comparison was applied in order to assign weightages for the factors. Multi-criteria decision-making technique was used to derive final forest fire risk model and map of the study area. GPS data was collected from the areas where there was frequent forest fire in order to support model validation. The final forest fire risk map of BMNP was categorized into four categories as extreme, high, moderate and low risk based on their fire susceptibility. The results revealed that 94.28 km^2 (4.5%), 868.10 km^2 (41.55%), 997 km^2 (47.73%) and 129.56 km^2 (6.2%) area of BMNP are categorized under extreme, high, moderate and low risk respectively. The result shows that there is significant area under fire risk which needs frequent follow up. It was recommended that incorporating other models, such as fire spread models and fire behaviour models are important for improved understanding fire management in the area.

Key words: BMNP, Explanatory attributes, Forest fire risk zone, GIS, Modeling.

CHAPTER ONE: INTRODUCTION

1.1. Back ground of the study

Forests are major natural resources and play an important role in maintaining environmental balance. The ecological condition of any given area can be better expressed by healthiness of a vegetation, mainly forest (Jaiswal et al., 2002 ; Gholamreza et al., 2012 ; Mohammedi et al., 2013), habitat composition and species richness (Demeke & Afework, 2014) in a given area.

Fire is the greatest enemy of standing vegetation and wild animals which causes ecological and environmental damage, and human suffering (Thakur and Singh, 2014). According to FAO (2010), fire is one of the major environmental challenges in the world and its occurrence is considered as the cause for destruction of more than 350 million ha of forests in 2000. In this report the worst fire hazard area in the world is in sub-Saharan Africa**,** where more than 170 million ha are burning annually. Moreover, wildfires are considered as a serious problem distressing many terrestrial ecosystems in the Earth system which affect forest conservation, create economic and ecological damage, cause human suffering and loss of biodiversity (Gholamreza et al., 2012; Malik et al., 2013; Mohammedi et al., 2013).

Even though it is very difficult and even not possible for human to control the Natural hazards like forest fire, there is still a possibility to reduce the fire frequency and damage by analyzing the factors responsible for fire and predicting forest fire risk zones (Jaiswal et al., 2002; Gholamreza et al., 2012). Forest fire risk zones are locations where a fire is likely to start, and then it can easily spread to other areas (Gholamreza et al., 2012; Malik et al 2013). Information on the distribution of forest fire risk zones is essential for the effective and sound decision making process in the forest management (Hussin et al., 2008; Malik et al., 2013; Mohammedi et al., 2013). Forest fire risk evaluation is a critical part of fire prevention, since pre-fire planning resources require objective tools to monitor when and where a fire is more prone to occur, or when will it have more negative effects (Chuvieco et al., 2010; Malik et al., 2013).

Remote sensing and Geographic information system (GIS) used to model forest fire risk and map fire prone areas, which can be useful in the decision making process for fire monitoring actions (Pradhan et al., 2007). Satellite remote sensing has opened up opportunities for qualitative analyses of forests and other ecosystems at all geographic and spatial scales. Understanding the behavior of forest fires, the factors that contribute for making an environment fire prone and the factors that influence fire behavior is essential for forest fire risk zone modeling and mapping (Jaiswal et al., 2002). Remote sensing and geographic information systems (GIS), provides the information and the tools necessary to develop a forest fire susceptibility map in order to identify, classify and map fire hazard area (Pradhan et al., 2007).

The topography of Ethiopia is rugged and this controls the climate of the country such as temperature and rainfall. Altitude ranges from 4620 m A.S.L. at the top of mount Ras Dashen to 116 m below sea level in the Danakil depression (Temesgen Gashaw, 2015). This altitudinal and topographic variation results in a wide variation of rainfall, humidity and temperature. Thus, the country consists of nine ecosystems that ranges from Afroalpine at the highest elevations to desert and semi-desert ecosystems at the lowest elevations (Temesgen Gashew, 2015).

Along the different ecosystems, there are many protected areas of land in Ethiopia including national parks, wildlife reserves, priority forests, biosphere reserves and community conservation areas. These areas act as biodiversity ‘banks’, important spiritual places, centers for traditional ecological knowledge and bringing revenues from tourism and carbon trading (Young, 2012). The Bale Mountains National Park (BMNP), which is established in 1970, is one of the protected areas in southeastern Ethiopia. It has the largest areas of continuous Afroalpine and Afromontane forest habitats in Africa (Alers et al., 2007; Maselli et al., 2010). It was established with the primary objective of conserving endemic species like the Mountain Nyala (*Tragelaphus buxtoni*) and the Ethiopian wolf (*Canis simensis*) and other valuable natural resources in the area.

Although BMNP is playing a vital role in environmental protection it is suffering from a frequent forest fire in the past two decades (Anteneh Temesgen et al., 2013; Temesgen Gashaw 2015). Therefore, adopting sound forest fire management strategies are mandatory to overcome the problem. Many studies were conducted using diverse approaches all over the world on forest fire risk assessments and mapping. Those approaches depend on the variables and the selected scale (Sonia, 2008).The final output is a prediction of the fire risk in space and time. There are various fire prediction system such as: the Canadian Forest Fire Danger Index (CFFDRIS), the National Fire Danger Rating System (NFDRS), and the Joint Research Center (JRC) (Sonia, 2008). Although the fire risk models development in many countries has reached a very advanced level, it is in its infant stages in Ethiopia.

1.2. Statement of the problem

Fire has been a source of ecosystem disturbance for thousands of years. Forest and wild land fire has been shaping landscape structure, pattern and ultimately the species composition of ecosystems. Fire has ecological role like influencing several factors such as plant community development, soil nutrient availability and biological diversity. Moreover, forest and wild land fire are considered to be a vital natural processes initiating natural exercises of vegetation succession. However, uncontrolled and misuse of fire can cause adverse impacts on the environment and the human society (Thakur and Singh, 2014).

Different studies indicated that there are recurrent and very serious forest fire in Bale Mountains massifs. For instance according to Temesgen Gashew (2015) and Anteneh Temesgen et al. (2013), forest fires that occurs between February and April 2000 destroys about 90,000 ha of forests. The study also implies forest fire that occurred in 2008 which destroyed about 11,947 ha of forests was recorded as the second most severe forest fire in BMNP. Most recently the study by Misrak Alemu et al. (2016) also reveals forest fire prone areas of Harenna Forests which is a part of BMNP.

Therefore, it is quite clear that forest fire is the most threatening factor of BMNP. Despite the observed increasing forest fire incidence in the BMNP, there are limitations of detailed forest fire risk modeling and mapping and identification of factors influencing forest fire, which is the center piece of the proposed study. The generation of fire risk map is even lacking for some parts of the country. Therefore, the development of efficient and detailed fire prevention strategies are very important for the study area.

Accordingly, this study is aimed to fill such information gap of modeling and mapping forest fire risk zone in fire management process. The forecast of forest fire risks can be achieved with the use of fire risk zone maps. Hence having proper information on forest fire prone areas and factors responsible for forest fire is necessary to develop forest fire management strategies. Therefore, this study attempts to identify the key explanatory attributes and model forest fire risk zones.

1.3. Objectives of the study

1.3.1. General objective

The overall objective of this study is to model and map forest fire risk zones of Bale Mountains National Park using remote sensing and GIS approach.

1.3.2. Specific objectives

The specific objectives of the study are:

To identify the key explanatory attributes of forest fire in BMNP.

To develop forest fire risk model and map fire risk susceptibility of the BMNP.

To validate the forest fire risk model developed in the study area.

1.4. Significance of the study

Although BMNP is considered as one of the bio diversity hot spot, loses thousands of hectares of forests due to forest fires in different periods of time. Accordingly an efficient fire prevention strategies are necessary. This study is expected to model and produce forest fire risk zone map of BMNP. Such maps will help forest department officials prevent or minimize fire risk activities within the forest and take proper action before fire breaks out.

Different Governmental and Non- Governmental organizations which are interested on fire monitoring will use this study as an input in the decision making process for fire monitoring and identifying appropriate site for specific management actions. Furthermore this study will help any researcher who wants to study further in relation to forest fire occurrences providing insight about the most fire prone areas and factors affecting forest fire in the study area.

1.5. Scope of the study

Forest fire, in many aspects is a broad discipline to investigate in all scenarios and problems related to it. To this end, this study has conceptual and spatial scope. Conceptually the study was dealt with forest fire risk zone modeling and mapping. It identify the explanatory attributes and finally validate the model. Spatially the study was confined only to the administrative boundary of BMNP.

CHAPTER TWO: LITERATURE REVIEW

2.1. Definition and concepts of forest fire

According to FAO, (2010) global forest resource assessment program, forest fire is any unplanned and/or uncontrolled vegetation fire. In this report it was also indicated that, forest fire includes management-ignited fires that exceed the restrictions in the fire plan and require suppression actions. Rawat (2003) defines fire as a chemical reaction of any substance that will ignite and burn to release a lot of energy in the form of heat and light.

The most common technical definition of fire is that it is the rapid combustion of fuel, heat and oxygen. To start a fire an external source of heat, which is measured in terms of temperature is required along with oxygen. Fuel is any material capable of burning like vegetation, branches, needles, standing dead trees, leaves, and man-made flammable structures (Saklani, 2008). Fire triangle is best explained by the Fig.1 which is developed by Roy (2008).

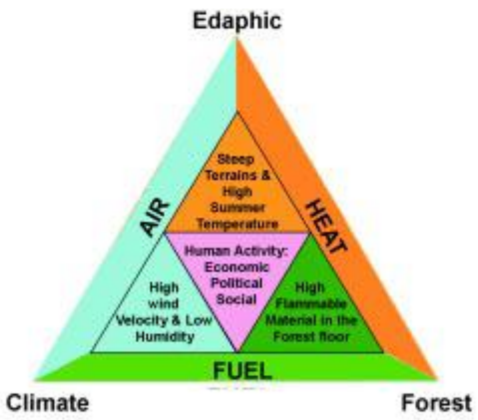

Fig. 2.1: Fire triangle.

Source: (Roy, 2003: 362)

2.2. Causes and Consequence of Forest Fire; Global and Ethiopia Perspective

2.2.1. Causes of forest fire; Global and Ethiopia Perspective

Forest fire can be classified based on their origin, into two main categories. These are; natural and manmade which will further classified as intentional and unintentional (Genanew Alemu, 2008; Saklani, 2008). Naturally, forest fire occurs mainly due to lightning or sometimes due to rolling stone and rubbing of dry tress with each other by strong wind. Lightning is an important source of natural fires which have influenced savanna-type vegetation in pre-settlement periods. Although some forest fires occur naturally, a combination of human activity, fuel availability, and climate accounts for the majority of forest fires. Natural forest fire is favored by climate and vegetation cover. Similarly high temperature of tropical and sub-tropical climate combined with strong wind in summer season will result in natural forest fire (Saklani, 2008).That means the contribution of natural fires is also insignificant in comparison to number of fires started by humans (Genanew Alemu, 2008; Goldammer, 1988).

In addition to Natural occurrences, the majority of forest fire occurs as the combined effects of human activity, fuel availability, and climatic condition (Genanew Alemu, 2008). According to FAO (2010), forest fire statistics at the global level indicates that the largest numbers of fire occurrence of the world are caused by human. In this report it is explained that at least 80 percent of forest fires of the world are caused by people and in some regions up to 99 percent.

Manmade causes are further classified as Intentional and unintentional. Mainly intentional fires are due to better growth of fodder grass (Saklani, 2008), demand for conversion of forest to other land uses (Genanew Alemu, 2008), for timber harvesting, land conversion, slash- and-burn agriculture, and socio-economic conflicts over question of property and land use rights (FAO, 2010). Unintentionally, fire occurs in a forest due to carless throwing of match -sticks and burning ends of cigarettes (Genanew Alemu, 2008).

Similarly, the majority of forest fire of Ethiopia is induced by human intentional action to execute their temporal needs (MOA, 2000). In connection to this MOA (2000) stated that Fires started by people account for 100 percent of the total fires. Of the human-caused fires, 20 percent are classified as intentional burning while negligence and carelessness accounts 80 percent. However, Genanew Alemu (2008) argues that there is a limitation of research conducted on fire causes and personal experience in the field was used for the last 20 years.

The causes of fire in BMNP are anthropogenic in which farmer’s set fire for various activities: honey collection, agricultural land preparation, improved forage quality, and reduce suspected livestock predators such as Leopards, *Panthera pardus*, spotted hyenas and *Crocuta crocuta* (Temesgen Gashaw, 2015). Data from four recently burnt vegetation types (Ericaceous belt, bamboo forest, Harenna forest and Hagenia/Juniperous forest) revealed that all were human induced incidences which could categorized as deliberate and accidental (Anteneh Temesgen et al., 2013).

2.2.2. Consequence of Forest Fire; Global and Ethiopia Perspective

Globally, no reliable, consistent and comprehensive statistics about the annual distribution and extent of forest fires exist (Genanew Alemu, 2008). Although statistical data on fire loss are weak, estimate indicates that about 350 million hectares of the world forest suffer wild land fires each year. This is equivalent to about 9 percent of total forest area, but the term wild land includes non-forest areas such as savannah, brush and open range. The actual damage to forests is less than 5 percent per year (FAO, 2010).

The magnitude of forest fires is not uniform; instead it is vary from region to region and year to year. For instance, Fire damage to forests in the Europe region (excluding the Russian Federation) constitutes less than 10 percent of the area reported for insect pests, diseases and 11 other disturbances. Compared with other regions of the world, non-fire disturbances are relatively well reported in Europe, with information received on over 90 percent of the forest area (FAO, 2010).

A study conducted in Africa indicates that the continent accounted for 64 percent of the global area burned by wildland fires in 2000, when 230 million hectares were burned, accounting for 7.7 percent of the total land area of the continent (FAO, 2005). As reported on FAO Regional Conference for Africa (FAO, 2005), two areas of particularly high fire frequency stands out: one is northern Angola and the southern Democratic Republic of the Congo, and the other southern Sudan and the Central African Republic.

Even though there is no reliable recorded data that permits analysis for extent of damage, in Ethiopia forest fire have resulted in considerable economical and biological loss. There were forest fires in early 1984 that affected a considerable forest area in the country. As a consequence of this about 308198 ha forest damaged (MOA, 2010). A major wildfire episode affected the afro-montane forests in 2000, mainly in Oromia Regional State. For instance according to Temesgen Gashaw, (2015) and Anteneh Temesgen et al. (2013) forest fires that occurs between February and April 2000 and which destroys about 90,000 ha of forests was the first big fires since 1984. The study also implies forest fire that occurred in 2008 which destroyed about 11,947 ha of forests was recorded as the second most severe forest fire in BMNP.

In the history of the country, the major forest fire incidence has been recorded in the year 2000. In this period more than 120 significant forest fire incidences reported from the various corner of the country. The second largest recorded forest fire incidences reported in the 1993 when 20 prevalence were reported.

