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INSTITUTE OF TECHNOLOGY

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

Forest Fire Risk Estimation and Modeling Using GIS and Remote Sensing Techniques: The Case Of Asebot Monastery, Oromia, Ethiopia

A thesis submitted to School of Civil and Environmental Engineering Graduate Studies of Addis Ababa Institute of Technology in partial fulfillment of the requirement for the Degree Masters Of Science in Geodesy And Geomatics (Specialization In Geomatics)

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APPROVAL SHEET

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This is to certified that the thesis prepared by Birhanu Melkam entitled by **"Forest Fire Risk Estimation and Modeling Using GIS and Remote Sensing Techniques: The Case Of Asebot Monastery, Oromia, Ethiopia"** submitted in fulfillment of the requirement for the Degree of Master of Scince in Geodesy and Geomatics (Specialization in Geomatics) complies with the regulation of the University and meets the accepted standards with respect to originality.

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DECLARATION

I hereby declare that the research entitled "**Forest Fire Risk Estimation and Modeling Using GIS and Remote Sensing Techniques**" has been carried out by me, under the guidance of Hamere Yohannes (PhD), School of Civil and Environmental Engineering, Addis Ababa University as a part of Master of Science in Geodesy and Geomatics (Specialization in Geomatics). I further declare that this work has not been submitted to any other University or Institution for the award of any Degree or Diploma.

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List of Acronyms

DEM.................................…...Digital Elevation Model

GIS……………………..……Geographic Information System

GPS…………………………..Global Positioning System

LST……………………………Land Surface Temperature

LULC…………………………Land Use Land Cover

McDM………………………...Multi-criteria Decision-Making

MIRBI………………………...Mid-Infrared Burn Index

NBR…………………………...Normalized Burn Rate

NDMI…………………………Normalized Difference Moisture Index

NDVI………………………… Normalized Difference Vegetation Index

NIR……………………………Near Infrared Band

RS……………………………..Remote Sensing

SI……………………………...Spectral Index

SRTM…………………………Shuttle Radar Topography Mission

SWIR…………………………Short Wave Infrared Band

TWI…………………………..…Topographic Wetness Index

USGS ………………………..…..United States Geological Survey

UTM…………………………..Universal Transfer Mercator

Abstract

Forest fires are a major threat to the environment, human health, and property. The Asebot forest area is particularly vulnerable to forest fires due to its unique geographical and environmental characteristics. To mitigate the risk of forest fires in this region, it is essential to identify the influential factors of forest fire risks and estimate post-fire degradation. This was achieved by using post-fire satellite images of 2021 and modeling the location of potential fire susceptibility in the Asebot forest area. Forest fires are a major threat to ecosystems and human populations, and early detection and monitoring are crucial for effective fire management. In this study, the weighted overlay analysis technique is being used for multi-criteria decision-making. The goal is to estimate the post-fire and model forest fire risk susceptibility. To perform this analysis, each data set is converted to raster format and reclassified to a common scale using ArcGIS spatial analysis. Pair-wise comparisons of factor layers are conducted to determine their relative importance or weight. Remote sensing techniques have become increasingly important for detecting and monitoring forest fires, as they offer a cost-effective and efficient way to gather data over large areas. In this study, the two commonly used remote sensing techniques are employed to estimate fire severity: Normalized Difference Vegetation Index (NDVI) and Burn Severity Index (NBR). The study found that approximately 38.419% of the area had very high and high burn severity, as classified by the Normalized Burn Ratio (NBR) index whereas, burn severity concerning NDVI, which is very high and high burn severity covered 52.277% of the study area. The findings of the study indicate that the area under consideration has varying levels of forest fire risk. The model produced in this study reveals that a substantial portion of the area is classified as having a high to very high risk of forest fires, with over 22% falling into these categories.

KeyWords: Forest fire, multi-criteria decision-making, RS, GIS; fire risk map; prediction, Forest fire susceptibility

Chapter One

1. Introduction

1.1. Background of the Study

Forests are the primary natural resources and nature's most enormous bounty to humanity that play a central role in sustaining ecological balance and shaping the journey of human civilization (Tiwari et al., 2021), (Suryabhagavan et al., 2016). Forest fires are considered environmental disasters that artificial or natural causes can bring on. In forested and grassland settings, fires are one of the main threats (Adab et al., 2013).

Natural or human-induced fires affect the natural ecosystem and wildlife significantly. Fires also threaten human life directly, especially if the settlements are close to the burning area, and indirectly by destroying the forests, which are the suppliers of oxygen (Alganci et al., 2010). Forest fire risk zones are the places where fires are most prone to originate and from where they can quickly spread to other areas. Climate, vegetation type, geographic and climatic aspects, proximity to roadways, and human populations are among the factors that speed up the fire (Kanga et al., 2012).

Forest fire activity globally has acquired critical dimensions in new, dangerous, and in certain specific years. This problem has affected chiefly large forest areas in the USA, Canada, Australia, and European countries (Asenova, 2018). In Turkey, particularly over the Aegean and Mediterranean Regions, forest fires have been causing major harm and threats (Alganci et al., 2010). Globally, the rising frequency of forest fires is a direct cause of deforestation, climate change, and a sharp decline in biodiversity (Tiwari et al., 2021). As a real-world threat, forest fires frequently cause substantial losses in terms of people, property, and the environment (Gai et al., 2011).

In order to reduce risks to natural resources, biodiversity, and life, it has been crucial to identify high-risk areas through the modeling of forest fire susceptibility (Chicas & Østergaard Nielsen, 2022). These days, wildfires can be found practically anywhere in the world. When a wildfire occurs, natural resources are burnt away, and the natural habitats of wild animals are destroyed (Heo et al., 2008). A forest fire was commonly occurring in various parts of Ethiopia every year with varying levels of damage and causative factors. For instance, in 2000, more than 150,000 ha of forest was damaged by fire, where severe damage occurred in Bale and Borana forests (Teketay, 2000).

Similarly, Asebot Forest, the current study area, had a past forest fire. Fire has become common in the area since 1962. However, the levels of damage were insignificant as the fires affected only the grass, herb, and shrub layers in some parts of the forest and were controlled before it spread to other places.

However, relatively high forest fire damage occurred in the year 2003 when 800 ha of forest was burnt at that time. The most severe forest fire occurred in Asebot forest in 2008, estimated at 12,700 ha of forest that, including both high forest and the adjoining woodland, was damaged (Worku & Zewdie, 2008). In addition, the forest fire that broke out on March 20, 2021, was difficult to control and damaged a substantial part of the Asebot grasslands, shrubs, and forests.

The risk assessment, detection, and assessment phases of fire management are the three areas where remote sensing technologies can be applied. Remotely sensed data are spectrally sensitive to surface vegetal properties and structure and offer quick, accurate, and trustworthy information for post-fire damage investigation (Alganci et al., 2010).

Thus, by using Multi Criteria Evaluation, the following variables are used to create a forest fire risk model: elevation, slope, aspect, Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Normalized Burn Ratio (NBR), land surface temperature (LST), wind speed, and proximity to roads and settlements.

1.2. Statement of the Problem

The ecology, property, and people are all severely harmed by forest fires, which occur frequently in real life. Rapid forest area reduction is a result of both human activities and global climate change (Gai et al., 2011). When forest fire burns in an uncontrolled, fire is a cause of ecosystem disruption. Forest fires are causing significant harm to the environment, human health, properties and putting life at risk. Historically, forest and wildland fires have occurred, affecting the landscape structure, pattern, and ecosystem species composition. Fire plays an ecological role in influencing a number of variables, including the development of plant communities, the availability of nutrients in the soil, and biological diversity (Roy, 2003).

According to (Vicente-Serrano et al., 2020), The ecological and socioeconomic effects of wildland fires include loss of forest, loss of biodiversity, loss of wildlife habitat, global warming, degradation of soil, loss of biophysical timber and feed, harm to water and other natural resources, and loss of natural regeneration. When a fire breaks out in a forest, it can be considered an environmental disaster that is caused by either human or natural factors (Adab et al., 2013). In addition to other man-made and natural disturbances, fires are essential for controlling the area, composition, and igniting mass of forests. It's essential to understand how fire contributes to the loss of forests worldwide in order to limit emissions from land use change and the global carbon cycle (Van Wees et al., 2021).

Forest fires have become a major concern for several environmental experts, on a global scale, fire is the most effective means of transforming tropical forests into agricultural areas, and it has severe impacts on the global atmosphere (Yakubu et al., 2015). Wildfires are prevalent almost everywhere in the world these days. If a wildfire occurs, natural resources are burnt away and the wildlife area is destroyed. Accordingly, environmental conditions (i.e., weather, temperature, water quality, etc.) can be changed (Heo et al., 2008). Russia in 2003, Australia in 2020, Canada in 2014, and Alaska Fire Season (US) in 2004 all experienced wildfires that expanded rapidly and severely damaged wide large areas of land (Igini, 2022).

Though no accurate documented data allows examination of the extent of damage and model caused by forest fires in Ethiopia, it has resulted in significant economic and biological loss (Tafesse, 2016). In the current study area, Asebot forests are threatened by fire.

Previously, various studies were conducted related to this research title in other study areas. Among these, Suryabhagavan et al (2016) used LULC, slope, aspect, elevation, settlement and road proximity to producing a fire risk in the Harenna forest, in southwestern Ethiopia. Kanga et al. (2012), used the topographic, accessibility, and fuel type factors to produce a forest fire model in Taradevi forest, India, Adab et al.(2013) conduct a study to produce a forest fire risk model in the northeast of Iran by using the factors (NDMI, elevation, slope, aspect, distance from rods and settlements). Tiwari et al., 2021; produced forest fire risk model in Pauri Garhwal, India, by using the topographic, climate, accessibility, and spectral index factors.

However, the studies mentioned above did not show the post-fire damaged areas. No related research has been done to develop a forest fire risk model or evaluate the degradation caused by forest fires in the current study region, the Asebot forest area , and the purpose of this study is to fill such a knowledge gap.

Thus, the current research has employed GIS and RS techniques to create a forest fire risk model and evaluate forest degradation using topographic factors (elevation, slope, and aspect), spectral index factors (LST, NBR, NDVI, NDMI, BAI, and MIRBI), climate factors (rainfall and wind speed), and accessibility factors (distance from roads and settlements).

1.3. The objective of the Study

1.3.1. General Objective

Estimating and modeling forest fire risk in the research area using GIS and RS techniques is the main objective of the project.