2.3. Impacts of fires on biological diversity and forest ecosystem functioning

Forest fires have many implications for biological diversity (Davies and Unam, 1999). At the global scale, they are a significant source of emitted carbon, contributing to global warming which could lead to biodiversity changes. At the regional and local level, they lead to change in biomass stocks, alter the hydrological cycle with subsequent effects for marine systems and Influence plant and animal species' functioning (http://www.fao.org).

In addition, due to increased percentage of smoke in environment, photosynthetic activity is reduced, and thus health of human beings and animals is also effected (Davies and Unam, 1999). In this study it was further argued that, the trees which fall due to forest fires become fuel for coming years & thus the frequency of forest fire increases and it may lead to growth of fire prone species in large quantity.

Forest fires, controlled or uncontrolled have intense impacts on the physical environment including: land cover, land use, biodiversity, and climate change and forest ecosystem (Roy, 1996). They also have huge implication on human health and on the socio-economic system of affected countries (Genanew Alemu, 2008). Burning of forest in South East Asia for instance resulted in 4 billion dollar economical damage and estimated 20 million people of the region are in danger of respiratory problem (Roy, 1996).

Researchers have founded the contribution of biomass burning to the global budgets of many radioactively and chemically active gases such as carbon dioxide, carbon monoxide, methane, nitric oxide, tropospheric ozone, methyl chloride and elemental carbon particulate (Genanew Alemu, 2008). Biomass burning is recognized as a significant global source of emission contributing as much as 40% of gross Carbon dioxide and 30% of troposphere ozone, At the regional and local scale, forest fires change biomass stocks, alter the hydrological cycle with knock-on effects for marine systems such as coral reefs, reduce visibility to near zero, impact plant and animal species functioning and detrimentally impact the health and livelihoods of the human population (Roy, 1996).

Apart from the effect on forest vegetation, fire can have a significant impact on forest vertebrates and invertebrates (Dennis et al., 2001). In forests where fire is a natural part of the system, species are adapted to a natural fire regime and can benefit from the result of a fire. However, in forests where fire is not a natural disturbance, it can have devastating impacts on forest vertebrates and invertebrates - not only killing them directly, but also leading to longerterm indirect effects such as stress and loss of habitat, territories, shelter and food (http://www.fao.org).

2.4. Parameters responsible for forest fire

It is not a single factor which determines forest fire, rather fire occurrences, intensity and spread depends on various integrated factors. As it was mentioned earlier, three factors are required for any fire to take place: These are availability of air, fuel and heat. All these three factors depend on many other factors which are described as below:

2.4.1. Topography

Topography is an important physiographic factor, which is related to wind behavior and hence, affects the fire proneness of the area (Gholamreza et al., 2012; Burgress, 2011). In this regard, three topographic factors; elevation, slope and aspect were described as below.

2.4.1.1.Elevation

Elevation is a crucial physiographic variable that is associated to wind behavior and therefore it affects fire capability, so it has a big role in fire spreading (Ozelkan and Ormeci, 2008). Elevation influences vegetation structure, fuel moisture and air humidity. Lower elevations are typically characterized by higher temperature and lower relative humidity (Burgress, 2011). It is mentioned in Gholamreza et al. (2012) that humidity and temperature have higher influence on fire at upper altitude areas than lower ones.

2.4.1.2.Slope

Slope is defined as the rate of change in elevation (Burgress, 2011). Typically it is measured in degrees or percent. Slope is one of the parameters that influences fire behavior. Slope can directly affect fire behaviour as it can influence fire's rate of spread and flame length (Burgress, 2011). Fire moves most quickly up slope and least quickly down slope. Also, in steeper slopes, rate of fire spread might rise, since flames are angled closer to the surface of ground and wind effects can supply the process of heat convection for the fire produced (Gholamreza et al., 2012). Slope increases the radiation and convection heat transfer up the slope. The steeper the slope the greater the up-slope heat transfer and thus, the higher the fire spread rate and intensity (http://learningcenter.firewise.org).

2.4.1.3.Aspect

Aspect describes the direction in which a slope faces and relates to the degree of solar exposure. It is measured by degree from 0° (North), through to 180° (South), back to 360° (North) (Burgress, 2011). For example, north and south facing slope faces away from the sun and thus is generally cooler and moister than east west slopes (http://learningcenter.firewise.org). Eastern aspect slopes are higher temperatures, minor humidity and lower fuel moistures because this aspects receive more direct heat from the sun (Misrak Alemu et al., 2016).

2.4.2. Accessibility/ human influence

As far as accessibility is concerned, proximity to settlements and distance from roads are the major factors that contributes a lot for forest fire ignition. Fire frequency has been found to be greater in close proximity to settlements, roads and agricultural lands (Burgress, 2011). Forests located near roads are therefore more fire prone (Jaiswal et al., 2002). Because human, animal and vehicle movement and activities on roads provide ample opportunities for accidental/man-made fires. Forests located near settlements can be more fire prone since the people living there can cause an accidental fire (Jaiswal et al., 2002).

2.4.3. Vegetation

Vegetation provides the fuel which fire burns, and it is an important aspect of fire triangle. Vegetation cover type have different properties which in turn affect fire behaviour (Burgress, 2011). This includes fuel quantity and fuel size. According to this study, fuel quantity is the amount of fuel available to burn and associated with particular vegetation type. Fuel quantity can therefore be expressed as amount of carbon per hectare (MgC/ha).

Fuel size and shapes determines the surface area to volume ratio of fuels. This varies significantly from forest stand and logs, to brush and grass. Grass and brush have high surface area to volume ratios. This means, less heat is required to reduce moisture content and accelerate ignition process (Burgress, 2011). In contrast, dense fuels such as forests have low surface area to volume ratio. This means more time is required for ignition and combustion as oxygen availability is low in dense fuels.

2.5. Role of Remote Sensing and GIS in forest fire assessments and modeling

After the launch of earth resources satellites several studies were conducted on forest fire and burnt area assessment. A GIS takes advantages of computer’s ability to store and process huge data (Santiago and kheladze, 2011). Given vast geographic extent over which to gather information, remote sensing and GIS offer an appropriate way of acquiring information on a regular and permanent basis even in areas where accessibility is limited (Hussin et al., 2008).

Remote sensing permit the capture of types of data that humans cannot sense such as near infrared and thermal part of the electromagnetic spectrum, which provide additional information (Hussin et al., 2008). Furthermore, remote sensing provide regular observations allowing for regular updates of the fire situation (Goldammer and Ronde, 2004). Additionally, remote sensing has the advantage of presenting different spectral reflectance characteristics between the fire scars and healthy vegetation especially in the infra-red part of the electromagnetic spectrum (Sowmya and Somasheka, 2010).

In addition to fire mapping using remote sensing, GIS has effectively been used for fire risk modeling (Yakubu et al., 2015). GIS makes it possible to store, retrieve and update spatial data as well as to derive cartographic models, by combining in different ways, the layers of information included in the database (Santiago and kheladze, 2011). The use of GIS approach allows combining different variables in order to establish fire risk areas. The main factors of such model are vegetation, topography, accessibility, fire history, and weather data (Hussin et al., 2008).

2.5.1. Potential Forest Fire Identification

Remote sensing data can be used to provide forest related information to governments and civil society in a timely and cost-effective way (Ahern et al., 2001). The use of satellite data to map forests has become an increasingly common way to pinpoint deforestation, active fires and logging in protected areas (CIFOR, 2004). Active forest fire is one of the major threats of the global forest resource which needs immediate response before it results in major loss (FAO, 2010).

However, before the advent of remote sensing technology, identification of active forest fire and potential sites were a challenging task for most foresters. Currently, however, this situation is not a problem due the advancement of remote sensing technology which provides high resolution imageries (Yakubu et al., 2015). These satellite imageries offer information not only for active forest fire sites but also the scares of burnt forest as well as the extent of fire damage (Kushla and Ripple, 1998). The most frequently used data source for forest fire information is NOAA/AVHRR data. Alternative data sources are MODIS, ATESR-2 and SPOT (Ahern et al., 2001; Roy, 1996).

Measurement of vegetation stress is one of the most frequent uses of remote sensing in forest fire management. Fuels, climatological data, terrain, vegetation type /density and moisture level (live and dead), historic fire regime, digital elevation models (DEMs) distance from road, vicinity to settlement etc. are important factors should be considered to identify potential forest fire sites within forest area (Burgan and Klaver, 2000). Fuels mapping is really a modeling exercise using the inputs listed above. One process to map fuels looks at departures of current vegetation / forest types from potential vegetation types (Arroyo et al., 2008). Additional information is needed for determining structural risk associated with biomass, fuel composition and fuel moisture status This requires high-spatial resolution data (imagery) to provide estimations of vegetation structure and biomass (Goldammer, 2001).

Hence, fuel condition or character is one of the major factors to be considered to identify potential forest fire sites within the forest (Burgan and Klaver, 2000). Fuel represents the organic matter available for fire ignition and combustion. Fuel condition information for forest fire study can be acquired by analyzing imageries from remote sensing data. Traditionally, fuel type is collected directly from the field with an intensive and accuracy measurement (Pickford, 1995). In case of forest fire hazard model it is required information of fuel type on large areas, and remote sensing has succeeded to overcome this task (Chuvieco and Congalton, 1988).

Besides to this, fire potential depends on the amount of dead and live vegetation and moisture contents in each (Chuvieco and Congalton 1988). The amount of dead and live vegetation is estimated from a high quality land cover map derived from a high resolution sensor, such as the IRS, Landsat TM or SPOT multispectral scanner or from lower resolution sensor such as NOAA-AVHRR or NASA Moderate Resolution Imaging Spectrometer (MODIS) (Roy, 1996). Once, the necessary information related fuel combustion properties are identified using remote sensing techniques, the next task needs to integrate it with other factors such as terrain condition and human factors to model forest fire (IAWF, 2001).

GIS takes advantage of its capability to combine different source of information (e.g. Fuel type, elevation, gradient, aspect and buffer road) for modeling or mapping potential forest fire risks. (Genanew Alemu, 2008). GIS plays a major role to model potential forest fire based on the existing relationship between forest fire and factors which directly or indirectly related to it. Hence, fire risk zonation model can be done using GIS to obtain the combined effect of fuel type, elevation, aspect, and distance or accessibility. Weighting is assigned to each variable as per their respective impact on forest fire hazard (Roy, 1996).

As it was further discussed in chapter three of this study, various approaches were used by different researcher to model forest fire risk susceptibility considering various variables which have impose their respective impact to forest fire. Each researcher attempted to model using GIS techniques based on the assumption that in forest fire hazard the availability of fuel type is a key factor on fire spreading. A fuel type provides a burning resource or plays as source of ignition based on its combustion properties (Mulyanto, 2001; Chuvieco and Congoltan, 1988).

Similarly, in Roy (1997) spatial modeling has been done to obtain the combined effect of fuel type index, elevation index, slope index, aspect index and the distance/accessibility index. Weighting over lay have been assigned as per the importance of particular variable contributing in fire environment. Finally, the obtained map was reclassified to obtain final fire risk zone map which depicts the degree of susceptibility with in the forest environment.

However, (Chuvieco and Congoltan, 1988) developed another approach to deal with forest fire hazard susceptibility. In this approach frequency ratio model used to produce forest fire susceptibility map .Using this model, the spatial relationships between hot spots occurrence location and each factors contributing hot spots were derived. The frequency is calculated from analysis of the relation between the observed hot spots and the attributing factors .Therefore, the frequency ratios of each factor factors type were calculated from their relationship with hot spot events. Hence, to calculate the forest fire susceptibility index (FFSI), each factors frequency ratio values were summed to the training areas .The hotspot susceptibility value represents the relative susceptible to forest fire occurrence.

2.5.2. Active Forest Fire Identification

To detect active forest fire, satellite borne sensors operate within the visible, thermal, and mid infra-red bands. Active forest fires can be detected by either sensing their thermal or mid-infrared signature during the day or night, or by detecting the light emitted from the forest fires at night. The sensors must also have frequent over flights with data available in near real time. Thus, monitoring of forest fire is highly dependable on the temporal resolution of the sensor, (Burgan and Klaver, 2000; Roy, 1996).

Satellite systems that have been evaluated for fire detection include AVHRR (NOAA-AVHRR) which has a thermal sensor and makes daily over flights, the Defense Meteorological Satellite Program (DMSP) Optical Line scan System (OLS) sensor (DMSP-OLS) , which makes daily overflights and routinely collects visible images during its nighttime pass (Yakubu et al., 2015) and the NOAA Geostationary Operational Environmental Satellite (GOES) sensor (NOAA-

GOES), which provides visible and thermal images every 15 minutes over the United States and every 30 minutes elsewhere (Genanew Alemu ,2008). Therefore AVHRR has been used most extensively for detecting and monitoring wildfires (Roy, 1996).

Except MODIS, the only instrument that has mission objectives of detecting wildfires with a working prototype of a global fire detection system, all of the sensors currently used were not designed with wildfire detection as an objective (Burgan and Klaver, 2000).

2.5.3. Post-fire assessment

The most important activity in forest fire management is the assessment of the burned area and protection of critical resources. Regarding this, remote sensing has already proven its usefulness for assessment of forest fire damage (Genanew Alemu, 2008). With space-borne remote sensing, the forest fire damage or the extent of burned area is determined by the single-date or multi-temporal analysis of the images (Miettinen, 2007). Once fires are extinguished, a combination of low resolution images (AVHRR) and higher-resolution images (SPOT, Landsat and Radar) can be used to assess the extent and impact of the fire (Genanew Alemu, 2008). Radar has proved effective in monitoring and assessing the extent and severity of fire scars in the boreal forest (Roy, 1996).

On national and international scales, OAA/AVHRR data have been most commonly used for burned area mapping (MODIS data, which has a similar swath width to AVHRR with sixteen times the resolution and superior geolocation accuracy, is quickly assuming this role (Miettinen, 2007). The VEGETATION instrument onboard SPOT4 is a new alternative source of data, (Chuvieco and Martin, 1994). At regional scales within national boundaries, high-resolution data from Landsat Thematic Mapper and SPOT/HRVIR are used to determine the extent of forest fire damage (Genanew Alemu, 2008). Space-borne radar data (mainly from ERS/SAR) has been used experimentally, but is not in operational use, probably because of the intrinsic complexity in computer processing of SAR images and unacceptable spatial resolution (Chuvieco and Martin, 1994).

2.6. Fire models

GIS is a system that is capable for collecting, storing, analyzing, and disseminating information about areas of the earth (Saklani, 2008). In short, it is a computer based system that can deal with virtually any type of information about features that can be referenced by geographical location. The use of the GIS approach facilitates in integrating several variables in order to establish and focus on the problem (Chuvieco et al., 2009). At the same time, it makes it possible to update or retrieve spatial information in different ways included in the database, to develop various models. It has been stated that when it comes to spatial decision aid, the analytical capability of the GIS has to be enhanced in respect of semi-structured problems involving subjective judgments (Beedasyl et al., 1999).