1.3.2. Specific Objective

The specific objectives of the reseach are;

- To analayze the influential factors of forest fire risks
- To estimate post-fire degradation by using post-fire satellite images of 2021
- To model the location of potential fire susceptibility in the Asebot forest area

1.4. Basic research questions

- What are the influential factors for the occurrence of forest fire risk?
- How much the study area affected by forest fire?
- Which part of the study area is potentially affected by forest fire risk?

1.5. Significance of the study

This study will provide scientific insights on the condition of the environment today. The following factors make it essential to estimate the damage caused by forest fires and model the risk of fires: It will help you comprehend how GIS and remote sensing are applied to the analysis of forest fires and provide information to various stakeholders for their use in making decisions about fire monitoring. Officials from the forest department can reduce or prevent fire risk activities in the forest with the aid of these maps. In addition, the study helps future researchers by shedding light on the places most vulnerable to forest fires and the variables influencing the occurrence of forest fires in the studied area.

1.6. Scope of the study

In order to estimate post-fire deterioration, post-fire Landsat images of spectral indices were used in this study, which was done in the forest region near Asebot Monastery. The study area's topography (slope, aspect, and elevation), climate data (temperature, rainfall, and wind speed), settlement proximity (road and settlement proximity), and estimated burned area result have all been used to calculate the final forest fire susceptibility model, which is used to predict the location of future potential fire risks in the area.

1.7. Outline of the study

This study is organized in six main chapters. The first chapter, which is divided into four sections contains Background, Statement of the Problem, Objectives (general and specific), Significance of the study, and scope of the study. Literature review is described under the second chapter, materials and methods are covered in the third chapter. The results of the analysis for the research is clearly descibed in the fourth chapter. Chapter five contains discussion, whereas Chapter Six conclusion and recommendation.

Chapter Two

2. Literature Review

2.1. Forest Fires and Environmental Impacts

Forest fires, also known as wildfires, are uncontrolled and often destructive fires that occur in forests, grasslands, and other wild land areas. These fires can spread rapidly, consuming everything in their path including trees, vegetation, and wildlife (Pausas & Keeley, 2021). Due to their excessive deforestation, increased soil erosion, and increased CO2 levels in the ecosystem, forest fires have emerged as a major worry for the economy, the environment, and public safety. It also has a negative impact on the number and distribution of tree species as well as forest inhabitants. In addition to destroying property and infrastructure, forest fires endanger human life (Naderpour et al., 2021). Forest fire is a usual disaster in real life, causing huge live, property and ecology losses (Gai et al., 2011). Forest fires can be considered as one of the most important environmental hazards. Natural or human-induced fires affect the natural ecosystem and wildlife significantly. Fires also threaten human life directly especially if the settlements are close to burning area and indirectly by destroying the forests which are the suppliers of oxygen (Alganci et al., 2010). Worldwide deforestation, biodiversity loss, and climate change are all directly impacted by the rising frequency of forest fires. The extent of the damage produced by forest fires is dependent on the topography and climate of the affected area (Tiwari et al., 2021).

The environment is significantly harmed by forest fires. The following are some of the key environmental consequences of forest fires: Habitat Destruction, forest fires can destroy the habitats of numerous plant and animal species. The delicate balance of ecosystems can be upset by the loss of habitat, which can cause certain species to become extinct or relocate. Air quality is the second: forest fires cause major releases of smoke and particulate matter into the atmosphere, which reduces air quality. This can have adverse effects on human health, especially for those with respiratory conditions (Földi & Kuti, 2016). The other is soil erosion, which occurs when the extreme heat from forest fires makes soil less capable of absorbing water by making it hydrophobic. This raises the possibility of erosion during periods of high precipitation, which affects aquatic ecosystems and causes sedimentation in water bodies. Carbon Emissions: Significant volumes of carbon dioxide are released into the atmosphere by forest fires, which increases greenhouse gas emissions and causes climate change. The release of carbon stored in trees and vegetation exacerbates global warming (Yefremov & Shvidenko, 2004). Water Quality: the runoff from burned areas can carry ash, sediment, and other pollutants into water bodies, affecting water quality and aquatic life. Loss of Biodiversity: A forest fire may cause a variety of plant and animal species to disappear from the environment. Following a significant fire incident, certain species might not be able to recover or re-establish themselves. Extended Ecosystem Shifts: Over time, severe or frequent forest fires can modify the ecosystems' structure and composition, which can have an impact on biodiversity and ecological processes over the long run (Bakirci, 2010).

2.2. Influential Factors Contributing for Forest Fire Risks

Forest fires are a serious environmental problem that can have devastating consequences on human lives, ecosystems, and the economy. Effective fire management and prevention techniques depend on having a thorough understanding of the elements that increase the danger of forest fires. The probability and intensity of forest fires can be influenced by a number of variables, including both natural ones like weather and climate patterns and man-made ones like land use practices (Chas-Amil et al., 2012).

The topography of an area plays a role in forest fire risks by influencing fire behavior and the availability of fuels. The following factors are influential (Estes et al., 2017):

1. Slope: Steep slopes can accelerate fire spread by allowing flames to travel uphill more rapidly. Fire burning upslope can also generate more intense heat, making it more challenging to control.
2. Aspect: An aspect is the direction that a slope faces. Compared to slopes facing north, those facing south are more likely to have fires because they tend to receive more sunshine and have drier vegetation..
3. Elevation: Higher elevations often experience cooler and moister conditions, which can reduce fire risks. However, at high elevations, forests may contain highly flammable vegetation types, such as coniferous trees.

Climate and weather patterns play a fundamental role in forest fire risks. Certain climatic conditions can create favorable environments for the ignition and spread of fires. The following factors are particularly influential:

1. Temperature: The drying out of fuels caused by high temperatures makes vegetation more flammable and increases the rate at which fire spreads.. Heatwaves and prolonged periods of hot weather can create ideal conditions for forest fires.
2. Precipitation: Insufficient rainfall or extended drought periods can lead to dry vegetation, increasing the availability of fuel for fires. Drier conditions make it easier for fires to ignite and spread rapidly.
3. Humidity: Low humidity levels contribute to the drying out of fuels, making them more prone to ignition. Additionally, low humidity reduces moisture content in vegetation, increasing its flammability.
4. Wind: Wind plays a critical role in fire behavior by influencing its speed, direction, and intensity. Strong winds can quickly spread fires over large distances, making them more difficult to control.

2.3. Factors related to forest fires

When modeling a forest's sensitivity to fire risk, environmental factors such as topographical features, man-made infrastructure, and climatic and morphological parameters—also known as influencing parameters—are crucial. However, economic factors exert a role in identifying the places that are most vulnerable and in zoning the likely risks (Naderpour et al., 2021). Wildfires are complicated natural disasters caused by both human activity and natural processes (Adab et al., 2013). Land use, elevation slope, aspect, temperature, relative humidity, and wind force are among the factors that can cause a fire. The value of forest resources and the density of population are vulnerability factors (Gai et al., 2011). There are four types of fire ignition factors to consider: vegetation, topography, meteorological factors, and human activity. The forest fire risk model is developed by parameters (altitude, aspect, topographic wetness index, slope, distance to roads and populated areas, normalized difference vegetation index, and temperature) which have a major influence on the possibility of causing fire.

2.4. Fire Risk Mapping

The cover change and fire-risk area mapping from remotely sensed imagery and GIS have helped to determine the extent of forest cover change, and mapping the fire-risk areas (Suryabhagavan et al., 2016). The manager can evaluate the risk and uncertainty associated with forest fires and estimate the potential losses that may result from them by using forest fire risk mapping. Using remote sensing and GIS techniques, forest fire risks are mapped, taking consideration of land use, slope, aspect, forest type and density, and proximity to populated areas based on weightage (Kanga et al., 2012).

2.5. Spectral Indices (SI) to Assess Post-Fire Degradation

Historical fire data analysis is an essential tool for understanding fire regimes, assessing wildfire risk, and informing management practices. Historical fire data helps in identifying areas with a higher risk of wildfires. This information is essential for prioritizing resources and implementing preventive measures in high-risk areas. Burned area can detected Using the fire extent derived from the medium resolution image. The capability of the LANDSAT-8 image-derived NBR and NDVI indices used to evaluate the severity of fires (Escuin et al., 2008).

A pixel-based time-series approach can effectively capture wildfire disturbance using both the Normalized Difference Vegetation Index (NDVI) and the Normalized Burn Ratio (NBR), particularly if images from soon after the disturbance are available. (Hislop et al., 2018). In many ecosystems across the world, NBR is the most widely used spectral index to assess burn severity using several sensors. NBR was found to be among the most effective SI in multiple comparative evaluations. Rather than using visible red, NBR uses the band pair SWIR and NIR, which has been demonstrated to be sensitive to changes in reflectance brought on by fire. Although NDMI and NBR are extremely similar, they use the shorter SWIR band rather than the longer one, which has been shown to be similarly sensitive to the moisture content of vegetation and soils (Fornacca et al., 2018).

The two most important and commonly utilized parameters in satellite-driven forest fire susceptibility mapping are vegetation cover extraction and moisture estimation (Tiwari et al., 2021). The NDMI helps to define sections of a crop or forest that are particularly vulnerable to forest fires in terms of water stress. By calculating the normalized separation between the Short-Wave-Infrared, which trees and crops reflect, and the Near-Infrared, which trees and crops absorb, the NDMI quantifies the amount of water content in vegetation. using equation 1 (Tiwari et al., 2021).

$$\mathrm{NDMI} = \frac{(\mathbf{SWIR - NIR})}{\boldsymbol{SWIR + NIR}} \tag{1}$$

In this case, the Short-Wave Infrared Band is defined by SWIR and the Near Infrared Band by NIR. The Normalized Difference Vegetation Index (NDVI), a widely used remote sensing method, measures the health and vigor of vegetation through comparisons between the reflectance of red light and near-infrared (NIR). It has been demonstrated that NDVI is a useful tool for determining and monitoring a variety of environmental incidents, including the extent of fires. Researchers can determine how severe and how much of an impact the fire has had on vegetation by comparing NDVI measurements before and after a fire occurrence (Hammill & Bradstock, 2006).

$$\text{NDVI} = \frac{(\mathbf{NIR-R})}{\boldsymbol{NIR+R}} \tag{2}$$

Where R stands for red and NIR for near infrared.

Satellite data has been used in a number of studies to map the various fire intensity levels found in burned areas. A spectral index known as the normalized burn ratio (NBR) is increasingly being used to determine the intensity of fires. An index called the Normalized Burn Ratio (NBR) is used to show the areas that have burned in extensive fire zones. Shortwave infrared (SWIR) and near infrared (NIR) wavelengths are combined in this formula, which is comparable to the NDVI. Healthy vegetation has a very high reflectivity in the NIR, and low reflection in the SWIR section of the spectrum, the reverse of what is found in areas devastated by fire. The difference between the spectral responses of healthy vegetation and burnt areas peaks in the NIR and SWIR portions of the spectrum. Recently burned areas exhibit low reflectance in the NIR and high reflectivity in the SWIR. NBR can be calculated as follows (D. P. Roy et al., 2006):

$$NBR = \frac{NIR-MIR}{NIR+MIR} \tag{3}$$

where NBR is for normalized burn ratio, MIR stands for medium infrared band, and NIR stands for near infrared band.

2.6. The role of GIS and RS for Forest Fire Modeling

The phases of risk assessment, detection, and assessment in fire management are where remote sensing technology can be applied. Spectral sensitivity to surface changes allows remotely sensed data to give rapid, accurate, and reliable information for post-fire damage assessments (Alganci et al., 2010). In order to correlate the magnitude and spatial distribution of the fire with the topographic parametres of the area, a GIS study was also carried out. Using raster–vector conversion, the burned area's spatial boundaries can be extracted from classified imagery (Alganci et al., 2010). Forest fire risk zones are identified using remote sensing and GIS techniques (Suryabhagavan et al., 2016).

These days, the use of GIS together with remote sensing technologies is growing in all areas related to the management, prevention, and forecast of forest fires (Tiwari et al., 2021).

CHAPTER THREE

3. Materials and Methods

3.1. Study area description

The Asebot Forest is located approximately 300 kilometers from Addis Ababa in the Western Harerge Zone of the Oromia Regional State. (Worku & Zewdie, 2008) . The study area lies between 9° 12' and 9° 21' North and 40° 31' and 40° 42' East. (Fig 1). Asebot Debre Wegege Aba Samuel and Kidest Selassie Monastery have been keeping the forest for a long time as a church. The sections of forest surrounding the two chapels were left in the monastery's possession throughout the Derg era (1974–1991). This is currently handled by Hallideghe Asebot National Park, with the exception of the woodland surrounding the church compounds. The terrain of the study site is characterized by rigid mountains. With immediate changes in facing, the elevation ranges between 1080 and 2447 meters above sea level (Tolla et al., 2022).

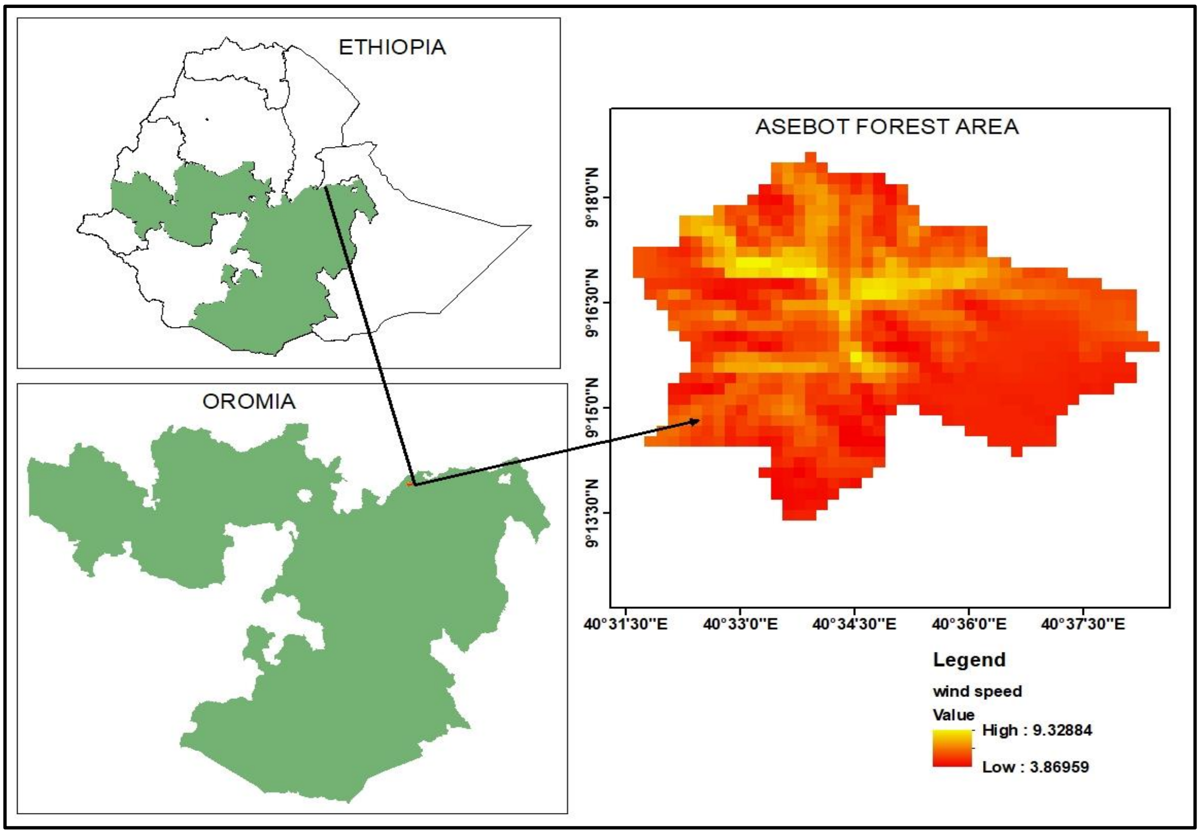

Fig 3.1: Location map of the study area

3.2. Data types and sources

Data for this study was gathered from a variety of sources. The following table provides an overview of the satellite imagery and additional data that are significant to this investigation (table 1).

Table 3.1: Sources and types of data used in the research

No	**Data**	**Data format**	**Purpose and description**	**Source**
1	Landsat 8 (Post fire image of 2021)	Raster (Tiff)	To estimate LST, NBR, NDVI, NDMI	https://earthexplorer.usgs.gov/
2	Precipitation data	Raster	To prepare rainfall map	Ethiopian meteorological agency
3	SRTM, DEM	Raster (Tiff)	To calculate slope, elevation, aspect and TWI	https://earthexplorer.usgs.gov/
4	Settlement and road shape file	Shape file	For proximity analysis	Digitizing from google earth
	Wind speed	Raster (Tiff)	To produce forest fire factor map	Global wind ATLAS Globalwindatlas.info
6	Study area Boundary	Shape files	To prepare study area location map	From geospatial agency
3	Point data (x,y)	Vector	For model validation	From GPS measurement
7	Previous studies, journals, published books		To execute the objectives and for literature review	Internet, library, and secondary sources ...

3.3. The Data Analysis Software

The following software has been utilized to analyze data for the current study, which is essential to successfully and efficiently accomplishing the objectives of the study (table 2).

Table 3.2: Software and its function

No	Software & tools	Function and description
1	Arc GIS	To calculate and map LST, NDVI, NDMI, and NBR using raster calculator and to reclassifying and prepare slope, aspect, elevation maps
3	IDRISISELVA 17.0	For pairwise comparison/ weight decision analysis
4	Google earth	To interpret images which is not clear on Landsat images.
5	Zotero app	Automatically generate citations while conducting research. It integrates with web browsers, making it easy to save and organize references from various online sources

3.4. Analysis of Data

3.4.1. Preparation of dataset

The SRTM satellite 30 m resolution DEM images that were acquired from the USGS Earth Explorer web page is used to calculate elevation, slope, and aspect. This enable us mapping the forest topography of the study area.

First, the boundary shape file feature of the study area used to mask the DEM image. Zone 37 was used to project the DEM to the UTM projection. The most important and commonly utilized criteria for satellite-driven mapping of forest fire susceptibility are vegetation cover extraction and moisture estimation (Tiwari et al., 2021). The study area's shape file can be used to mask Landsat-8 satellite photos that are downloaded. The normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), normalized burn ratio (NBR), and land surface temperature (LST) were calculated using the extracted pictures.Distances to settlements and roads are digitized and prepared from Google Earth. Wind speed, temperature and rainfall datasets were obtained from the Ethiopian Meteorological Agency.

3.4.2. Influential Factors responsible for Forest Fire

The following are some of the factors that can accelerate forest fires: vegetation, topography, and human activity and meteorological factors (Zhao et al., 2021).

3.4.2.1. Topographic factors

Topography is an important physiographic factor, which is related to wind behavior and hence, affects the fire proneness of the area. Topography influences the probability of fire occurrence, such factor includes altitude, slope, aspect, and TWI, and these factors have been selected as influencing factors (Zhao et al., 2021). Fire travels most rapidly up slopes and least rapidly down slopes (Kanga et al., 2012). The occurrence and spread of fires are significantly influenced by the topographic moisture index. It is easier for fires to start and spread quickly in dry areas than in rainy ones (Zhao et al., 2021).

3.4.2.2. Meteorological Factors

Three potential meteorological factors—temperature, rainfall, and wind speed—can cause forest fires (Tošić et al., 2019). Areas with high temperatures are more likely to be ravaged by fire. The upward radiation, the downward radiation, and the atmospheric radiation that reaches the earth make up infrared radiation (Zhao et al., 2021). In this study, the ArcGIS 10.7 raster calculator used to calculate the land surface temperature using Landsat 8. Global wind ATLAS (Globalwindatlas.info) is used to acquire wind speed data, and the rainfall data from Ethiopian Meteorological Agency. Each component were reclassified and standardized. According to Halder et al. (2022) The following formulas were used to compute the land-surface temperature:

$$L = \left(\frac{Lmax - Lmin}{DNmax}\right) xBand + Lmin \qquad (1)$$

where L represents the or atmospheric spectral radiance in watts/(m^2*srad * μm), $Lmax$ denotes the DN value-based maximum spectral radiance (SR), $Band$+$Lmin$ represents the selected band-based minimum spectral radiance (SR), $DNmax$ denotes the maximum values of the digital number, and $Qcal\ max - Qcal\ min$ indicates the maximum and minimum difference of sensor calibration, respectively. When the DN significance values were converted to the SR, the TIRS satellite dataset band was changed from the SR to the BT using the thermal band-related coefficients that were supplied in the satellite metadata files.

$$\mathrm{BT} = \frac{\mathrm{k_2}}{\mathrm{Ln}(\frac{\mathrm{k1}}{\mathrm{L\lambda}} + 1)} - 273.15 \qquad (2)$$

Where BT stands for the brightness temperature values on a Celsius scale and K_2 and K_1 are the values of the particular band-based thermal alteration coefficients.