Models are the simple representations of the complex real world i.e. models are the approximation of the real world (Saklani, 2008). The complex processes of the living earth are not easy to understand but we can model them in a simple understandable manner. More of models are very useful for understanding various processes in real world and thus predicting the future events on the basis of our understanding. This will help us in planning the future action of plan and thus preventing, reducing or controlling the negative event and enhancing positive events i.e. to maintain the balance of the whole life processes in this living earth (Albini, 1986).

Building a model is an art, and cannot be automated (Burgress, 2011). It requires a lot of skill such as knowing the laws of physics, economics, sound sense and experience. Building of model starts with defining the goal of model which includes scope of the model, input parameters, which parameters are taken into account, and which physical models will be ignored and which input parameters are needed (Burgress, 2011).

Pattern of forest fire spread are modeled using fine scale mechanistic or broad scale probabilistic approach (McCormick et al., 2002). Former looks at the small scale constraints (e.g. percentage of moisture in fuel) that enable the fire to keep burning whereas in the latter, fire spread is determined by the size and connectedness of fuel patches distributed across the fire landscape.

Innumerable forest fire spread models exist for taking decision towards fire management using the spatiotemporal database system (Burgress, 2011). This study further discuss that Current models do not account for the causative factors of forest fire occurrence. Therefore, forest fire research can be considered as one of the most appropriate areas, where Geographic Information System (GIS) approach can be effectively applied (Burgress, 2011)

We use the term fire model to mean mathematical relationships that describe the potential characteristics of a fire (Arroyo et al., 2008). Fire models are often informally referred to as fire behaviour models, fire effects models, or smoke models. According to Andrews and Queen (2001) fuel models are sets of parameters required by the associated fire model.

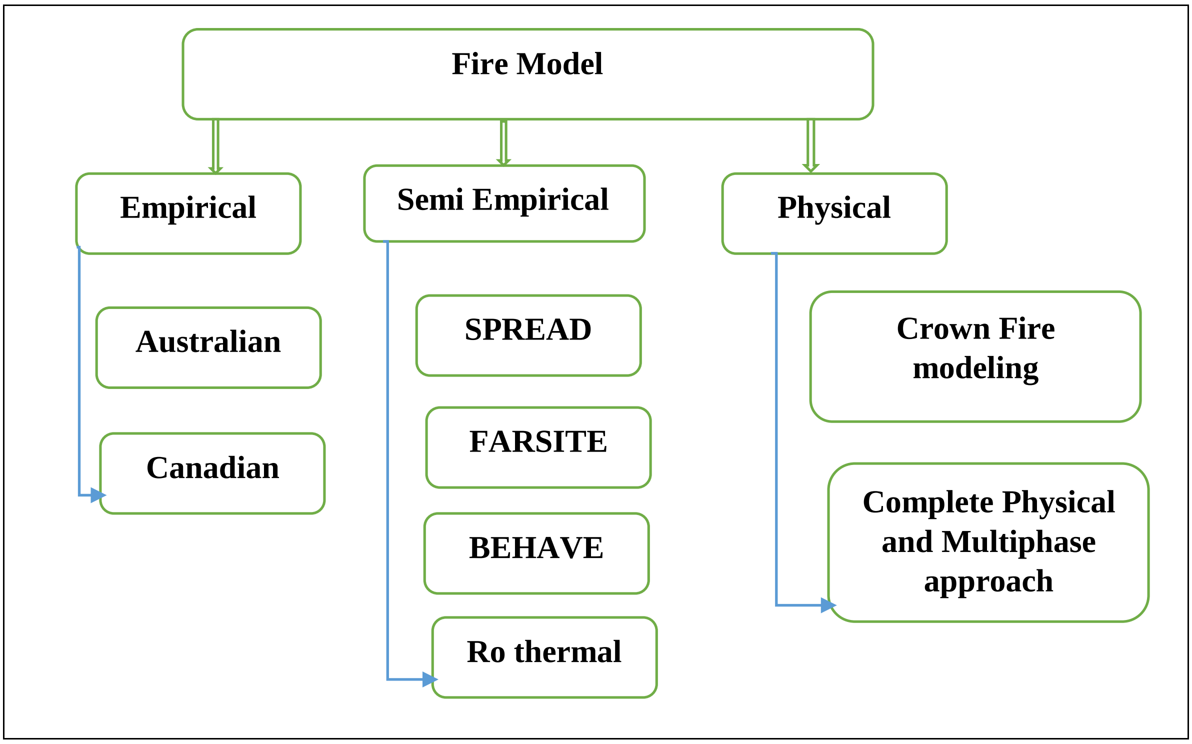

Fig. 1.2: Fire model types.

Source: Saklani, (2008)

1. Empirical Models: Also known as stochastic models. Empirical models totally rely on statistical descriptions of the relationship between some measured input parameters and their corresponding output parameters that describe some aspect of wildland fires. According to Andreas et al. (2001), a good example is the McArthur danger meter which predicts the rate of spread of Australian grassland fuel based on temperature and humidity. This sort of models can only be applied within the conditions they have been established for and a lot of well documented fires are needed to support sound statistical analysis.

2. Semi empirical Models: These models are based on the conservation of energy i.e. the energy transfer to the unburned fuel is proportional to the energy released by the combination of the fuel. Semi-empirical models have usually a rationale based on physical laws but the solution of the equations is accomplished by statistical analysis (Saklani, 2008).

3. Physical Models: These are the most reliable models, but to develop such models one requires a good knowledge and understanding of the physical relations sufficient to achieve the desired objectives. Physical models are based on the analysis of the underlying physical and chemical processes (Albini, (1986). The advantage of this sort of models is that they hold for any set of

input parameters because the physical laws are universally applicable. A major disadvantage is the difficulty to measure key input parameters in the field and thus applying and verifying the models in a practical test.

According to Saklani, (2008), forest fire models are classified into four main groups:

(1) Fire Risk Models: For pre-fire planning, it combines various parameters including weather, vegetation, and topography. The final map thus produced is quantitatively divided into different zones. These types of models are termed as Deterministic Models. On the other hand, statistical models use fire danger indices, estimated form regression models, e.g. generalized linear models to estimate probabilities of fire occurrence under various environmental conditions.

(2) Fire Behaviour Models (Fire Suppression): These model types are developed and used to characterize the propagation and spread of fires under different environmental conditions. Fire spread models are classified into three classes**:** Physical (Theoretical or analytical), Empirical and Statistical. The one-dimensional models has been used to model fire growth in two dimension using various approaches such as dividing the forest bed into various cells with different probability of burning depending on the conditions of the cell and other surrounding cells (Saklani, 2008).

(3) Fire Effect Models: These have been defined to predicate the effect of forest fire in different components of eco-system.

(4) Expert system Models: These models have been developed to imitate the actual fire event. The purpose is to provide the management tools for initial strategies, and evaluate the capabilities of fire protection organization. It combines stochastic components with deterministic components and expert opinions (Saklani, 2008).

CHAPTER THREE: MATERIALS AND METHODS

3.1. Study site description

3.1.1. Location

Bale Mountains National Park (BMNP) is located in Oromia regional state, southeast of Addis Ababa, Ethiopia, within geographical coordinates of 6º29' – 7º10' N Latitude and 39º28' – 39º57' E Longitude (Fig.3). The local boundary of BMNP lies within five *weredas* (districts): Adaba (west), Dinsho (north), Goba (northeast), Dalo Mana (southeast) and Harenna Buluk (southwest). The Bale Mountains are part of the Bale-Arsi massif, which forms the western section of the south-eastern Ethiopian highlands. The park encompasses approximately 2,200 km2 of Mountains and forest. The park covers the largest area above 3000 m a. s. l. in Africa. *Tullu Dimtu*, altitude 4377 m a. s. l. is the highest peak in the park and the second highest in Ethiopia. (BMNP GMP, 2007).

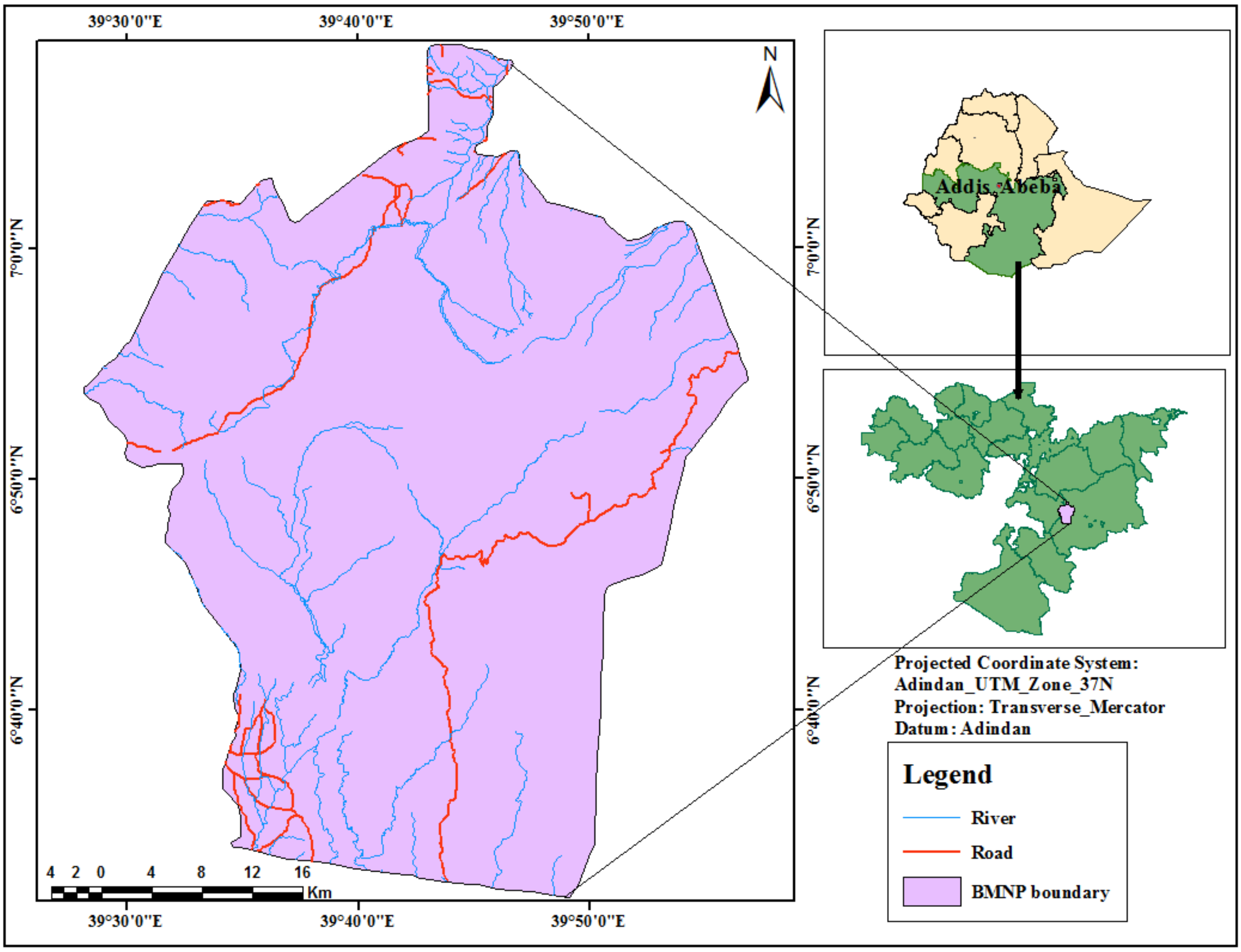

Fig. 3.1. Location map of Study Area

3.1.2. Physical Environment

3.1.2.1. Ecology

Geologically, the Bale massif consists of Tertiary (Oligocene) lavas, which covered the Mesozoic marine sediments by underlying the Precambrian rocks after the Eocene uplifting of Ethiopian highlands. During the Plio-pleistocene rifting phase, the Arsi-Bale massif was separated from the northwest Ethiopian mountains by the rift valley system, which also isolated the southwest Arabian part of land mass (Walellegn Alem, 2007).
Hence Bale Mountains were formed from volcanic eruption lava in the Miocene an Oligocene geological periods early before the formation of the Great Rift Valley system, probably about 40-25 million years ago (Walellegn Alem, 2007). Since the crust of the Bale Mountains is of volcanic origin, are fairly fertile silty loams of reddish-brown to black colors. The present topography of Bale Mountains is a reflection of long term, probably over 20million years of weathering processes that experienced due to heat and pressure that had been originated from the Oligocene lava outflows (BMNP GMP, 2007).

3.1.2.2. Climate

As a result of the great altitudinal variation in Bale Mountain massifs, considerable variations of climatic conditions are recorded in the National Park. The Bale Mountains is characterized by having eight months rainy season (March to October) and followed by another four months dry season (November to February). Rainfall is well distributed throughout the wet season, ranging from 1000 to1400mm annually (Walelegn Alem, 2007).

Temperature records from the Bale Mountains indicate that the wet season are comparatively warm and the dry seasons are extremely nocturnal cold and diurnal warm. The lowest recorded temperature at highest plateau of Bale (Sanette) was -15ºC and the maximum record was 26ºC (Hillman, 1986). Similarly the lowest recorded temperature in Dinsho area was -6ºC. Relative humidity ranges from 17% to 100% during the dry and wet periods respectively (Hillman, 1986).

3.1.2.3. Hydrology

The Bale Mountains are important water source like a tower that supports the life of millions of people and other organisms in the adjacent lowland areas. According to BMNP GMP, (2007) there are four major rivers thought to be originated from BMNP and described in table 3.1.

Table 3.1: Major Rivers and their tributaries in the BMNP

No.	Major Rivers	Tributaries
1	Wabe shebele	Abasa, Arba, Baranda, Boko, Furuna, Gondedoh, Layleeso, And Solay,Wachekora, Mararo, MalkaSegel
2	Web Albabo	Dalcha, Danka, Dimbeba, Gareno, Gesse, Kebesha, Kaficho, Keyrensa, Lolla, Micha, Shaya, Shaya-Gugesa,Teynta, Tegona, Toroshoma, Wolla, Wasama, Web and Zetegnmelka.
3	Dumal	Six un-named tributaries
4	WelmelGeremba	Rira, Shawe, Shisha and Yadot

Source: Walellegn Alem, (2007:14).

3.1.3. Biological Diversity

BMNP is considered as one of the world's richest biological diversity both in fauna and flora. The area contains not only endemic species to Ethiopia, but also species that are found only within the Bale Mountains themselves (Asmamaw Demeke and Verma, 2013). As a result of greater altitudinal variation, and the isolation of the Ethiopian highlands from other similar highlands in Eastern Africa by the surrounding hot dry lowlands, it supports the highest density of endemic mammals together with bird and vertebrates. So far 78 mammal and 278 Bird species are recorded in the park.