Calculate the NDVI, $\mathrm{NDVI} = \left(\frac{\mathrm{NIB-R}}{\mathrm{NIR+R}}\right)$ (3)

The Normalized Different Vegetation Index, or NDVI, has values that range from + 1 to −1 depending on the area. Using the maximum and minimum NDVI map values, the Pv, or proportion of vegetation, was determined. The following formula can be used to determine the proportion of vegetation:

LSE=0.004×Pv+0.986

Transformation of the Kelvin values to the Celsius values was carried out with:

$$\mathrm{LST} = \frac{\mathrm{BT}}{1+[\frac{\lambda \mathrm{BT}}{\mathrm{P}}]\ln(LSE)} \qquad (4)$$

Where λ denotes the emitted radiance wavelength.

3.4.2.3. Human Activity Factors

Most of forest fires are caused by human activity; they can result from people throwing cigarettes, residual fire from sacrifices, or other human-caused incidents. (Eugenio et al., 2016). Human activity has the potential to generate fire sources that start forest fires in tourist destinations or populated areas (Tien Bui et al., 2016). Roads and populated areas can therefore be considered as igniting factors. The affected area is higher than roads because of the frequent activities of the population in the residential areas (Zhao et al., 2021). Therefore, the current study will be performed accordingly by giving higher weight for populated or settlement area than road proximity.

3.4.3. Estimate the burned area using Spectral Indices

Common spectral indices used to identify burned areas, such as Normalized Difference Moisture Index (NDMI), Normalized Difference Vegetation Index (NDVI), and NBR, are computed using Landsat OLI data. NBR is designed to distinguish burned and unburned areas by amplifying the different spectral responses of the NIR and SWIR2 bands of Landsat. NDVI utilizes the Red and NIR bands to assess the photosynthetic capacity of vegetation. NDMI has similar spectral components as NBR but uses the Landsat SWIR1 band, which is more sensitive to vegetation moisture content (Liu et al., 2023). Using the spectral indices (SI) of post-fire Landsat images, the burned area was analyzed and estimated in the current study. Normalized Burn Ratio (NBR, were employed for the detection of burn area in post-fire assessment. To calculate the NBR for landsat8 the research used the following formula (Liu et al., 2023):

$$NBR = \frac{(Band\ 5 - band\ 7)}{(Band\ 5 + Band\ 7)} \tag{5}$$

Moreover, the presence of vegetation greatly affects the igniting of fires. Each vegetation has different moisture content, and not all types of vegetation have the same probability of igniting fire. Hence, to evaluate the growth and coverage of vegetation, NDVI is the best indicator. (Adab et al., 2013). Bands 4 and 5 in Landsat-8 images are used to extract NDVI, and it can be calculated as follows:

$$NDVI = \frac{(Band\ 5 - band\ 4)}{(Band\ 5 + Band\ 4)} \tag{6}$$

Where Band 5 is the near-infrared band (0.76–0.9 µm), Band 4 is the red band (0.63–0.69 µm). NDMI has similar spectral components as NBR but uses the Landsat SWIR1 band, which is more sensitive to vegetation moisture content. NDMI can be calculated as follows (Liu et al., 2023):

$$NDMI = \frac{(\text{Band 5} - \text{Band 6})}{(\text{Band 5} + \text{Band 6})} \tag{7}$$

3.4.4. Modeling the Location of Forest Fire Susceptibility

A model of forest fire risk was created using twelve criteria. The topographical factors which includes (slope, elevation, topographic wetness index (TWI), and aspect), spectral index factors: normalized burn ratio (NBR), normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), climate factors: land surface temperature (LST), wind speed, and rainfall. Human activity factors (proximity to settlements and roads).

3.4.4.1. Multi-criteria decision-making (MCDM)

In this study, the weighted overlay analysis technique were applied to perform multi-criteria decision-making. Before performing MCDM to estimate the post-fire and model forest fire risk susceptibility, each data set converted to raster format. In addition, reclassified in to a common scale using ArcGIS spatial analyst. According to (Kanga et al., 2012) and (Suryabhagavan et al., 2016), the risk categories associated with each factor are very low, low, moderate, high, and very high. Pair-wise comparisons of factor layers was used to determine their relative importance or weight, the Idrisi Selva software was employed. The software allows users to assign weights to different factors based on their significance in a given analysis. Therefore, the weights calculated from the IDRISI selva are presented in the (Table 3.3).

Table 3.3: Pair-wise comparisons of factor layers

Layers	A	B	C	D	E	F	G	H	I	J	K	L	Weight
Slope (A)	1												0.2257
NDVI (B)	1/2	1											0.1856
NBR (C)	1/2	1/2	1										0.1462
LST (D)	1/2	1/3	1/3	1									0.1103
NDMI (E)	1/3	1/3	1/2	1/3	1								0.0843
Elevation (F)	1/4	1/2	1/2	½	1/3	1							0.0644
Rainfall (G)	1/5	1/4	1/3	½	1/2	1/2	1						0.0495
Aspect(H)	1/6	1/5	1/4	1/3	1/2	1/2	1/2	1					0.0393
Dist. from Sett (I)	1/7	1/6	1/5	¼	1/3	1/2	1/2	½	1				0.0307
Wind speed(J)	1/7	1/6	1/5	¼	1/3	1/2	1/2	½	½	1			0.0273
TWI (K)	1/8	1/7	1/6	1/5	1/4	1/3	1/2	½	½	1/2	1		0.0215
Dist. from road (L)	1/9	1/8	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1/2	1/2	1	0.0152

Consistency ratio = 0.02, Consistency is acceptable.

Table 3.4: Factors risk level and weight of causative criteria with corresponding sub-classes

No	Influence Factors	Classes	Risk level	Weight
1	Slope(degree)	>45 35-45 25-35 15-25 <15	Very high High Moderate Low Very low	0.2257
2	NDVI	<0 0 -0.15 0.15 - 0.3 0.3 - 0.45 >0.45	Very high High Moderate Low Very low	0.1856
3	NBR	<-0.06 -0.06 – 0.02 0.02 – 0.1 0.1 -0.18 >0.18	Very high High Moderate Low Very low	0.1462
4	LST	>40 36-40 33-36 30-33 <30	Very high High Moderate Low Very low	0.1103
5	NDMI	<0 0-0.04 0.04-0.06 0.06-0.08 0.08-0.223	Very high High Moderate Low Very low	0.0843
6	Elevation(m)	<500 1500-1700 1700-1900 1900-2200 >2200	Very high High Moderate Low Very low	0.0644
7	Annual Rainfall (mm)	12.559 –15.0269 15.0269 –16.809 16.809 –18.463 18.463 – 20.099 20.099 –22.511	Very high High Moderate Low Very low	0.0495
8	Aspect	W-NW-SW-FLAT N NE SE-E S	Very low Low Moderate High Very high	0.0393
9	Dist. from Settlement	400 800 1200 1600 8000	Very high High Moderate Low Very low	0.0307

10	Wind speed (m/s)	<2 2-3 3-4 4-6 >6	Very low Low Moderate High Very high	0.0273
11	TWI	<2 2-3 3-4 4-6 >6	Very high High Moderate Low Very low	0.0215
12	Dist. from road	300 600 900 1200 8000	Very high High Moderate Low Very low	0.0152

Forest Fire Risk Model = Slope*0.2257 + NDVI*0.1856 + NBR*1462 + LST*0.1103 + NDMI*0.0843 + Elevation*0644 + Rainfall*0.0495+ Aspect* 0.0393 + Dist. From Sett* 0307 + Wind speed*0.0273+ TWI*0215 + Dist. from road*0.0152

3.4.4.2. Model Validation

Validation of the model can be performed in order to check the prediction accuracy (Tiwari et al., 2021). Model Validation is a key step in the development of susceptibility and determination of its quality additionally; the critical strategy in prediction modeling is the validation of predicted results, so that the results can supply a meaningful interpretation with respect to forest fire susceptibility (Pourtaghi et al., 2016). In this study, 106 GPS points were gathered from a previously burned area in order to validate the forest fire risk model sample. Different data were collected from various sources and produced from multi-spectral satellite images in order to carry out the specified objectives.

The study was conducted using the flowchart bellow. (Fig.3.2).

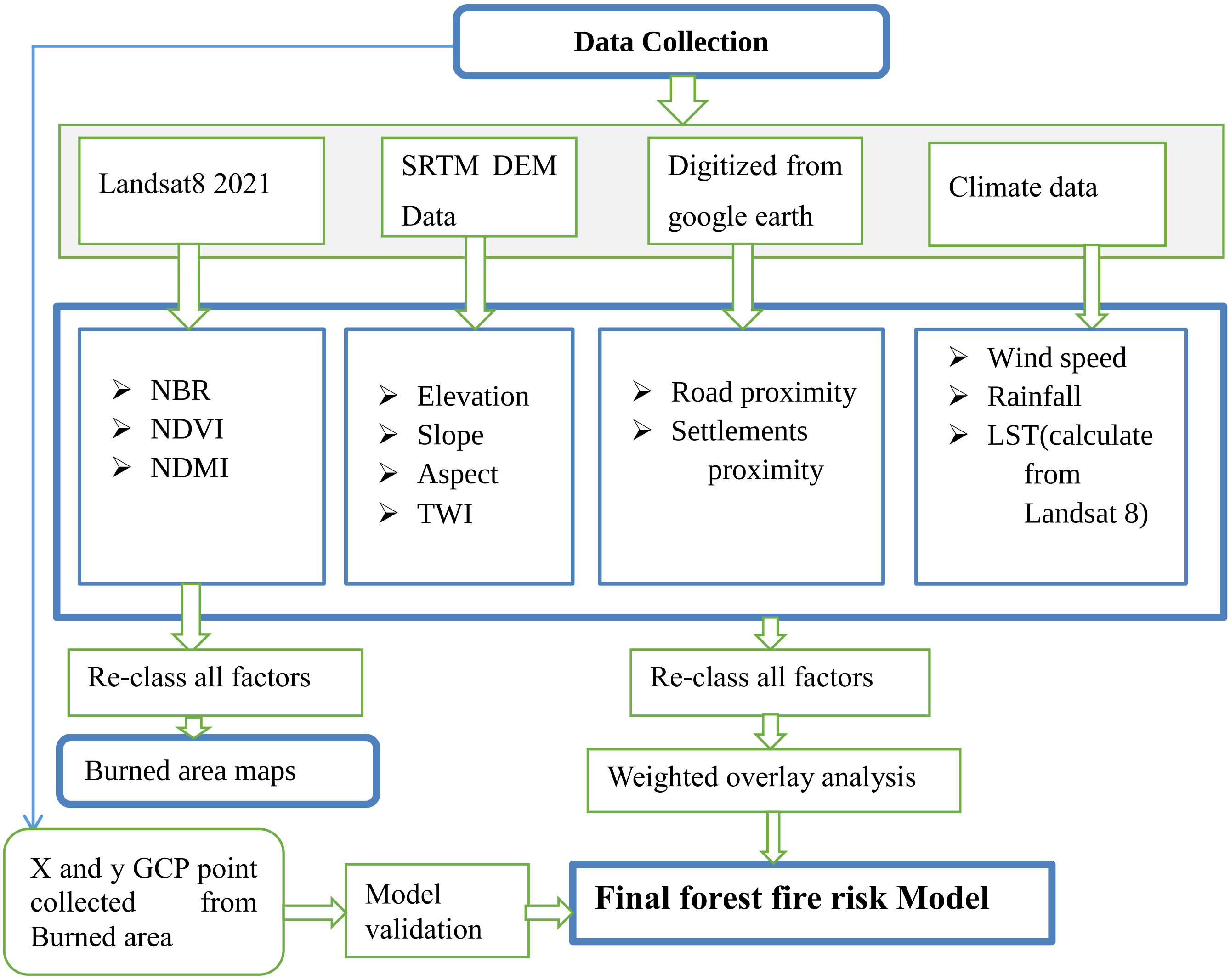

Fig 3.2. The study's overall methodological flowchart

Chapter Four

4. Results

4.1. Influential Factors responsible for Forest Fire

4.1.1. Elevation

Elevation has a significant influence on forest fires through its impact on climate and vegetation types. For effective forest fire management and prevention strategies, it is important to comprehend these interactions. Based on this study the elevation of the study area was classified into five elevation and risk level classes. That is, <1500m (very high), 1500-1700m (high), 1700-1900m (moderate), 1900-2200m (low), and >2200m (very low). From the total area very high risk covers 13.64%, high risk covers 42.24%, moderate, low and very low risk covers 21% 18.81% and 4.3% respectively (Fig 4.1 and Table 4.1).

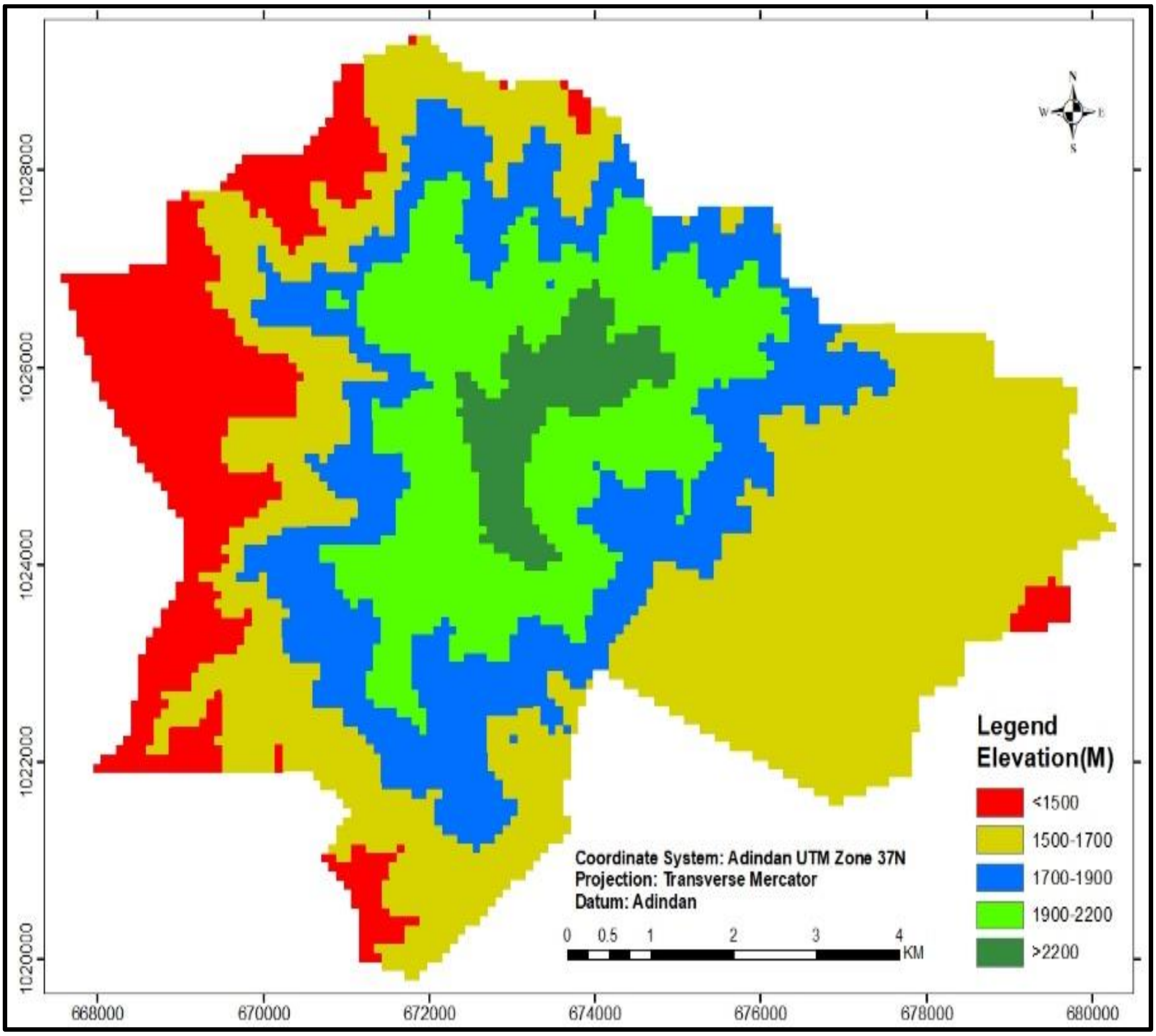

Fig 4.1: Re-classed Elevation map of the study area

Table 4.1: Elevation fire risk level and area coverage of the study area

No	Elevation(m)	Risk level	Area(Ha)	Area (%)
1	<500	Very high	917	13.64
2	1500-1700	High	2840	42.24
3	1700-1900	Moderate	1412	21.00
4	1900-2200	Low	1265	18.81
5	>2200	Very low	289	4.30
	Sum		**6724.315**	**100.00**

4.1.2. Slope

The influence of slope on forest fires is undeniable. Steeper slopes contribute to more intense and rapid fire spread, and increased fuel availability. By using a similar ways of elevation this study classify the fire risk level into five categories. Slopes in the study area were also classed into five. Slopes greater than 45 degree, covers 45.499Ha of the study area and 35-45 degree covers 454.218Ha of the total is very high fire risk area. The remains 92.569% of the total area was moderate, low and very low fire risk level (Fig 4.2 and table 4.2).

Table 4.2: Slope classes fire risk level and area coverage of the study area

No	Slope(degree)	Risk level	Area(Ha)	Area (%)
1	>45	Very high	45.499	0.677
2	35-45	High	454.218	6.755
3	25-35	Moderate	1365.700	20.311
4	15-25	Low	1984.825	29.519
5	<15	Very low	2873.758	42.739
Sum			**6724.315**	**100**

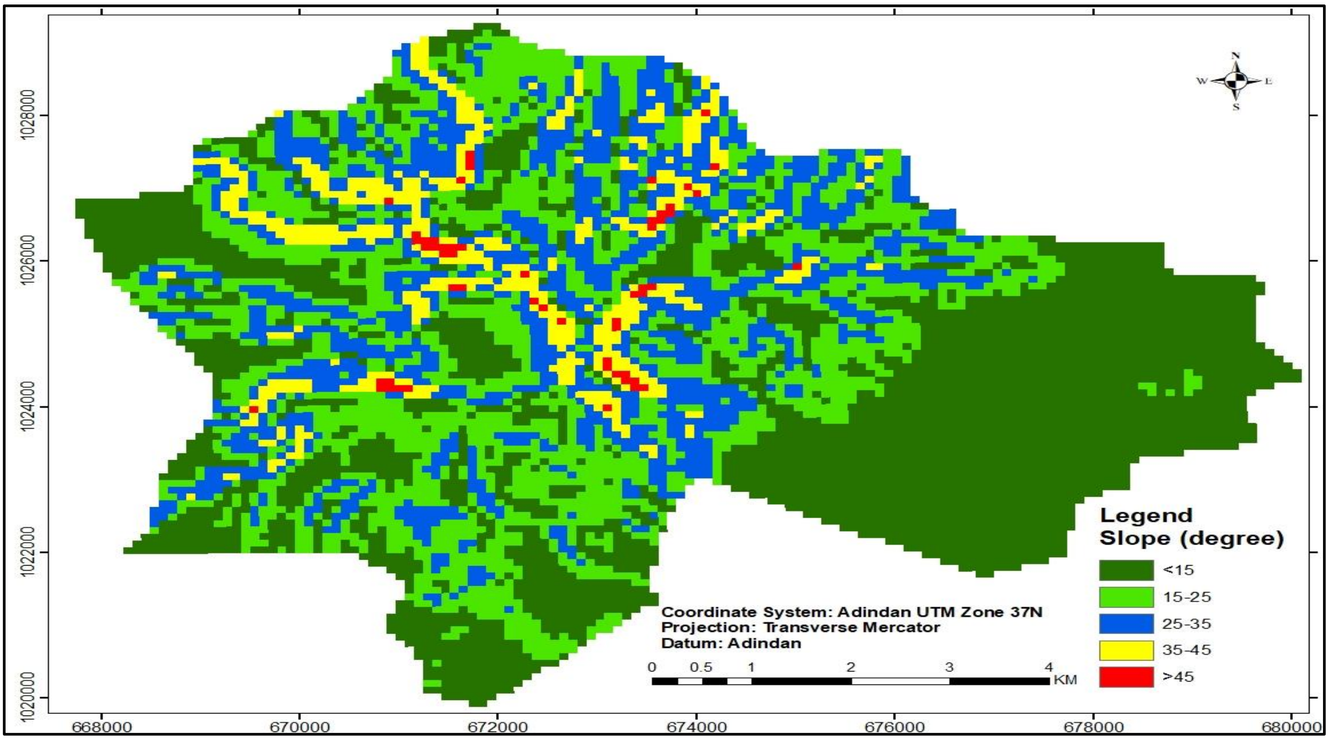

Fig 4.2: Re-classed slope map of the study area

4.1.3. Aspect

Based on the results of this investigation, the study area's aspect was categorized into five risk level classes. This includes the following areas: north (high), northeast (moderate), southeast and east (low), west, north-west, south-west, and flat (very high), and south (very low fire risk). Hence, Very high risk covers 35% , high risk for 14%, and moderate, low, and very low risk for 51% of the total area. (Fig 4.3 and Table 4.3).