Among the endemic mammal species existed at Bale Mountains National Park is Ethiopian Wolfe (*Canis simensis*), Mountain Nyala (*Tragelaphus buxtoni*), Bale monkey (*Cercopithecus djamdjamensis*), Strack's hare (*Lepus starcki*) and Giant Molerat (*Tachyoryctes macrocephalus*), Wattled ibis (*Bostrychia carunculata*), Blue winged goose (*Cyanochen cyanoptera*), Rouget's Rail (*Rougetius rougeti*), Spot breasted plover (*Hoplopterus melanocephalus*) and White-collared pigeon (*Columba albitorques*) (BMNP GMP, 2007). The Harenna forest is used to harbor big mammals such as Elephants (*Loxodonta africana*) and Buffalo (*Syncerus caffer*).

According to the BMNP GMP (2007) reports the total number of species of vascular plants is about 6000. The total number of taxa for the Bale floristic region is estimated about 1650 species. Of these, about 1400 species occur between an altitude of 1500 and 4377m a. s. l. There about 600 endemic taxa in the Flora of Ethiopia and Eritrea, of which 177 (29.5%) are also endemic to Bale floristic region (BMNP GMP, 2007). The Bale Mountains National Park and surrounding areas could be divided into southern and northern sides of Bale Mountains. The vegetation in the southern side falls within moist montane forest vegetation type while the northern side classified as Dry evergreen montane forest. (BMNP GMP, 2007).

The BMNP and surrounding areas provide a complete altitudinal zonation of vegetation starting from the broadly deciduous woodland in the lower parts, extending through various types of moist montane forests to ericaceous woodland, and culminating at Helichrysum dominated moorland (Temesgen Gashaw, 2015). According to BMNP GMP (2007) the vegetation of the southern part of the park categorized into; *Octea-Olea-Podocarpus-Syzigium, Syzigium-Polysciass-Allophylus-Erythrina, Shefleria-Hagenia-Erythrina-Galiniera, Hagenia-Hypericum-Schefflera-Myrsine, Erica arborea trees, Erica arborea- E.trimera and Helichrysum citrispinum- H.splendidum.*

3.1.4. Land use in and around the BMNP

Agriculture is the major sector that supports the livelihood of households and communities in and around the Bale Mountains National Park. Agriculture in the Bale Mountains involves two major activities: Farming and Livestock husbandry. Farming takes place up to altitude of 3500. Relatively the lower slopes use to produce barley and the upper slopes mainly used for vegetables like onion, potato and cabbage. The Northern and Northwestern localities of the park, including Rira grows Barley as the major crop. Areas like Angeso to the east of the Park grow Onion than any other crop (Temesgen Gashaw, 2015).

The common characteristics of the people living in and around BMNP do practice livestock husbandry although at different scale. The average number of each livestock type owned per household is relatively higher compared to many areas in the country. For the Bale people animals mean a source of income, transport, food, and fame. Hence cattle are found everywhere in the boundary of the park. The Afroalpine plateau is the place where livestock husbandry takes place in a large scale (Walelegn Alem, 2007).

The western part of the plateau, Web valley, is being utilized by a number of livestock from the surrounding kebeles and some permanently resident livestock. Whereas the eastern part, Sanette, area serves for very few individuals having a large number of livestock per head (BMNP GMP 2007). The density per type of livestock varies significantly from one locality to another. At the Sanette plateau Sheep and Goats are the most dominant while cattle are in the Web valley. As the survey made by the park experts indicated that there are, 119,383cattle, 9,522 horses and donkeys, and 39,404 Shoats with in the entire park boundary during the survey period. This figure varies with season; it increases during the dry season and when agricultural lands outside the park boundary are sawn with crops (BMNP GMP 2007).

3.2. Materials

For this study, Cloud free images of Landsat 8 OLI of 2015 (with path/row 167/168 and 055/056) were downloaded from USGS Global Visualization Viewer Website in (GeoTIFF) format and used to prepare land use land cover. In addition to the satellite data, Digital Elevation Model (DEM) of the study area was obtained from 30 m resolution SRTM data to derive elevation, slope and aspect. Topographic map of the scale 1:50,000 from EMA were used for digitizing roads and settlements. In addition to the topographic map from EMA, road and settlement geodatabase obtained from BMNP office was used to derive settlement and road map. GPS data were collected from field in order to support the accuracy assessment of the classifications of the satellite data and to validate the results of modeling. A flowchart of the procedures followed is presented in Fig 3.11. All the input datasets were georeferenced to Adindan UTM Zone 37N system and thematic maps were generated.

ERDAS Imagine 2014 ArcGIS 10.3 and Microsoft excel 2013 software packages were used for this study. ERDAS Imagine 2014 was used in image classification to produce LULC map. ArcGIS 10.3 software was used for data storage and analysis in its different tools. Different tools of ArcGIS was utilized in order to produce the necessary Factor maps. Factor maps of forest fire-risk were reclassified and standardized by ArcGIS 10.3. Microsoft excel 2013 was used to perform autocorrelation analysis of the explanatory attributes.

3.3. Methodology

3.3.1. Explanatory attributes identification

The fire proneness of any area depends on many factors such as Land Use Land Cover (LULC) type/density, humidity of the area, slope, elevation, aspect, proximity to settlements and distances from roads. Those parameters ware used by different authors in different studies. For example, Rajeev et al. (2002); Rawat, (2003); Pradhan et al. (2007); Genanew Alemu, (2008);

Saklani, (2008); Gholamreza et al. (2012); Sharma et al. (2012); Malik et al. (2013); Mohammadi et al. (2014); Thakur and Singh, (2014); Sivrikaya et al. (2014); Pourghasemi, (2015); Misrak Alemu et al. (2016) used vegetation type, vegetation condition (NDVI), elevation, slope, aspect , distance from roads, distance from settlements and climatic factors. Those parameters listed above were adopted in each study based on the features of the study area. Accordingly LULC, slope, aspect, elevation, proximity to settlements and distance from road were adopted as explanatory attributes for the present study based on previous study and fire history of the study area.

According to Anteneh Belayneh et al. (2013) and Temesgen Gashew (20015), the major causes of forest fire in BMNP are mainly anthropogenic factors which is related with settlement supported with forest cover types, weather condition, physiographic factors and proximity to road. Based on those factors responsible for forest fire in BMNP the following parameters was selected for the present study; biophysical factor (LULC, elevation, Slope, aspect), Proximity to settlements and distance from roads. Once the possible explanatory attributes were identified from previous studies, autocorrelation of the explanatory attributes and regression analysis was performed to identify the best explanatory attributes for forest fire risk zone modeling.

3.3.1.1. Autocorrelation analysis

Correlation analysis was done in excel in order to justify the relationships of each identified explanatory attributes. The formula of correlation analysis performed was taken from excel 2013 help tools and given as below.

$$correl(x,y) = \frac{\sum(x - x_{mean})(y - y_{mean})}{\sqrt{\sum(x - x_{mean})^2 - (y - y_{mean}{}^2)}} \text{.....................................} \textbf{(Equation 3.1)}$$

Where x and y are the sample means average.

3.3.1.2. Regression analysis

Regression model was used to investigate relationships between occurrence of forest fire and explanatory variables. The primary goal of regression model is to find the best model to describe the relationship between a dependent variable and multiple independent variables (Ozdemir & Altural, 2013). In the present study, fire presence is the dependent variable, while land use land cover types, physiographic factor (Slope, aspect, elevation), Proximity to settlements and distance from roads are the independent variables.

OLS and GWR regression models were used to explore the relationship between dependent and the selected independent variables. Forest fire risk model were created using Geographically Weighted Regression (GWR) technique (Kuenda, 2014) to identify and understand the patterns of the relationships of forest fire risk model and explanatory variables, and how these relationships varied across space. GWR regression method is a relatively new method and applicable for relating spatially no-stationary variables (Kuenda, 2014). GWR is a statistical technique that allows variations in relationships between predictors and outcome variable over space to be measured within a single modelling framework (Fotheringham et al., 2002). The coefficient of determination (Adjusted $R2$) and the Akaike Information Criterion (AIC) were used to compare the model's performance as it was given in Burgres, (2011).

$yi\ (u)\ = \beta0i\ (u)\ +\ \beta1i\ (u)\ x1i\ +\ \beta2i\ (u)\ x2i\ +\ \ldots\ +\ \beta mi\ (u)\ xm$…..**Equation 3.2**)

Where yi is the dependent variable; $\beta0i$ to βmi indicate the parameters that describe the relationship around the coordinates (u) of the ith point in space (site-specific); and xmi is the mth variable in the ith point.

3.3.2. Forest fire risk zone Modeling and mapping

3.3.2.1. Overall Model Structure

The development of a fire risk model was based on those models developed by Burgress, (2011); Rathaur, (2006). In this approach, the individual fire risk factors (explanatory attributes) were identified and grouped into sub-models which shares similar characteristics. In the present study two sub-models which was used in developing the final fire risk model was developed (Fig 3.2). These are the Biophysical and Ignition sub models. A final fire risk model output is produced by combining these sub-models using weighted combination as used in Burgress, (2011).

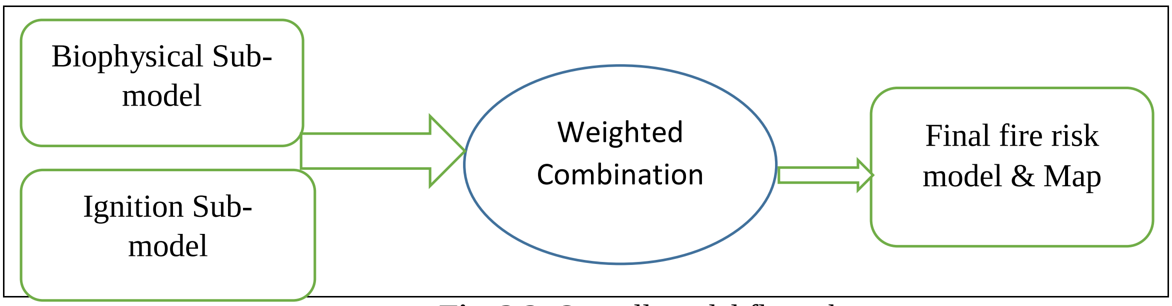

Fig. 3.2. Overall model flow chart

3.3.2.2. Biophysical Sub-model

The biophysical sub-model includes Land use land cover, Elevation, Slope and Aspect. As it was discussed in Literature review Section of this study, these topographical and Land use factors are the most important factors which will influence the location at which fire is likely to start. Fig. 3.3 indicates the steps followed to integrate these factors and develop the biophysical Sub-model.

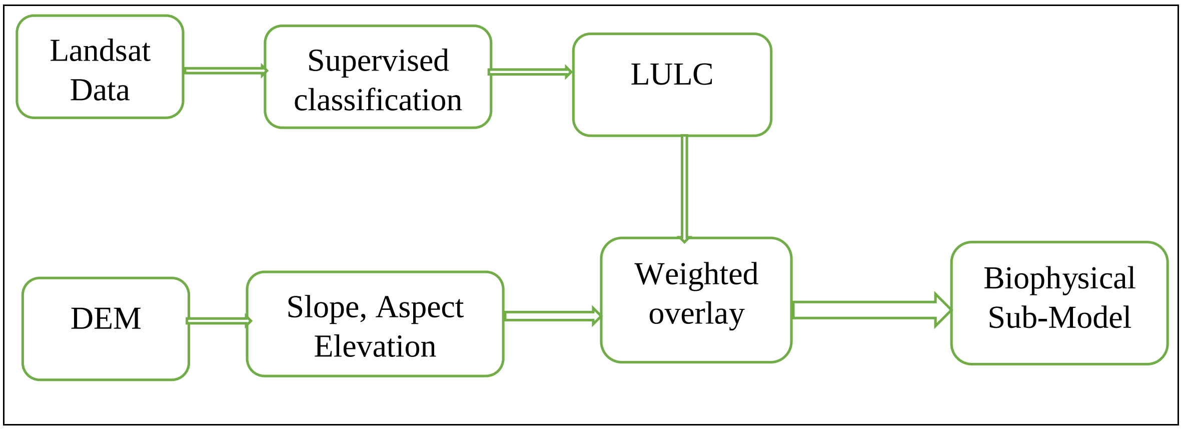

Fig. 3.3: Biophysical Sub-model flow chart

3.3.2.2.1. Classification of factors into different risk values for biophysical sub model

In the present study, it was Landsat 8 OLI that was used for generating Land use land cover class of the study area. The classification was done on the basis of reflectance characteristics of different land-use/land-cover types using false colour composites (band 7, 5 and 4) of Landsat 8 image. Supervised classification approach with maximum likelihood classifier decision rule was used for land use land cover type classification. Based on the field visit the study area was classified into five vegetation class (See Appendix 5). These are: Harenna forest, Erica and Bamboo forest, Afro Alpine, Juniper woodland and Grass land.

Elevation, Aspect and Slope were generated from SRTM 30 m resolution DEM data. Spatial Analyst tools of Arcmap10.3 was employed to generate these factors from DEM data. The projection of the output was corrected to projected coordinate system, Adindan UTM Zone 37 prior to generating the factors. The factor maps were then reclassified for assigning weightage. Weights were given to each factor according to their influence on fire behavior based on reviewed literatures and the opinion of the experts in the field. Table 3.2 shows different risk class with different value range of different parameters. This table is used in the reclassification of different risk maps in the models.

Table 3.2*:* Biophysical sub-model factors with risk values

s. no	variables	classes	ratings
1	Land use land cover type	Grassland, Afroalpine, Erica and Bamboo forest, Harenna forest,	4,3,2,1
2	Elevation	1532-2532, 2532-3532, 3532-4032, 4032-4532	4,3,2,1
3	Slope	>30,15-30, 5-15, 0-5	4,3,2,1
4	Aspect	East, West, South, North	4,3,2,1

4= very high, 3= high, 2= moderate, 1= low

Land use land cover (LULC) risk map has been generated taking in account the vegetation characteristics like type density and moisture content of the area where the vegetation grows. Vegetation type contributes greatly in the ignition and spreading of fire due to flammability difference. Fuel flammability greatly affects the ignition process of fire (Misrak Alemu et al., 2016). Though the environment is suitable (oxygen and heat) for a fire to start, it cannot start in the absence of fuel. Erica, Afroalpine and grass land are reported in different studies as they are source fire incidence in BMNP. It is generated by reclassification of LULC map into four risk classes. Fig. 3.4 shows the risk class on the bases of vegetation type.

Elevation and slope risk map has been generated using SRTM 30 m resolution data. Elevation is important as with increase in elevation oxygen supply will reduce and thus the chances of fire decreases with increase in elevation. Figure 3.5 shows the elevation risk zone map. Similarly, slope is also an important factors which determines rate of fire spread. Different aspect will be exposed to sun with different angle and for different duration which will affect the moisture content of the area. Thus aspect map with different risk zones are generated and given as under in Fig. 3.7. With increase in angle of slope, fire risk increases hence slope risk map (Fig. 3.6) has been generated.