Table 4.3: Fire risk level of aspects in the study area

No	**Aspect**	**Risk level**	**Area(Ha)**	**Area (%)**
1	W-NW-SW-FLAT	Very high	2353.509	35.000
2	N	High	941.404	14.000
3	NE	Moderate	941.404	14.000
4	SE-E	Low	1681.078	25.000
5	S	Very low	806.917	12.000
	Sum		**6724.312**	**100**

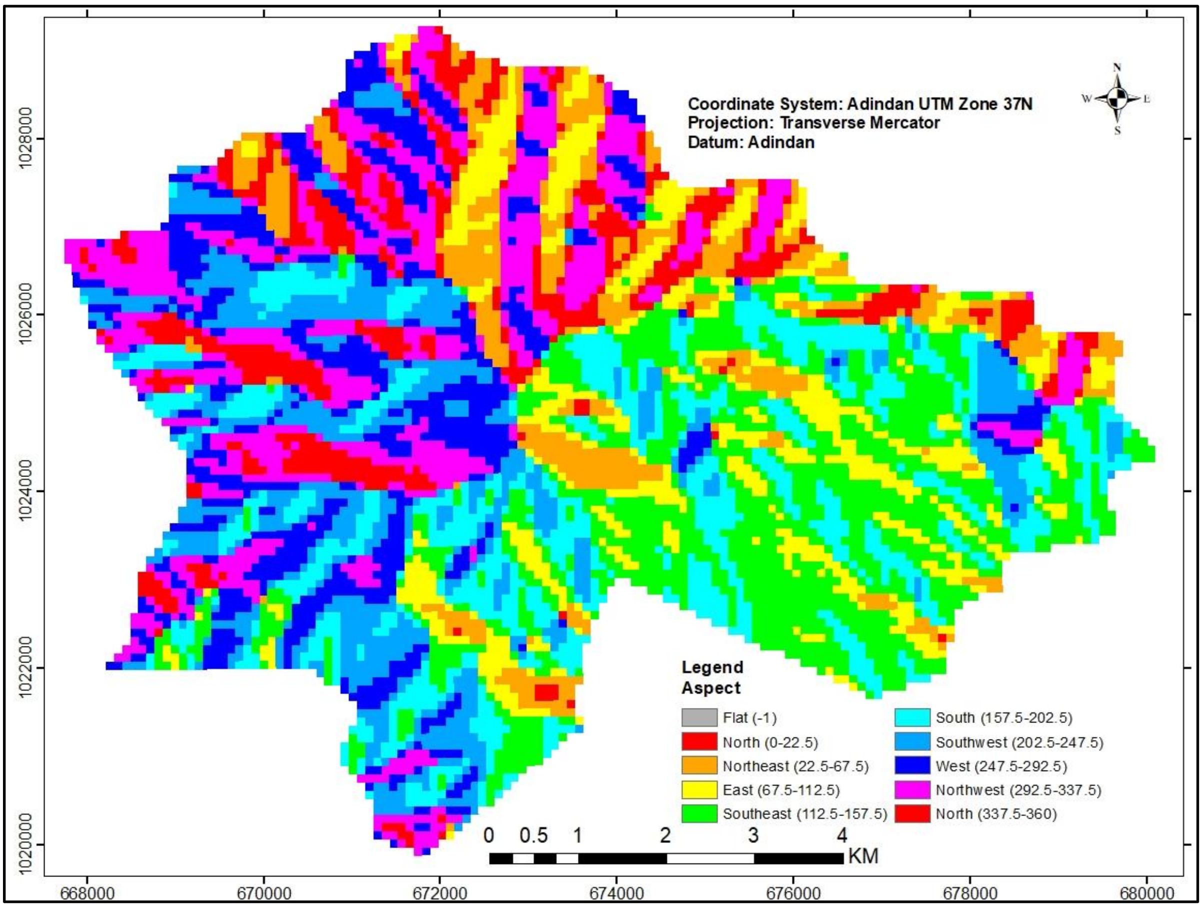

Fig 4.3: Aspect map of the study area

4.1.4. Topographic Wetness Index (TWI)

The TWI value reclassified into five categories (<2, 2-3, 3-4, 4-6, and >6), as Table 4.4 illustrates. A total of 2254.843Ha, or 33.534% of the study's area, have TWI values less than 2. The next highest fire risk level is associated with TWI values between 2-3, covering an area of 1924.306Ha or 28.614% of the total study area. The moderate fire risk level is associated with TWI values between 3-4, covering an area of 1531.868Ha or 22.782% of the total study area. The low fire risk level is associated with TWI values between 4-6, covering an area of 623.5064Ha or 9.273% of the total study area. The lowest fire risk level is associated with TWI values greater than 6, covering an area of 389.7883Ha or 5.797% of the total study area (Fig 4.4).

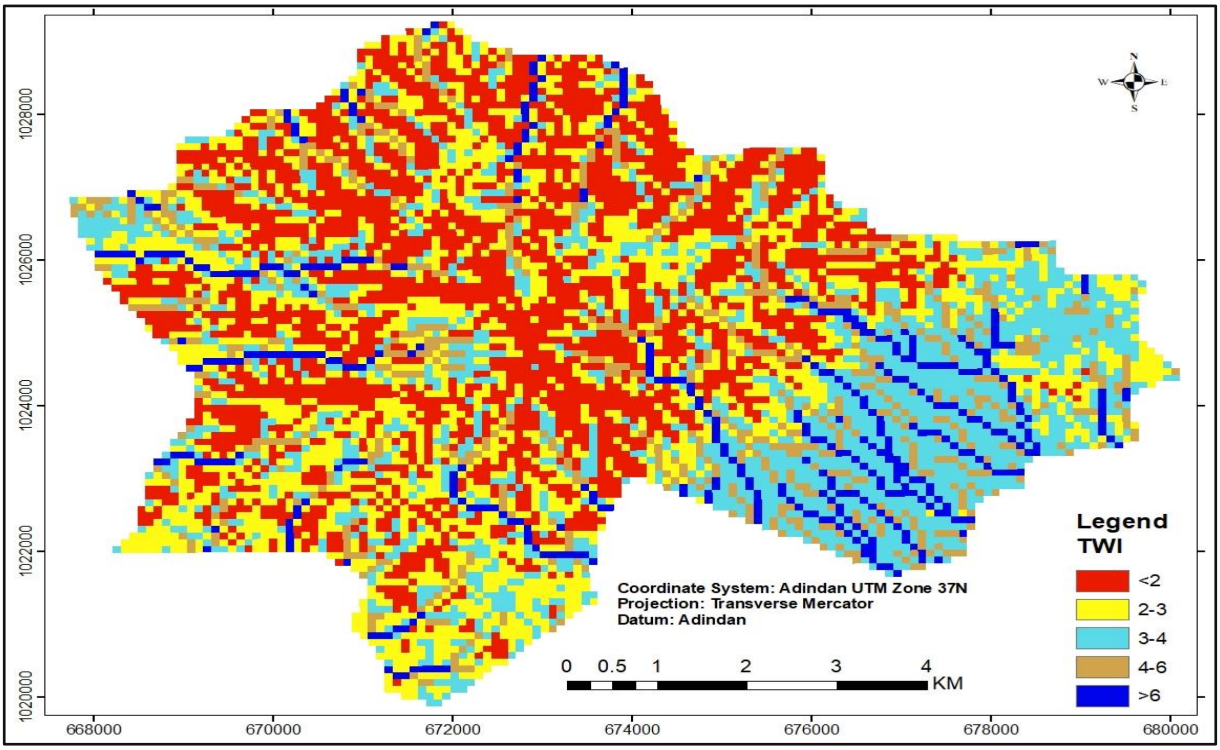

Fig 4.4: The topographic index map of the study area

Table 4.4: Topographic wetness index associated fire risk level

No	TWI	Risk level	Area (Ha)	Area (%)
1	<2	Very high	2254.843	33.534
2	2-3	High	1924.306	28.614
3	3-4	Moderate	1531.868	22.782
4	4-6	Low	623.5064	9.273
5	>6	Very low	389.7883	5.797
	Sum		**6724.312**	**100**

4.1.5. Road proximity

In the current study, the area proximity to the roads associated to risk level of fire was classified in to five that is, Very high (<300m), High (300-600m), Moderate (600-900m), Low (900-1200m), and Very low (>1200m). As indicated in (Fig 4.5), the very high, high, moderate and low risk level of fire covers 13.83%, 12.755%, 9.994% and 7.918% the total area of the study. The remaining risk level of fire covers 55.503% of the total area, which is the greatest coverage (Table 4.5).

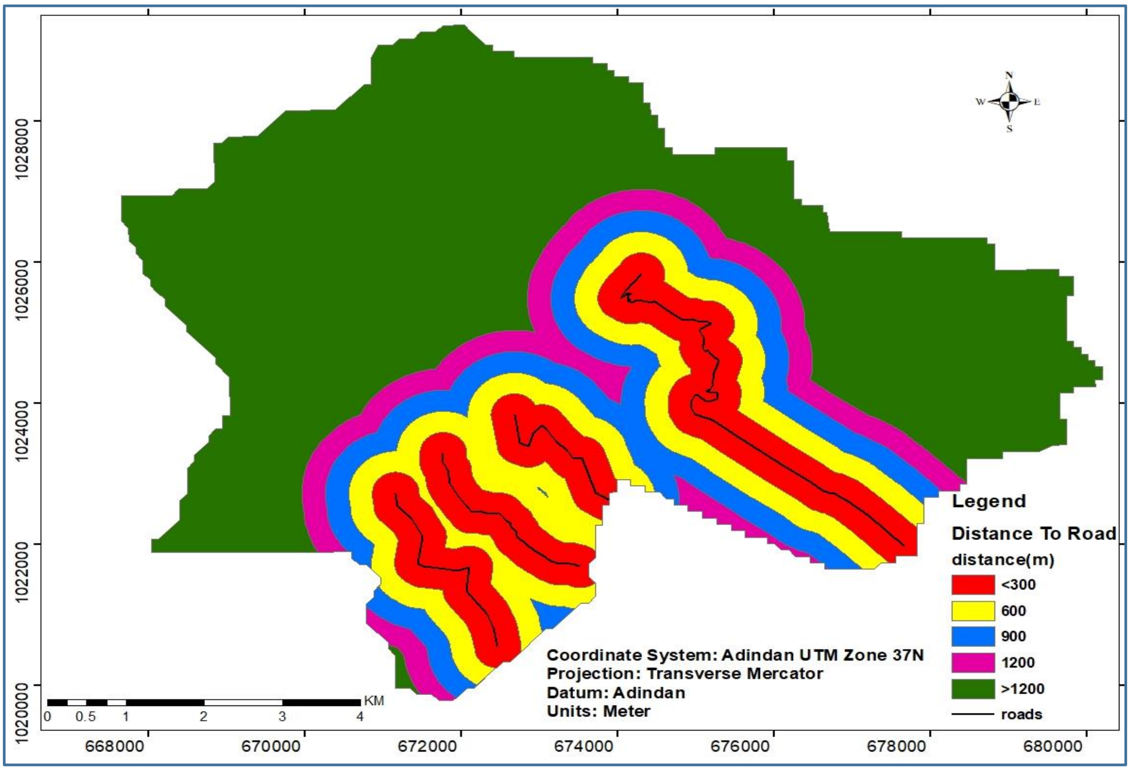

Fig 4.5: proximity map o of the study area

Table 4.5: proximity from the roads and risk level of the study area

No	Distance	Risk level	Area(Ha)	Area (%)
1	300	Very high	929.9426	13.830
2	600	High	857.6933	12.755
3	900	Moderate	672.0553	9.994
4	1200	Low	532.4569	7.918
5	8000	Very low	3732.164	55.503
SUM			**6724.312**	**100.000**

4.1.6. Settlements proximity

In the current study, the area proximity from settlement associated to risk level of fire was classified in to five similar to proximity to road that is, Very high (<400m), High (400-800m), Moderate (800-1200m), Low (1200-1600m), and Very low (>1600m). As indicated in (Fig 4.6), the very high, high, moderate and low risk level of fire covers 7.4%, 8.77%, 10.3% and 10.22% the total area of the study. The remaining risk level of fire covers 63.2949% of the total area, which is the greatest coverage (Table 4.6).

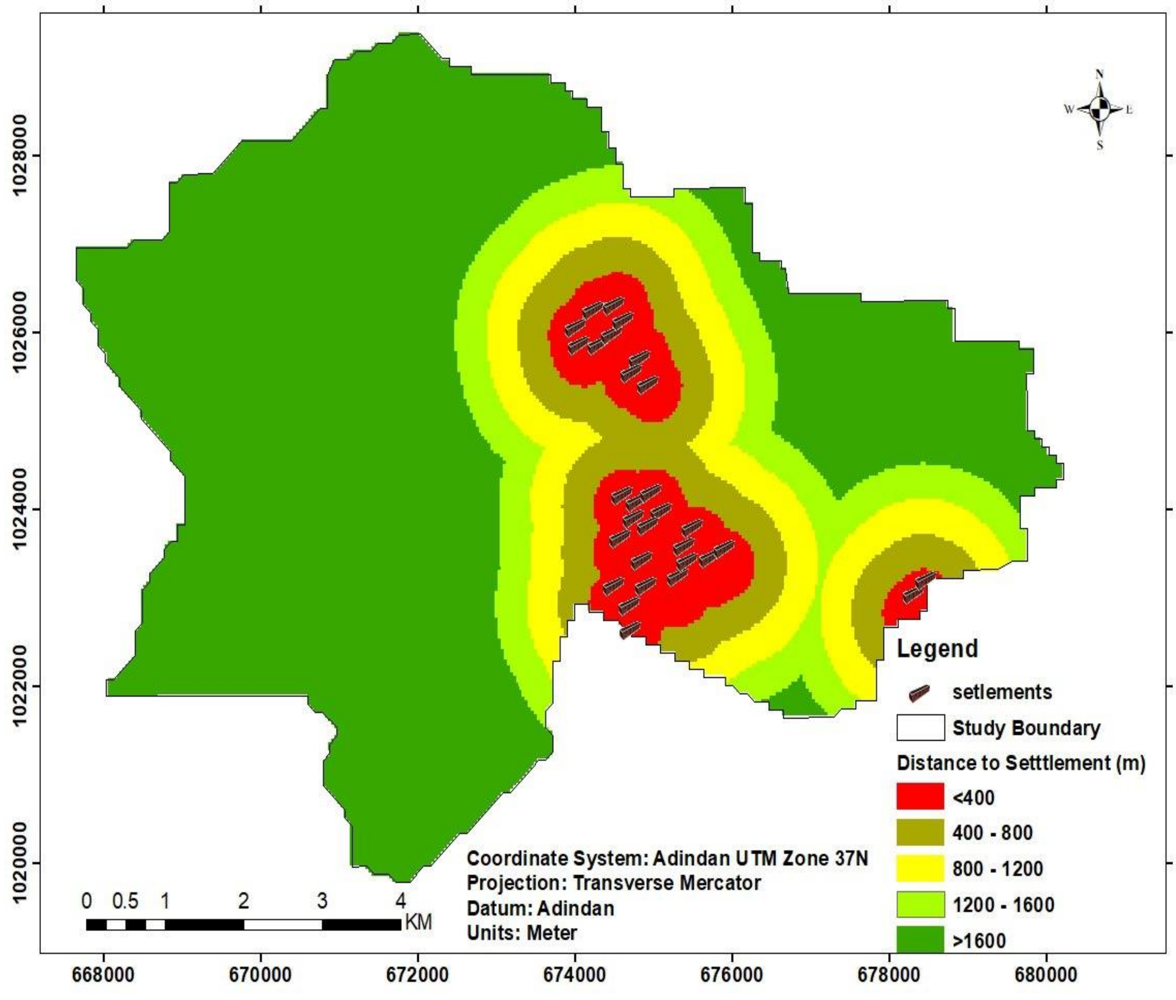

Fig 4.6: Settlement proximity map o of the study area

Table 4.6: proximity from the settlement and risk level of the study area

No	Distance from settlement(m)	Risk level	Area(Ha)	Area(Ha)
1	<400	Very high	497.9584	7.405344
2	800	High	589.7542	8.770477
3	1200	Moderate	692.9511	10.30516
4	1600	Low	687.5017	10.22412
5	>1600	Very low	4256.147	63.2949
Sum			**6724.312**	**100.000**

4.1.7. Wind speed

According to the study, the results of an analysis conducted on the speed, risk level, area, and percentage of different speed categories in a specific area. The findings shows that, Speed category <4 m/s corresponds to a very low risk level, covering an area of 35.572 hectares, 4-5 m/s is associated with a low risk level, encompassing an area of 2308.053 hectares, 5-6 m/s indicates a moderate risk level, occupying an area of 2382.356 hectares. Speed category 6-7 m/s is linked to a high risk level, covering an area of 1145.352 hectare and >7 m/s corresponds to a very high risk level, encompassing an area of 852.979 hectares of the total area (Table 4.7 and figure 4.7).

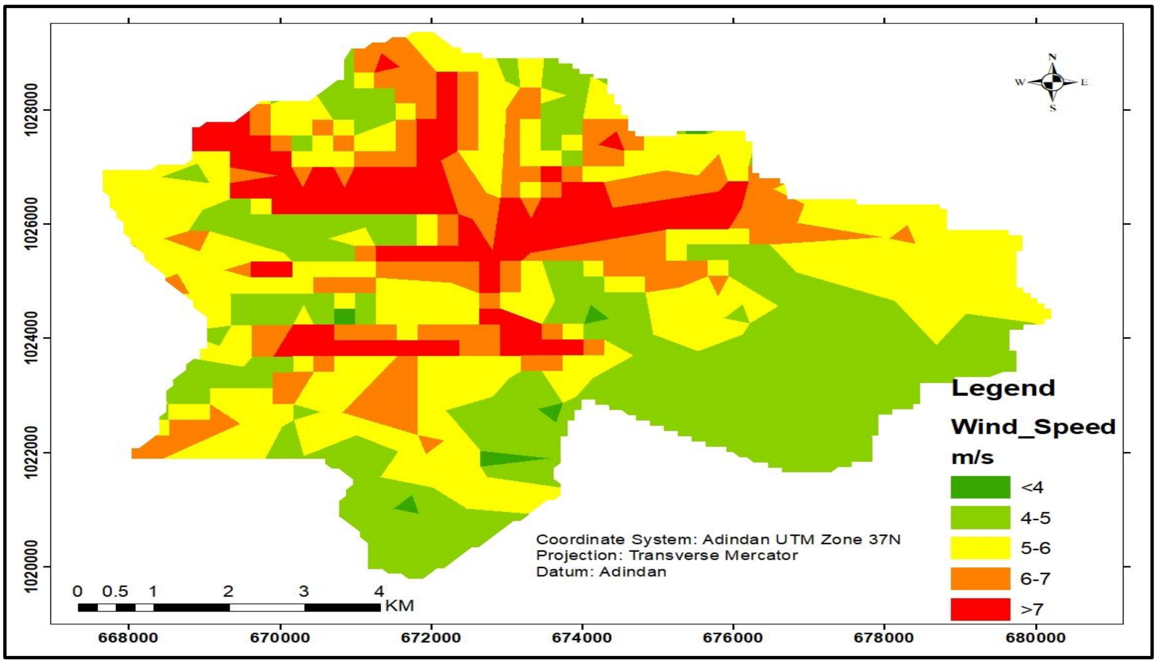

Fig 4.7: Wind Speed Map of the study area

Table 4. 7: wind speed and fire risk level of the study area

No	speed(m/s)	Risk level	Area(Ha)	Area (%)
1	<4	Very low	35.572	0.529
2	4-5	Low	2308.053	34.324
3	5-6	Moderate	2382.356	35.429
4	6-7	High	1145.352	17.033
5	>7	Very high	852.979	12.685
Sum			**6724.312**	**100**

4.1.8. Rainfall

According to the study, annual rainfall range of 12.559 to 15.0269 mm is classified as very high accounts for 16.213% of the total area; 15.0269 to 16.809 mm is classified as high risk accounting for 21.725% of the total area. Annual rainfall range of 16.809 to 18.463 mm, which is classified as moderate risk represents 21.817% of the total area. The rest low risk and very low risk covers 21.866% and 18.379% respectively (Table 4.8 and Fig 4.8).