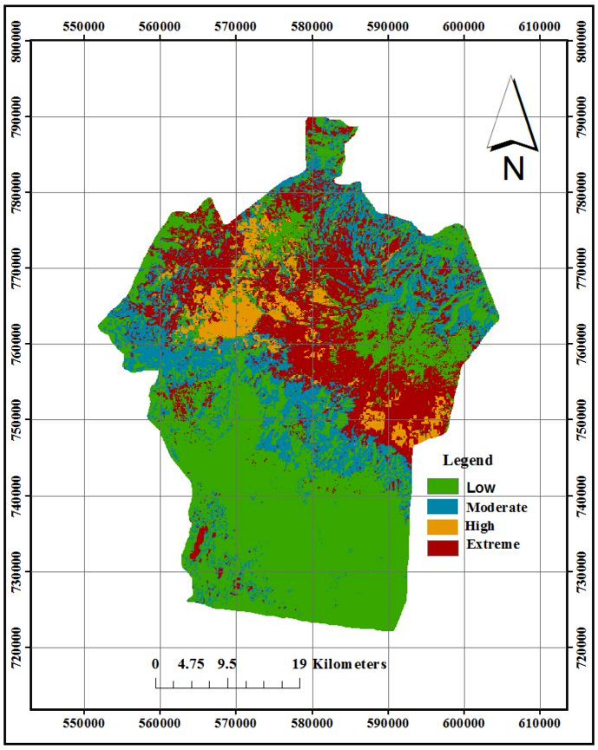

Fig. 3.4. Land use land cover index map

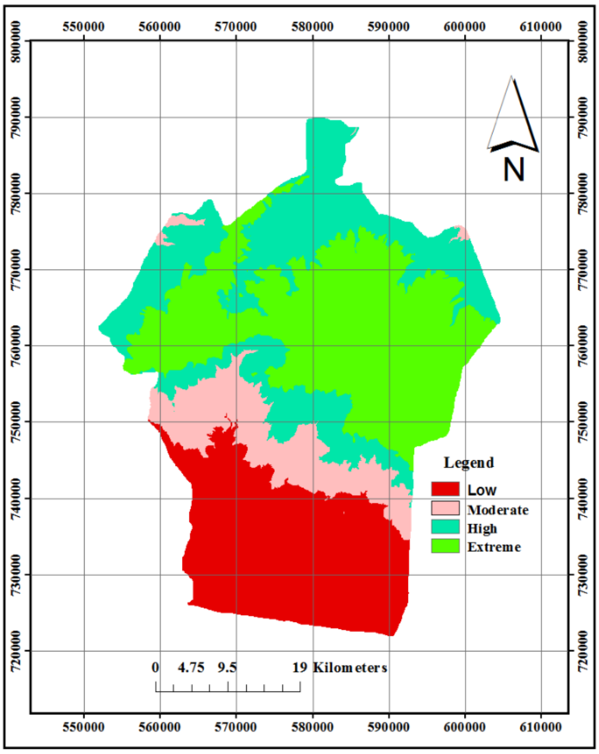

Fig. 3.5. Elevation index map

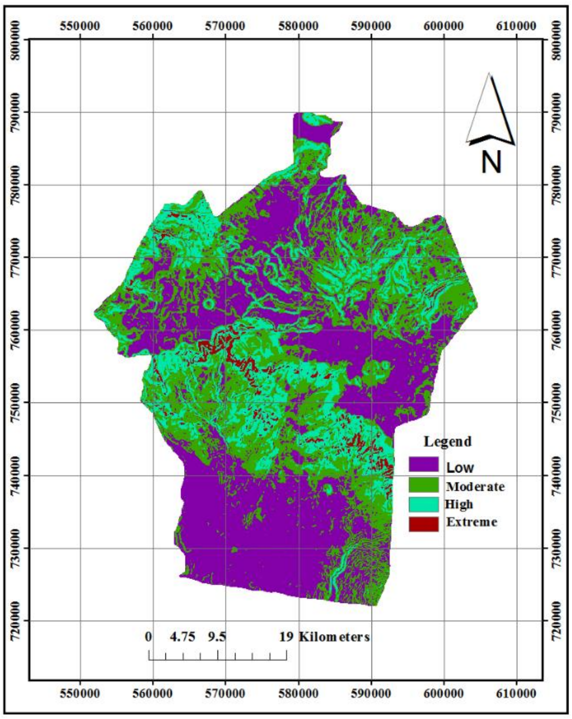

Fig. 3.6. Slope index map

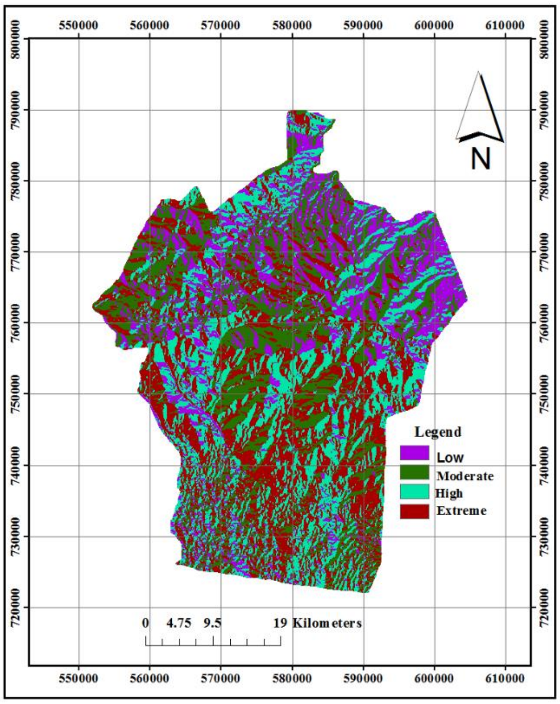

Fig. 3.7. Aspect index map

3.3.2.3. Ignition Sub-model

The Ignition sub-model includes Road and Settlement factors. This factors influence the ignition process of fire as it provides conducive environment for fire to be ignited. Below is the general flow chart followed to produce ignition sub-model.

Figure 3.8 indicates the steps followed to integrate these factors and develop the Ignition Sub-model.

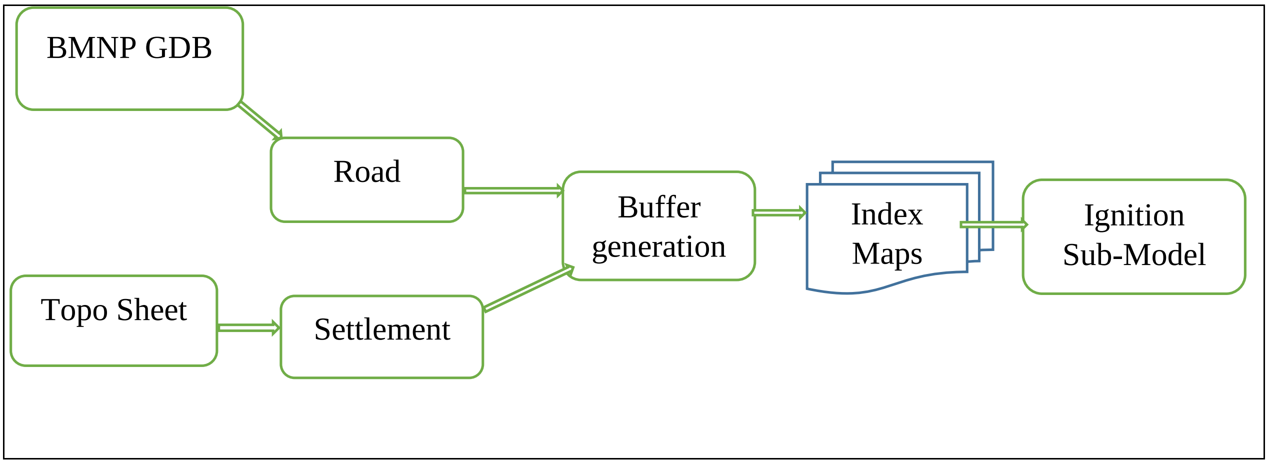

Fig. 3.8: Ignition Sub-model structure

3.3.2.3.1. Classification of factors into different risk values for Ignition sub model

The areas closer to the settlement or road are high fire risk areas and therefore are given higher ratings. The rating decreased with the increase in distance from the settlement or road (Thakur and Singh, 2014).

Table 3.3: Ignition sub-model factors with risk values

Variables	Classes	Ratings
Distance from road	<100, 100-200, 200-300, >300	4, 3, 2, 1
Distance from settlement	<500, 500-1000, 1000-1500, >1500m	4, 3, 2, 1

4= very high, 3= high, 2= moderate, 1= low

According to Table 3.3, risk factor maps of road and settlement were generated. The results of each factor maps were given on Fig. 3.8 and Fig. 3.9 respectively.

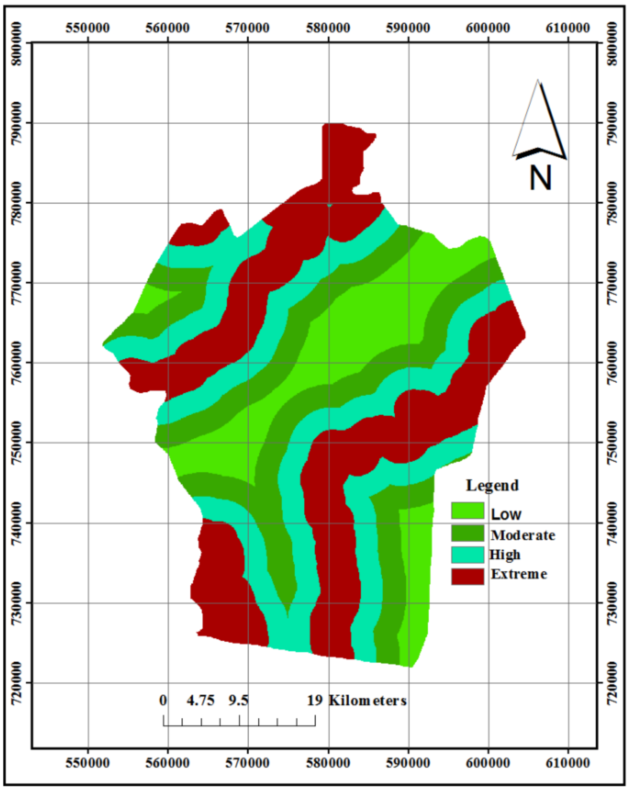

Fig. 3.9: Road index map

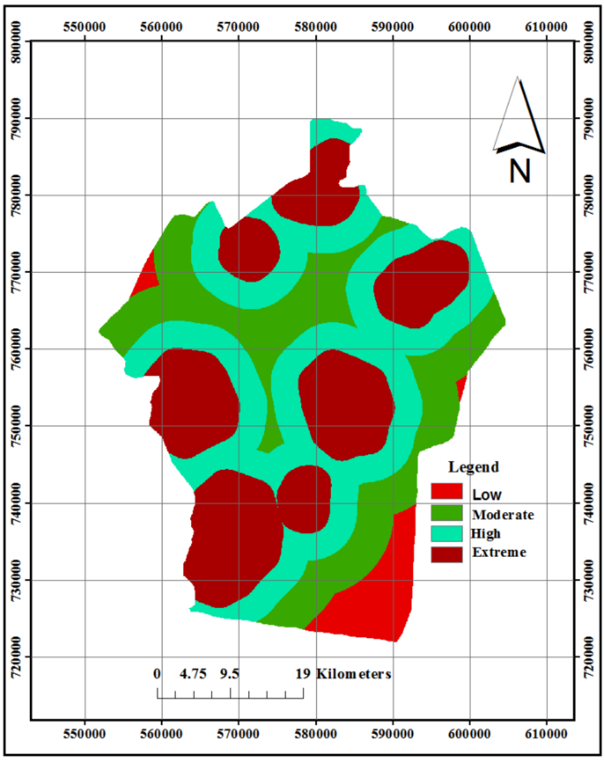

Fig. 3.10: Settlement index map

3.3.2.5. Formation of Sub-models

The formation of each sub model was accomplished by combining the values in each raster layer to produce a single, final output. In order to overcome the subjectivity issues in assigning weights to the factors of each sub model, pairwise comparison was performed. According to Burgress, (2011), this method is advantageous since it allows the rating and comparison of factors against each other before weights are derived. The rating system, which indicates how much more or less a factor is important in relation with other factors was based on findings from fire related literatures.

The pairwise comparison was performed in a matrix Table 4 developed from Burgress, (2011). Criteria are placed on the vertical (A_1 to A_n) and horizontal axis (C_1 to C_n). Values that reflects the importance between factors are then assigned to each cell (e.g. cell a_{12} express the importance of factor A_1 against C_2). The ratings are then standardized by dividing the value in a cell (e.g. a_{11}) by its column total (a_{m1}). This generates a new matrix in which each cell is assigned an Eigenvalue. The weights for each factors are derived by averaging the Eigenvalue in each row (a_{11} to a_{1n}). A consistency ratio is then calculated to determine the success of the evaluation. This is done by using the eigenvalue (lambda maximum) to calculate the Consistency index (CI) as follows:

$$\mathrm{CI} = (\lambda_{\max -} \frac{n}{n-1}) \text{ .... } \textbf{(Equation 3.2).}$$

Where n is the matrix size

The consistency of the judgement can check by calculating the consistency ratio (CR) of CI with appropriate value from Average random consistency (RI). Thus CR = CI/RI. According to Saaty (1980), the C.R value should be less than 0.1 in order to say the consistency is good.

Table 3.4: Matrix used in pairwise comparison

	C_1	C_2	C_n
A_1	a_{11}	a_{12}	a_{1n}
A_2	a_{21}	a_{22}	a_{2n}
A_n	a_{m1}	a_{m2}	a_{mn}

Source: Burgress, (2011)

3.3.2.5.1. Formation of Biophysical Sub-model

Land cover type is considered as the most important factor contributing to fire risk as it was indicated in different studies. For example, Burgress (2011) found that land cover type had the greater significance value compared to other factors (including Elevation, Slope and Aspect), when a logistic regression was performed on those factors. This was further supported by Saklani (2008) where fire occurrence is more explained by vegetation density and type than any other Topographic factors. Vegetation type was also given the highest weight on the study of Jaiswal et al. (2002) based on the justification that forest fire cannot occur unless inflammable material is present even though an environment may be favorable to fire. In Sharma et al. (2012) vegetation types was also given the greatest weight over Slope, Aspect and Elevation.

Elevation, Slope and Aspect are important in explaining fire occurrence, but it is not clearly indicated on the literature which has greater influence over the other. In most of the literatures (Malik et al., 2013; Sharma et al., 2012; Burgress, 2011) elevation and slope were found to be more significant over aspect. The above discussion of the relative importance of these factors was used to assign ratings to the different factors. Weights were given as shown in table 3.5.

Table 3.5: Pairwise comparison and weighted matrix of Biophysical sub-model

Rating	LULC	Elevation	Slope	Aspect	
LULC	1	2	2	3	
Elevation	0.5	1	1	2	
Slope	0.5	1	1	2	
Aspect	0.33	0.5	0.5	1	
Total	2.33	4.5	4.5	8.00	
weight	LULC	Elevation	Slope	Aspect	Average/priority
LULC	0.43	0.44	0.44	0.38	0.42
Elevation	0.21	0.22	0.22	0.25	0.23
Slope	0.21	0.22	0.22	0.25	0.23
Aspect	0.14	0.11	0.11	0.13	0.12

CR= 0.003839

As it is indicated on equation below, the explanatory attributes of Biophysical sub-models have been multiplied by their respective weight to generate Biophysical fire risk zone map of the study area.

$$\mathbf{BM = 0.42(LULC) + 0.23(E) + 0.23(S) + 0.12(A)} \quad \textbf{(Equation 3.3)}$$

BM= Biophysical sub-models, LULC = Land Use Land Cover, E = Elevation, S = Slope, A = Aspect.

3.3.2.5.2. Formation of Ignition Sub-model

In the present study, equal rating were assigned to factors in ignition sub-model (Table 3.6). This is because different studies related with human factors affecting fire occurrence, was found that distance from road and distance from settlements are significant (Burgress, 2011).

Table 3.6: Pairwise comparison of Ignition sub-model

Rating	Distance to settlement	Distance from road	
Distance to settlement	1	1	
Distance from road	1	1	
Total	2	2	
weighting	Distance to settlement	Distance from road	Average/ priority
Distance to settlement	0.5	0.5	0.5
Distance from road	0.5	0.5	0.5

CR= 0

Similarly, as it is indicated on equation below, the explanatory attributes of Ignition Sub-model have been multiplied by their respective weight to generate Ignition Sub-model fire risk zone map of the study area.

$$\mathbf{IM = 0.5(DS) + 0.5(DR)} \quad \textbf{(Equation 3.4)}$$

IM = Ignition Sub-model, DS = Distance to settlement, DR = distance from road

Table 3.7: Pairwise comparison for final fire risk models

Rating	Biophysical	Ignition	
Biophysical	1	3	
Ignition	0.33	1	
Total	1.33	4	
weighting	Biophysical	Ignition	Average/priority
Biophysical	0.75	0.75	0.75
Ignition	0.25	0.25	0.25

CR= 0.089

As indicated in equation 3.5 below, Biophysical and Ignition sub-models have been multiplied by their respective weight to generate forest fire risk zone map of the study area.

$\mathbf{FFRZ = 0.75(BM) + 0.25(IM)}$………………………………………… **(Equation 3.5)**

FFRZ = Forest Fire Risk Zone

BSM = Biophysical Sub-Model

ISM = Ignition Sub-Model

3.3.3. Model validation

Validation is an important process to undertake while creating any kind of model. In order to determine the accuracy of model's performance, it is necessary to compare model's result to the real world (Burgress, 2011). The final forest fire risk model of this study was then validated by comparing the predictions with the actual distribution of fires in the model validation datasets with past fire incidences data collected from field visit. For the purpose of validation the researcher has collected GPS points from those areas where there was past forest fire occurrence in the study area. Accordingly GPS data collected from parts of grassland area, Afroalpine and some parts of Harenna forests were used for model validation.

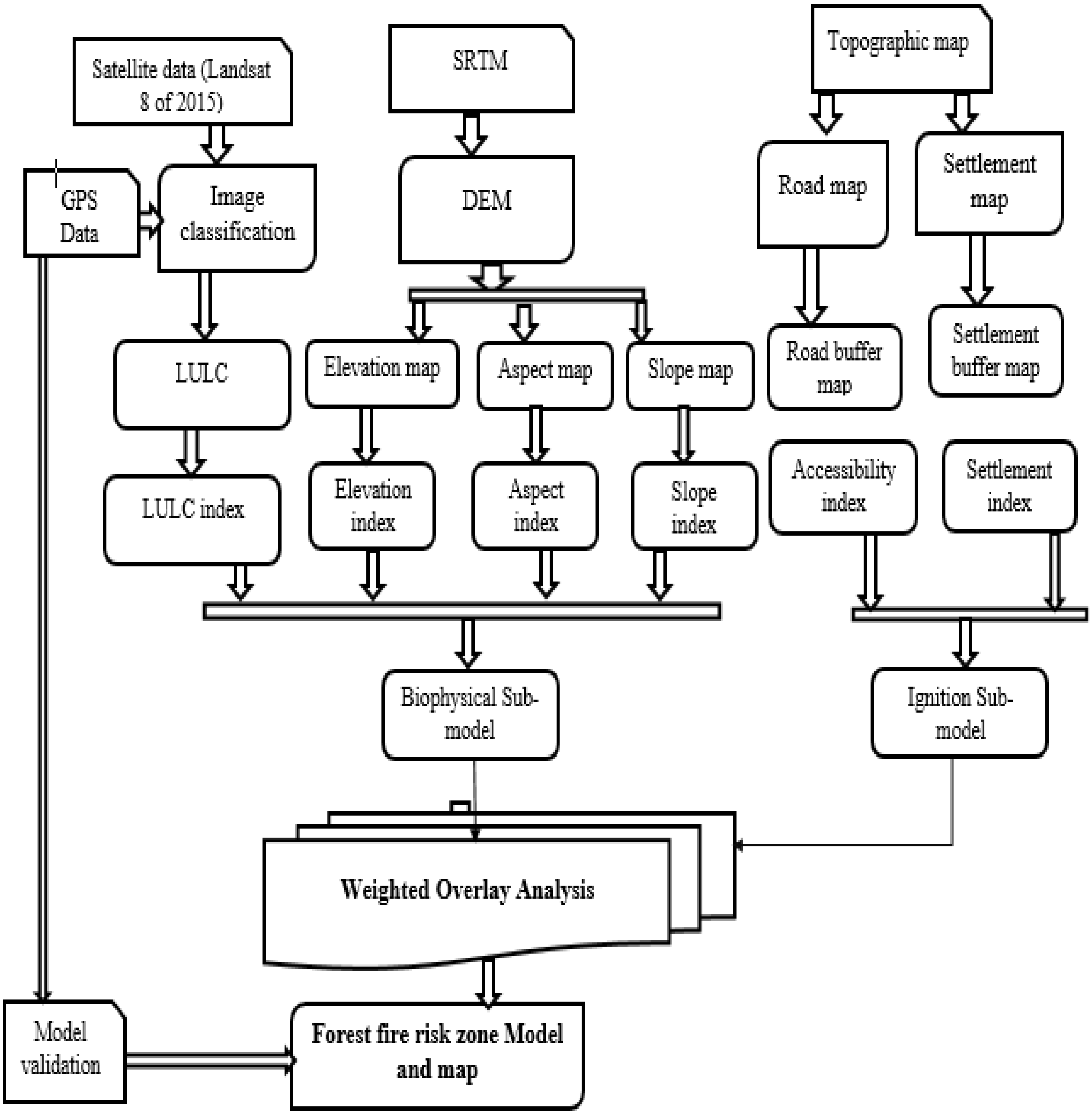

Fig. 3.11: Methodology Flow chart

CHAPTER FOUR: RESULTS

The previous chapter described methods used in this study. This sub-section of the study tried to present the main results based on the collected data. It is structured in a way that relates these results to the order of research objectives. Explanatory attributes of the model is therefore presented first, followed by results of sub models. The result of model validation is last to be presented.

4.1. Results of Explanatory attributes identification

As discussed in chapter three of this study, the possible explanatory attributes (LULC, slope, elevation, aspect, proximity to road and proximity to settlement) were identified after a through literature review. After identification of explanatory attributes, forest fire risk zone modeling was performed. Before conducting the model, as one of the objective of this study is revealing factors that will determine forest fire, correlation analysis was performed in order to understand how those explanatory attributes are associated to forest fire modeling,. Table 4.1 shows the correlation test results of the explanatory attributes.

Table 4.1: Correlation matrix of explanatory attributes of forest fire modeling

Class	LULC	Elevation	slope	Aspect	Settlement	Road
LULC	1					
Elevation	0.178	1				
slope	0.025	0.359	1			
Aspect	0.246	0.128	0.03	1		
Settlement	-0.41	-0.367	-0.126	-0.2	1	
Road	-0.38	-0.261	-0.102	-0.219	0.234	1

As it is indicated in table 8 above, LULC shows a positive relationship with aspect, elevation and slope where coefficient of correlation is 0.246, 0.178, and 0.025 respectively and negative relations with proximity to settlement and distance from road. Similarly, proximity to settlement and distance from road are negatively correlated with each other and with the other explanatory attributes.

Although it is not the aim of this study to compare the performance of OLS and GWR models, OLS and GWR regression model was performed in addition to correlation analysis, in order to select the key explanatory attributes and explain the relationships of the explanatory attributes to forest fire risk modeling.

Table 4.2 shows the statistical results of OLS for selecting the independent variables to be included into multiple regression analysis.

Table 4.2: Table shows OLS regression results

variable	coefficient	SE	t-statistics	probability	Robust SE	Robust_t	Robust pro	VIF
Intercept	0.135302	0.090097	1.501741	0.133750	0.080117	1.688800	0.091832	-----
Elevation	0.124557	0.014299	8.710748	0.0000*	0.013972	8.914954	0.0000*	1.6552
Slope	0.069485	0.017100	4.063438	0.0006*	0.017290	4.018845	0.0000*	1.1492
Aspect	0.112947	0.012162	9.286501	0.0000*	0.011840	9.539615	0.0000*	1.0698
LULC	0.194491	0.013591	14.310686	0.0000*	0.013594	14.30719	0.0000*	1.5635
PS	0.215084	0.015212	14.138780	0.0000*	0.014969	14.36838	0.0000*	1.0353
DR	0.206691	0.012809	16.136528	0.0000*	0.012795	16.15361	0.0000*	1.1377

** Indicates that the explanatory variable is statistically significant at p <0.001. SE= standard Error, VIF= variance inflation factor, PS= proximity to settlements, DR= distance from road.*

The results of coefficient of explanatory attributes presented in the table above indicates that there is significant and positive relationship between explanatory attributes and the dependent variable. This means, with the increment of all explanatory attributes, forest fire risk will increase and viseversa. Similarly, the model confirms that the explanatory attributes are closely related to the dependent variable (R^2 = 0.62). This shows that the model can explain forest fire risk by 62% in the study area.

As it is briefly presented on the table 4.2, low Variance Inflation Factor (VIF) values (< 7.5) demonstrate that there is no multiple co-linearity between the attributes and there is no redundancy of explanatory attributes selected. VIF value > 7.5 indicates that there is a redundant explanatory attributes in the model. The regression model results reveals that the above mentioned variables are statistically significant (Table 4.2). Similarly, statistics results of the Jarque- Bera presents that the residuals are normally distributed (Table 4.3). All variables are statistically significant because the Koenker (BP) values are relatively higher. The Moran Index measures the level of spatial autocorrelation among the residuals, and in this case the value (0.083) indicates that there is no spatial autocorrelation.

Table 4.3.: Statistics results of Ordinary Least Squares indicator

	Joint F	Joint Wald	Jarque-Bera	Koenker (BP)
value	150.96	1378.53	5.512	2.731
probability(> *F*)	0.0000*	0.00000*	0.0002*	0.0007*

* denotes statistically significant at 0.001 level, Moran I=0.083

Table 4.4: Comparison of OLS and GWR model performance

	OLS	GWR
AIC	295.31	279.8
R^2	0.62	0.643

The lower Akike Information Criterion (AIC =279.8) of GWR indicates that GWR model is best in terms of describing the relationship between explanatory attributes and dependent variables than OLS where AIC is 295.31(Table 4.4). In addition to AIC, the increment of adjusted R^2 value from 0.62 in OLS to 0.643 in GWR shows that GWR model best describe the relationships of explanatory attributes and forest fire risk.

4.2. Forest Fire Risk Zone Modeling and mapping

4.2.1. Biophysical sub-model

As it was discussed in chapter three of this study, the biophysical sub-model consists of four explanatory attributes namely; land use land cover, slope, aspect, and elevation. After analyzing the results of each explanatory attributes individually, the result for the combined effects of those attributes was given as below.

This map shows the different risk zones in accordance with the properties of vegetation, aspect, slope and elevation. The biophysical risk map finally comes as follows. As indicated on Fig. 4.1, the biophysical sub-model shows that the extreme fire risk area (red colour), which constitute about 128 km^2 of total area is located around some parts of Erica belts and Afro Alpine of the park where there is high slope and medium to low elevation. According to table

4.1 bellow, the larger areas, mainly Afro alpine, juniper wood land and grassland parts of the park is covered by high fire risk index (blue colour) which constitute about 587.1 km^2.

The moderate fire risk zone (deep green colour), which constitute about 904 km^2 is located in Erica belts and north eastern parts of Afroalpine followed by lower fire risk zone (light green colour) located in the Southern parts (Harenna forest) and some parts of Erica belts (Fig 4.1). This class of risk zone constitutes about 472.35 km^2 of the total area. This is similar with the results of land use land cover and slope explanatory attributes of the sub-model, while it is in opposite side with the result of aspect explanatory attribute (see section three of this study). This is because lower value was given to aspect in overlaying the explanatory attributes into combined effects of biophysical attribute.

Generally, this result shows that the significant areas (about 715.1km^2) of the study area fall under extreme and high fire risk zones. This is mostly determined by the effects of vegetation types and the effects of slope and elevation. Vegetation types found in those areas are Erica, Afroalpine and grass land which are very susceptible to forest fire due to their high ignition capabilities. In addition to vegetation types, this areas are characterized by having high to steep slope and low to moderate elevation. As low to moderate elevation results in high temperature, low relative humidity and availability of dry organic matters the ignition capabilities of the vegetation are increased. Having high to steep slope also makes this area very prone to forest fire. Slope determines the speed of fire spread, as fire travels most rapidly up slopes than down slopes. Therefore, applying different forest fire management techniques is very important in those areas.

The result also shows that larger areas (about 1,376.35 km^2) of the area fall under moderate and low forest fire zones. This is also determined mostly by vegetation types. This area is largely covered by Harenna forests which has low susceptibility to fire ignition. In addition to vegetation types, this result is raised from the influence of slope and aspects. This area is located in moderate to low slope, which minimize fire spread as fire spreads more in upper slope than lower slopes. As this area is facing towards the southern parts it gets low sunlight and this minimizes the chance of dry fuel availability which in turns lower the chances of fire ignition.

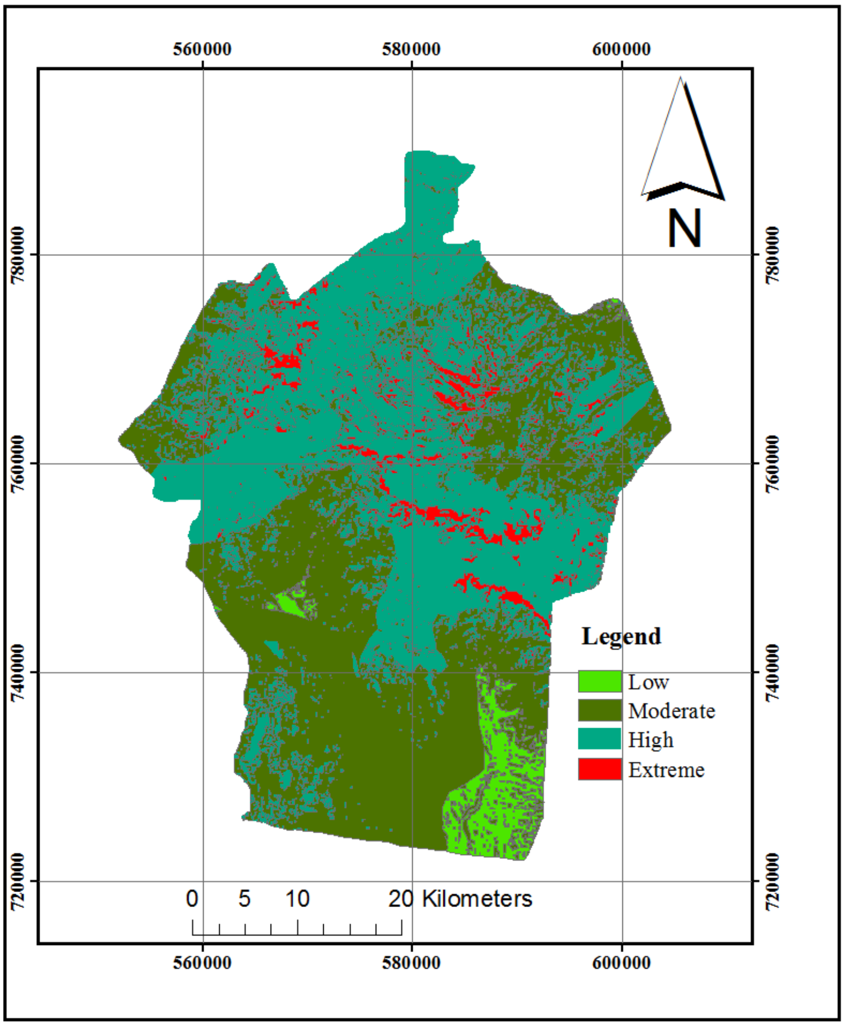

Fig. 4.1: Biophysical sub-model map

Table 4.5: Table shows area coverage of Biophysical sub-model map

Risk zone	Degree of Fire Risk	Area (km^2)	Description of risk zones
4	Extreme	128	High slope, medium to low elevation, grassland, Erica and Afroalpine vegetation types.
3	High	587.1	High slope, medium elevation, Eastern and Western aspects, grassland, Afroalpine and Juniper woodland vegetation types.
2	Moderate	904	Medium slope, high elevation, Southern and Northeastern aspects, and Harenna forest.
1	Low	472.35	Flat slope, Very high elevation, Southern aspect and Harenna forest.

4.2.2. Ignition sub-model

As it was given in chapter three of this study, the Ignition sub-model has two explanatory attributes; road accessibility and settlement. These attributes have a great influence on forest fire ignition process as it was discussed in chapter three of this study. The ignition sub-model has been developed by assigninig higher values to the areas very easily accessible and low values to the areas very far from acssesibilities interms of both settlement and raod. Thus the areas very close to the settlement and road comes under extreme fire risk zone (red colour) which constitutes about 701.3 km^2, while those areas very far from settlement and road accessibility comes under low fire risk zones (light green colour) and covers about 56.56 km^2 of the total area (Fig. 4.2).

Table 4.6: Table shows area coverage of Ignition sub-model map

Risk zone	Degree of Fire Risk	Area(km^2)	Description of risk zones
4	Extreme	701.3	Very close to Settlement and Roads
3	High	917.66	Close to Settlement and Roads
2	Moderate	420.96	Moderately far from Settlement and Roads
1	Low	56.56	Verry far from Settlement and Roads

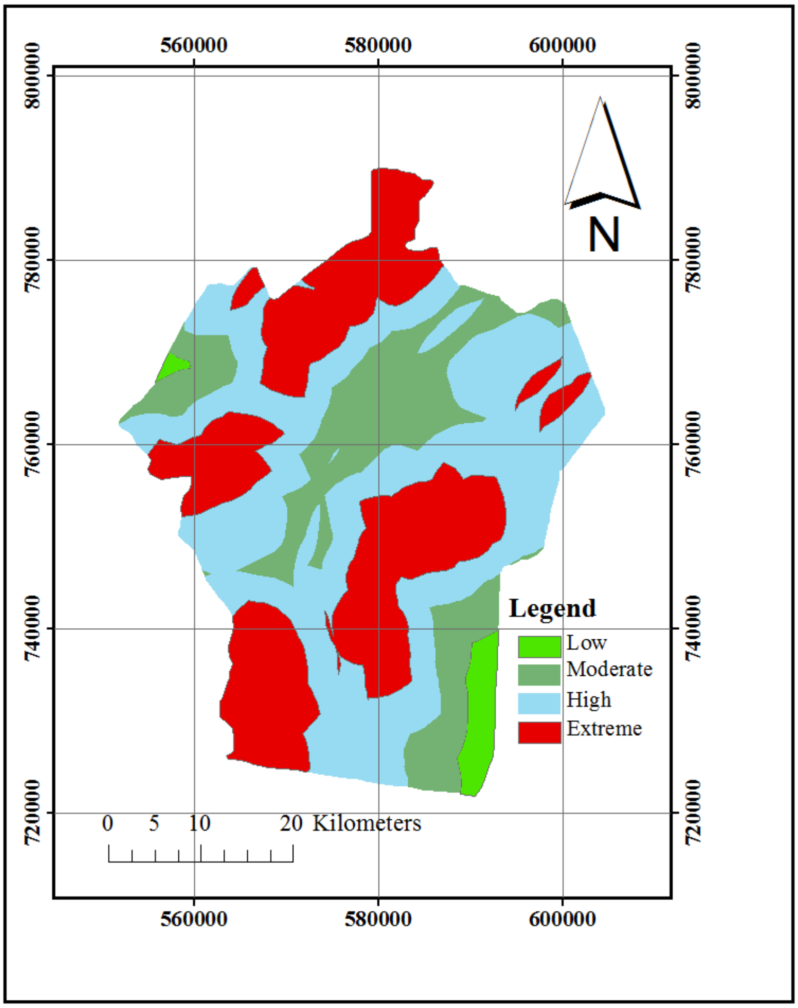

Fig. 4.2: Ignition Sub-model map

4.2.3. Final forest fire risk model

As it is presented on the figure 4.3, the study area was categorized into four fire risk zones (low, moderate, high and extreme) which shows fire risk susceptibility of the study area. Accordingly, low fire risk area (light green colour) which constitutes about 129.56 km^2 or 4.5%, is located in South eastern part of the park in parts of Harenna forest, followed by moderate fire risk areas (deep green colour) which is located in Southern parts of the park (most of the Harenna forests) and North eastern and North western parts of the park covering about 997 km^2 or 41.55% (Table 4.7). This is an expected results due to the fact that, these area is located where there is no significant influence of all the explanatory attributes considered in the current study.

Table 4.7 shows that, maximum area comes under high fire risk zones (Blue colour) which constitutes about 868.1 km^2 or 47.73%. This zone located in the Afro Alpine (the central) parts, in the Northern (grassland and Juniper woodland) parts of the park and in some areas of Harenna forest. This is because the area is found under high influence of the explanatory attributes both from biophysical and ignition sub-models. The extreme fire risk area which covers about 94.28 km^2 or 6.2 % is located largely in Erica forest and some parts of Afro Alpine areas (Fig. 4.8).

Generally, the final forest fire risk zone map shows that there is significant areas which comes under extreme and high fire risk zone covering about 1670.9 km^2 or 46.5 % (Table 4.7). This implies that it is very important to apply different fire management strategies in order to prevent the possible forest fire occurance in the study area.

Table 4.7: Table shows area coverage of final forest fire risk zones

Fire Risk Zones	Degree of Fire risk	Area (km^2)	Percent (%)	Description of Fire Risk Zones
1	Extreme	94.28	6.2	High slope, medium to low elevation, grassland,Erica and Afroalpine vegetation types.Very close to Settlement and Roads
2	High	868.10	47.73	Close to Settlement and Roads High slope, medium elevation, Eastern and Western aspects, grassland, Afroalpine and Juniper woodland vegetation types.
3	Moderate	997	41.55	Southern and Northeastern aspects, and Harenna forest.

				Moderately far from Settlement and Roads.Medium slope, high elevation,
4	Low	129.56	4.5	Flat slope, Very high elevation, Southern aspect and Harenna forest.Verry far from Settlement and Roads

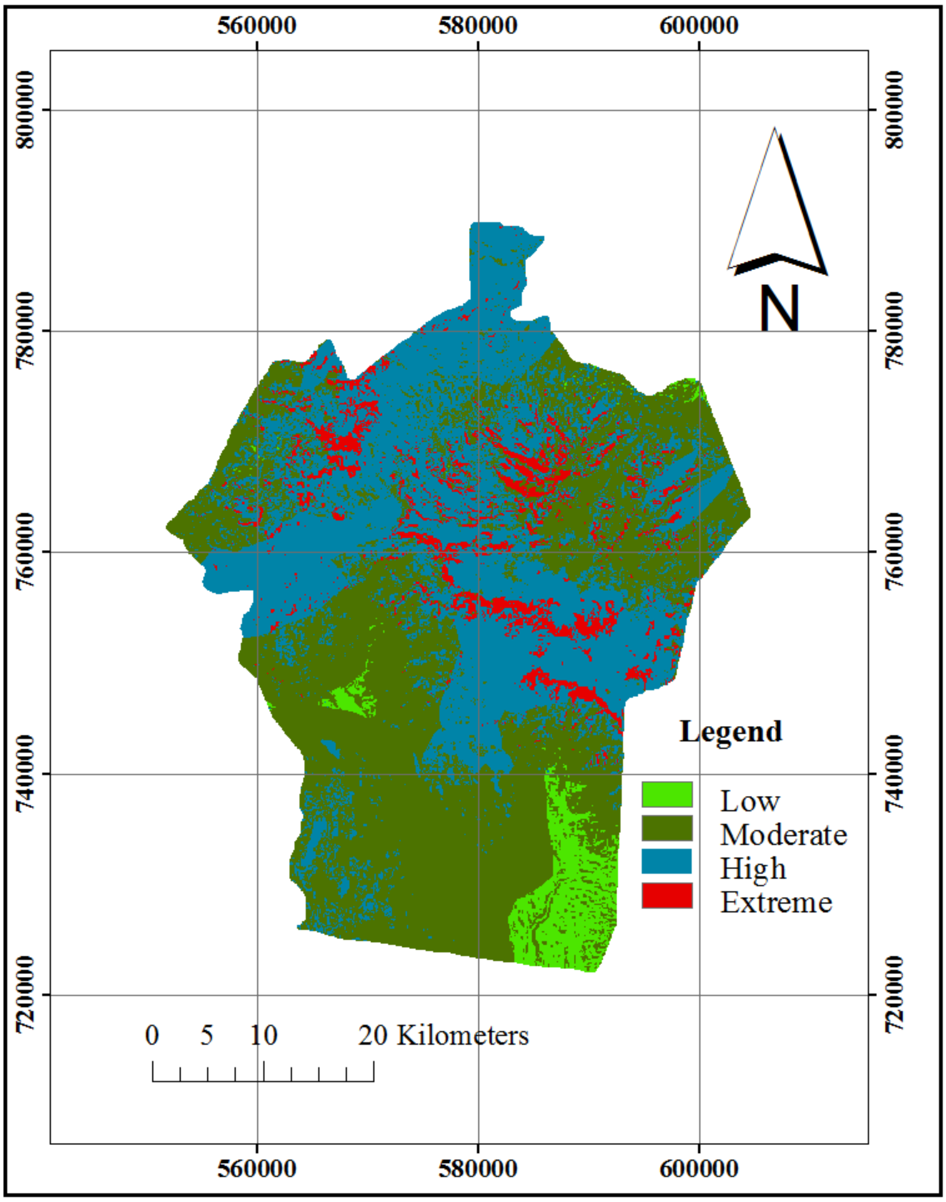

Fig.4.3: Final Forest Fire Risk Zone Map

4.3. Model validation

The model was validated by overlaying the final fire risk zone map with the GPS data collected from pre fire affected areas in the study area. The points were collected from those areas where there was frequent fire incidence especially in the grassland, Erica forests and Afroalpine parts of the study area. Accordingly, most of the GPS points are overlapping with those areas under extreme and high fire risk zones of the final risk map. Therefore, it is possible to conclude that the model performance is very good and representative.

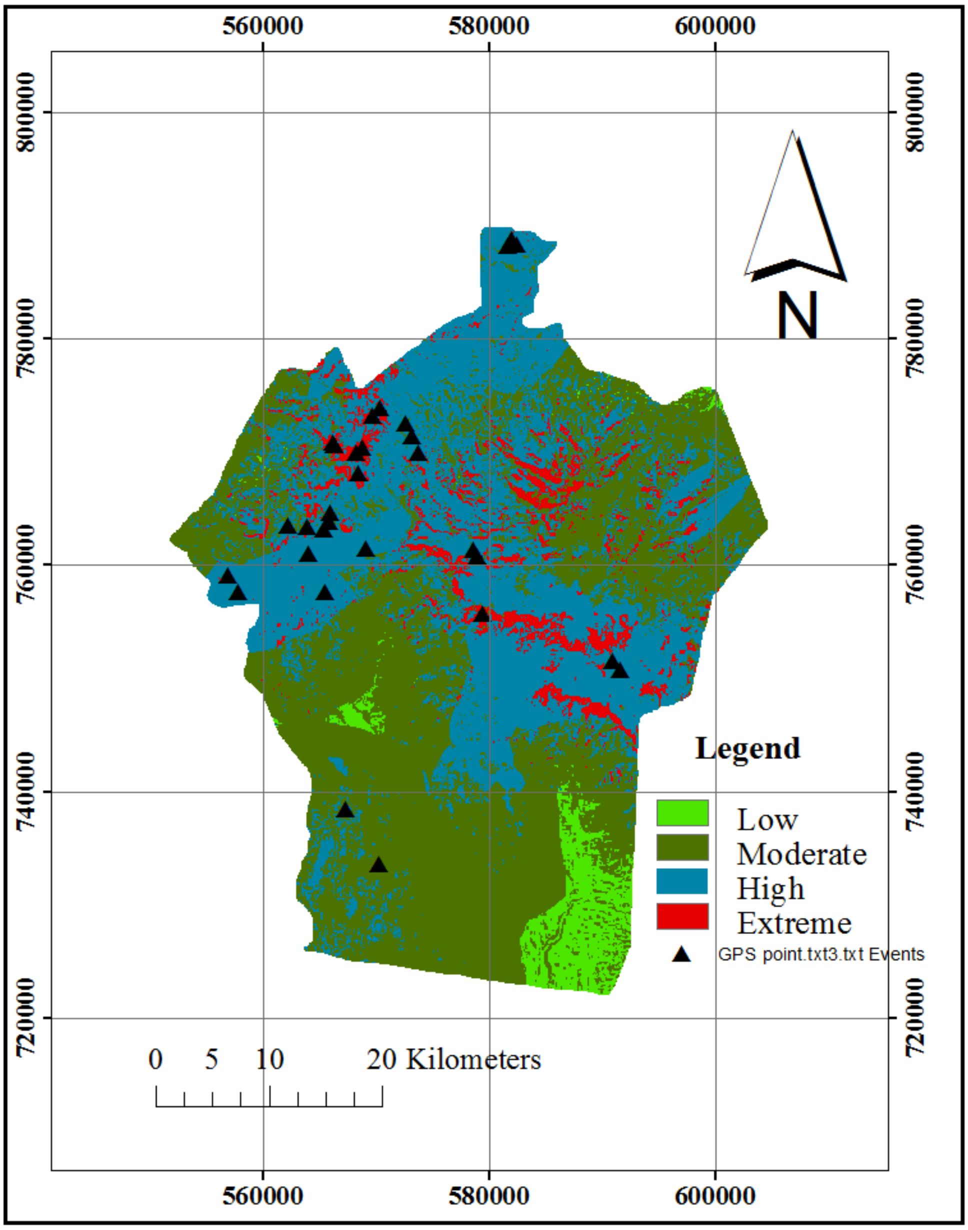

Fig. 4.4: Model validation map

CHAPTER FIVE: DISCUSSION

5.1. Explanatory Attributes

As it was presented in chapter four of this study, six explanatory attributes were identified for forest fire risk zone modeling and mapping in BMNP. These are: lulc type, slope, aspect, elevation, proximity to settlements and distance from roads. Those factors were used by different authors in different study area. Some of them are; Rajeev et al. (2002); Rawat, (2003); Pradhan et al. (2007); Genanew Alemu, (2008); Saklani, (2008); Gholamreza et al. (2012); Sharma et al. (2012); Malik et al. (2013); Mohammadi et al. (2014); Thakur and Singh, (2014); Sivrikaya et al. (2014); Pourghasemi, (2015); Misrak Alemu et al. (2016).

The above mentioned explanatory attributes were used for this study and proven for their effective contribution of forest fire risk zone modeling and mapping. Therefore, the result of this study is in line with the previous work of different authors. For example, Saklani (2008) argues that lulc risk map is one of the very important maps in determining the fire risk zones. This is because different species of plants have different fuel characteristic and these fuel characteristics also depends on slope aspect, fuel density, elevation.

Elevation, slope and aspect of the terrain also have influence on fire-risk, as they control the vegetation density and composition in the area. Steeper slopes lead to less fuel moisture and less air humidity and this will promote forest fire ignition and spread (Malik et al., (2013). This is further supported with Misrak Alemu et al. (2016).

Proximity to settlements and distance from roads are also an explanatory attributes which have direct influence on fire ignition. This study reveals that the area under close proximity to settlements and roads are very prone to fire ignition. The study by Genanew Alemu (2008); Anteneh Belayneh et al. (2013); Miarak Alemu et al. (2016) also argues that areas near to settlements are of very high fire risk zones. This is due to human population pressure and the corresponding demands for agricultural land, grazing land, built-up and forest products.

5.2. Forest Fire Risk Modeling and Mapping

Modeling and mapping a fire risk zone by using GIS and Remote Sensing technique is a complicated task as different parameters are taken into account for analyzing their effects in forest fire in different sub models. A detailed knowledge of the entire environment of the study area and the characteristics of the vegetation of the study area are required. In addition to this it requires a lot of patience and time to know the area, so that a more accurate and reliable map can be generated for the use by the people who are interested and also to the forest department who can use the map for fire management purposes (Saklani, 2008).

As it is presented in section four of this study, the biophysical sub-model risk map which has been given maximum weightage in the final forest fire risk model is generated by the combination of LULC risk zone map, aspect risk zone map, slope risk zone map and elevation risk zone map. The majority of extreme and high fire risk areas are located in parts of the study area covered by grass, Erica and Afroalpine. This is an expected outcome due to the importance value assigned to lulc map (provides fuel which fire burns), and because the greatest value was originally assigned to the grass land area. In a similar risk study by Misrak Alemu et al. (2016) in Harenna forest and Burgress (2011) grass land cover types associated with high fire risk.

This area also located at areas characterized as extreme fire risk in terms of slope (steep slope) and elevation (medium to gentle slope). This is also similar with the results of Misrak Alemu et al. (2016) and Ercanoglu et al. (2006) which associates steep slope and gentle elevation as extreme fire risk. This is further supported also by Lawrence et al. (2006) who argues that vegetation in higher slopes is seasonally dry and gets fire during summer months (Once fire starts, it spreads faster through up-slopes than downslopes, and along steeper slopes than gentle ones. This result is different from the findings of Burgress (2011) because in this study areas under steep slopes and gentle elevation were assigned low risk areas. This difference could result from the different conditions that form wildfire regimes between study areas in very different locations.

In addition, extreme to high fire risk zones are located mostly in eastern and western parts. This is because this side gets more sunlight during day time which results in higher temperature and this will in turn facilitate drying of organic matter. This result is in line with the findings of Genanew Alemu (2008); Lawrence et al. (2006) and Misrak Alemu et al. (2016) which also reveals that areas facing towards eastern and aspects are prone to forest fire. However, the result of this study also reveals that some parts of northern aspects, which was originally assigned low weight are fall under high fire risk zone. This is different from the above mentioned previous studies. This could arise from the original weight assigned to vegetation types (grass land) found in northern parts of the park.

Moderate and low fire-risk susceptible areas are found in most parts of Harenna forest. This is because this area largely dominated by moist forest with flat slope. This result is similar with the findings of Misrak Alemu et al. (2016); Lawrence et al. (2006); Ercanoglu et al. (2006) Mohammadi et al. (2014); Anteneh Belayneh et al. (2013) and Genanew Alemu (2008) which argues that fire is least likely occur in the areas where there is flat slope. This result is different from the findings of Burgress (2011) because in this study areas under high elevation and flat slope are associated with high forest fire risk. This difference could also arise from different conditions that form wildfire regimes between study areas in very different locations.

As it is clearly indicated in section four of this study, extreme and high fire risk area is located where there is extensive road network and high permanent and non-permanent settlements. Those areas are parts of grass land, Afroalpine, Erica and parts of Harenna forests. This is because the local people use fire deliberately for different purposes such as forest clearing purposes, honey harvesting and slash burning. This result is in line with the study of Anteneh Belayneh et al. (2013) which argues that fire incidence in the BMNP is perhaps due to a dramatic increase of human and livestock populations in the last few years. The study further argues that most of the recurrent fires in the BMNP are largely human induced.

In addition to intentional fire occurrence there is also accidental fire occurrence in the study area. This is further argued by Misrak Alemu et al. (2016) and Anteneh Belayneh et al. (2013) as lack of environmental awareness of the settlers has also been a reason for frequent occurrence of fire in the study area. In addition to settlements, human and vehicular movement and activities on tracks provide opportunities for accidental and intentional fires (Misrak Alemu et al., 2016). This is because areas closer to roads are found to be of high fire-risk areas. This is further supported also by Burgress, (2011), who produced fire risk map showing that, out of several human induced wild fire ignition factors, the greatest danger was associated with proximity to settlement and road network.

CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

Fire risk modelling using multi criteria analysis and integrating different layers was developed for BNMP, Ethiopia. The general objective of the study was to model and map forest fire risk zone of BMNP. Achieving this general objective was made possible by dividing it into three specific objectives.

The initial aim was to identify the key explanatory attributes of forest fire risk zone modeling. This was achieved by a thorough literature review supported with autocorrelation and regression analysis. The possible identified explanatory attributes were checked for their relationships to each other and the dependent variable (forest fire risk zone). Finally, six explanatory attributes (lulc, slope, elevation, aspect, proximity to settlement and distance from road) were identified as they are the most important factor in modeling forest fire.

Forest fire risk zone modeling was performed as to achieve the second objective of the study. The model was divided into two; biophysical sub-model and ignition sub-model. The final forest fire risk modeling was performed using weighted overlay analysis in ArcGIS 10.3. The biophysical sub model has got higher weight as it comprises the most important explanatory attributes.

The final model shows that there is extreme fire risk areas which covers about 94.28 km^2 or 6.2 % is located largely in Erica forest and some parts of Afro Alpine areas, whereas low fire risk areas which constitutes about 129.56 km^2 or 4.5%, is located in South eastern part of the park in portion of Harenna forests.

The model was validated by overlaying GPS data collected in the field from pre fire affected areas with the final forest fire risk model result. The result shows that the model is reliable because almost all GPS points were lied on the extreme and high fire risk areas of the model.

6.2. Recommendations

For this study, the following recommendations are made both for the study area and future research work.

- Frequent follow up is needed in those areas identified as having extreme and high forest fire prevalence.

- The BMNP management has to work on how illegal settlements in the park can be reduced.

There is further scope of carrying research in forest fire modeling in continuation or independently.

- To improve the model output and other parameters more reliable it is recommended for future researches to include more parameters like climatic variables such as wind speed, wind direction, relative humidity and rain fall and temperature data.
- One can increase temporal resolution of the model into daily, weekly, and monthly for better forest fire management.
- Adding important parameters and adjustments one can carry out re- research on forest fire risk zone modeling and mapping regionally or nationally.
- Other models such as fire spread models and fire behaviour models can be incorporated for improved understanding of fire management in the area.

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APPENDIX

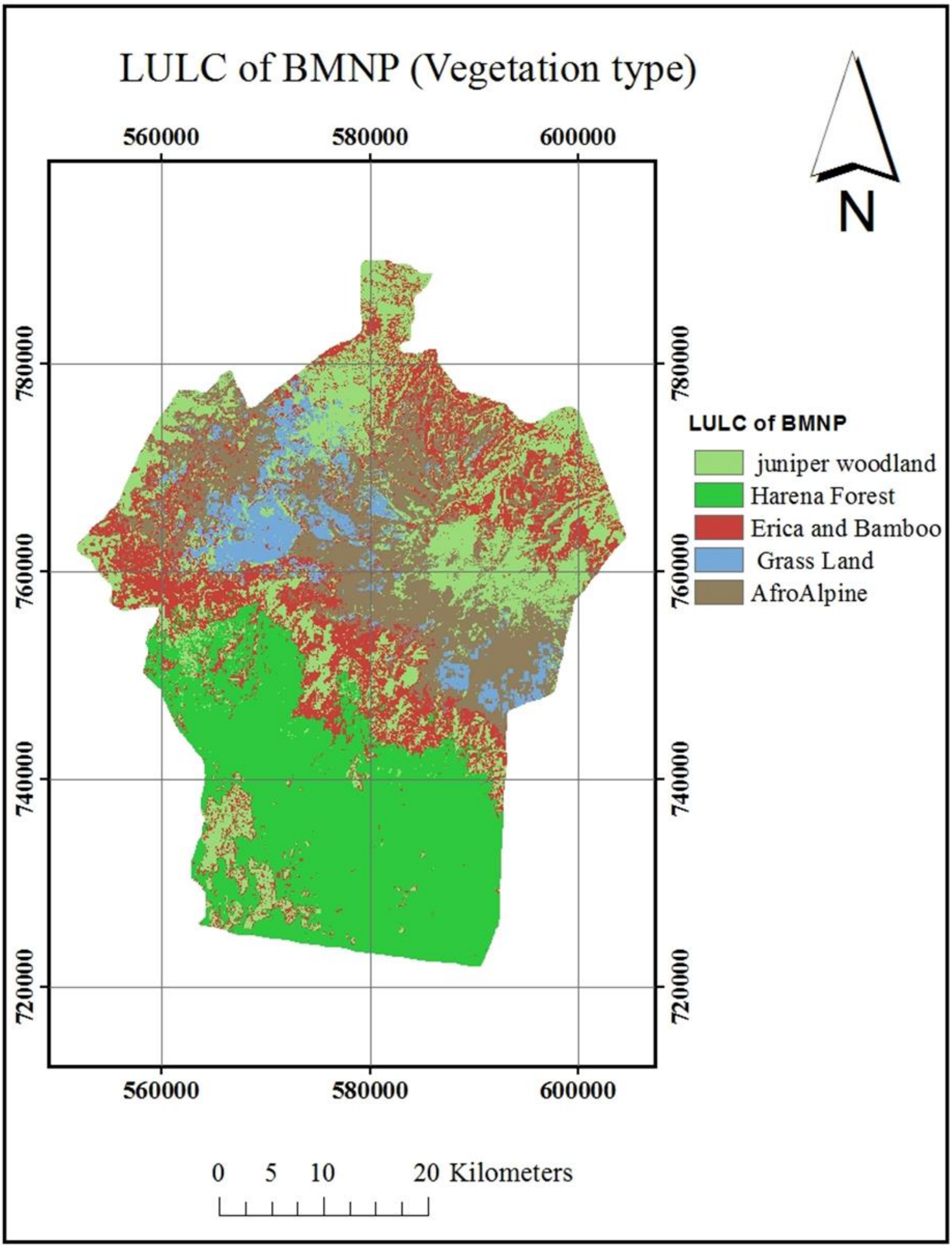
Appendix 1. GPS data collection in BMNP (Source: field survey, 2016).

Appendix 2. Settlement in BMNP (source: BMNP, 2016)

Appendix 3. Nyla in BMNP, Dinsho Park (source: field survey, 2016).

Appendix 4. Fire incidence in the Ericaceous vegetation (source: Anteneh et al., 2013, pp 34).

Appendix 5. LULC (vegetation type) of BMNP (Source: computed from ErdasImagine 2014).



Appendix 6. GPS points (source: field survey, 2016).

no.	E(m)	N(m)
1	581664	789789
2	581886	789566
3	582187	789408
4	582187	78949265
5	582029	788773
6	581457	788439
7	581949	785190
8	582553	788328
9	580997	788138
10	581778	788249
11	563959	763390
12	62247	763520
13	565422	763229
14	566030	764632
15	565818	763917
16	566338	770598
17	568851	770466
18	566232	770836
19	568243	769937
20	568560	768190
21	569777	773217
22	570465	773905
23	572688	772529
24	573270	771418
25	573794	769989
26	556963	759075
27	557890	757620
28	560601	755650
29	564107	761060
30	565629	767620
31	569134	761457
32	578725	761390
33	575418	760795
34	578990	760332
35	579453	755768
36	590963	751535
37	591690	750807
38	567355	738452
39	570318	733584
40	572647	733055

Appendix 7. OLS scatter plot result for elevation, slope, aspect, lulc, settlement and road explanatory attributes respectively versus final fire risk model (source: computed from ArcGIS 10.3).