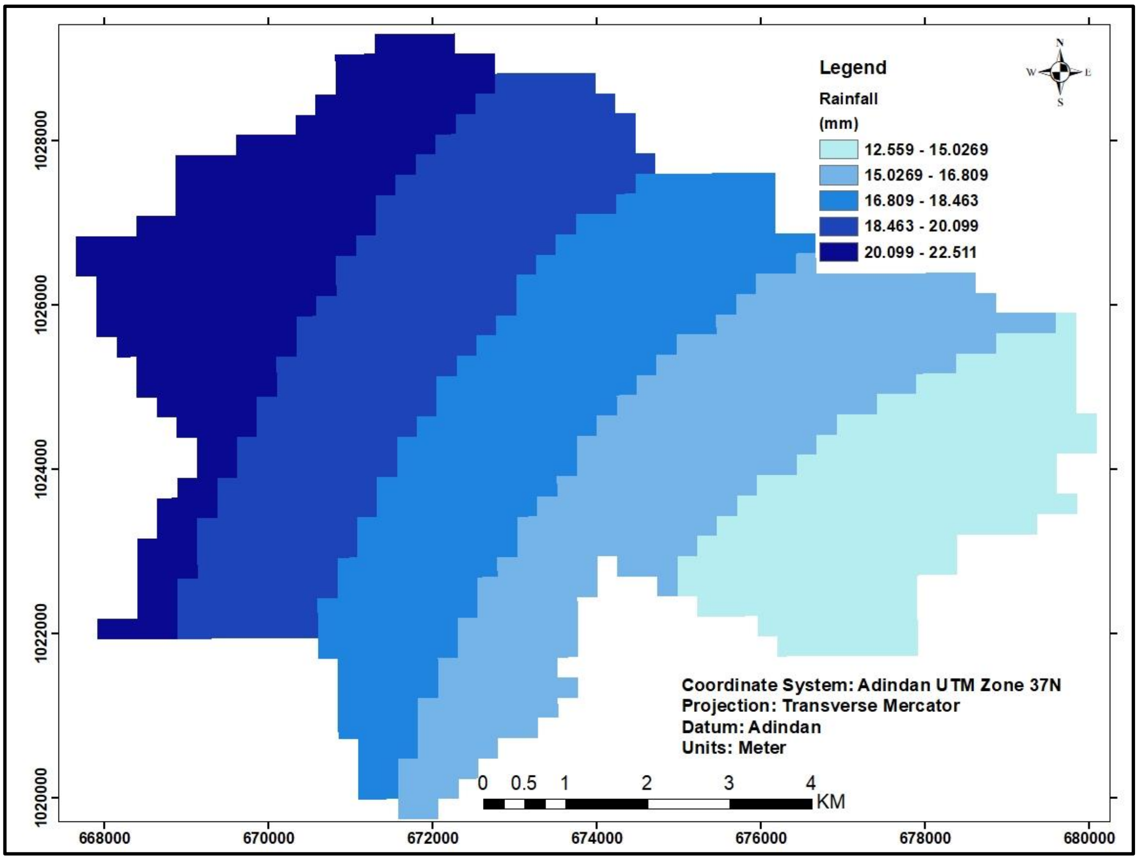

Fig 4.8: Annual rainfall map of the study area

Table 4.8: Annual Rainfall risk level and area coverage

No	Annual Rainfall (mm)	Risk level	Area(ha)	Area (%)
1	12.559 – 15.0269	Very high	1090.213	16.213
2	15.0269 – 16.809	High	1460.857	21.725
3	16.809 – 18.463	Moderate	1467.043	21.817
4	18.463 – 20.099	Low	1470.338	21.866
5	20.099 – 22.511	Very low	1235.861	18.379
SUM			**6724.312**	**100.000**

4.1.9. Land Surface Temperature (LST)

Land surface temperature has a significant influence on forest fires through its impact on climate. Understanding these interactions is crucial for effective forest fire management and prevention strategies. According to the current study, the land surface temperature of the study area was classed in to five risk level classes. That is, >40^{o}c (very high), 36-40 ^{o}c (high), 33-36 ^{o}c (moderate), 30-33 ^{o}c (low), and <30 ^{o}c (very low). From the total area very high risk covers 10.35%, high risk covers 30.293%, moderate, low and very low risk covers 26.095%, 19.656% and 13.606 % respectively (Fig 4.9 and Table 4.9).

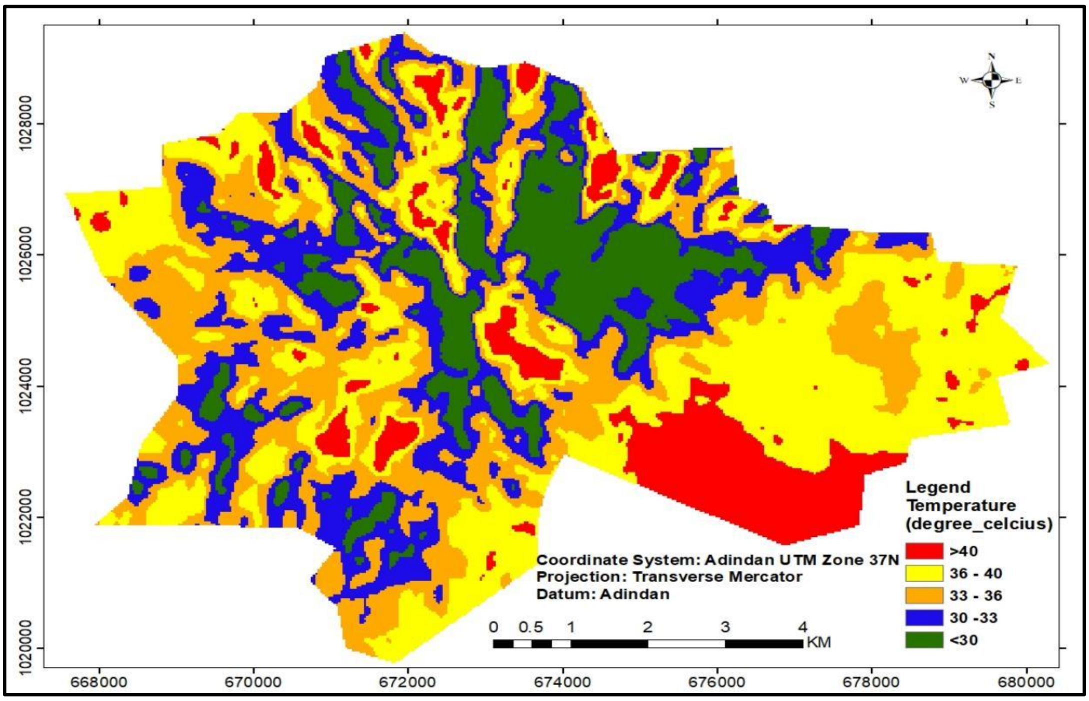

Fig 4.9: Land surface temperature of the study area

Table 4.9: land surface temperature of the study area

No	**LST(o_c)**	**Risk level**	**Area(Ha)**	**Area (%)**
1	>40	Very high	695.966	10.350
2	36-40	High	2036.996	30.293
3	33-36	Moderate	1754.709	26.095
4	30-33	Low	1321.731	19.656
5	<30	Very low	914.910	13.606
	Sum		**6724.312**	**100.000**

4.1.10. Normalized Difference Moisture (NDMI)

The Normalized Difference Moisture Index (NDMI) is commonly used to assess vegetation moisture content. It is particularly useful in monitoring and predicting forest fire risks. The result of the study shows that 55.157% of the area is very high fire risk zones (red color), high fire risk zone (yellow color) constitutes about 14.431%) and moderate fire risk zone covers 5.544%). The rest 6.265% and 18.603% of the park categorized under Low-risk and very low risk zone respectively (Fig. 4.10 and table 4.10).

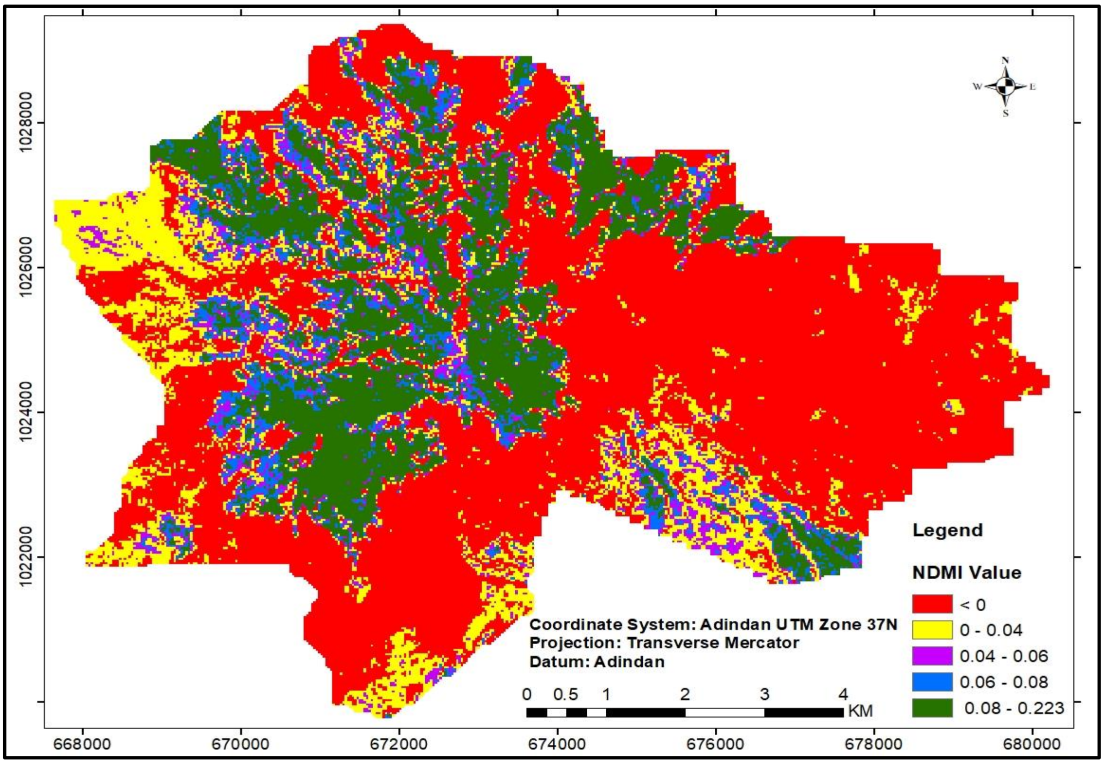

Fig 4.10: Normalized Difference Moisture Index (NDMI) map of the study area

Table 4.10: Normalized Difference Moisture Index (NDMI) risk level and area coverage

No	NDMI Value	Risk level	Area(Ha)	Area (%)
1	<0	Very high	3708.929	55.157
2	0-0.04	High	970.385	14.431
3	0.04-0.06	Moderate	372.796	5.544
4	0.06-0.08	Low	421.278	6.265
5	0.08-0.223	Very low	1250.924	18.603
Sum			6724.312	100.000

4.2. Estimate the burned area using Spectral Indices

4.2.1. Normalized Burn Ratio (NBR)

In the current study area, the value of calculated normalized burn ratio classified as five classes. The risk level of fire Very high (the value less than -0.06), High (-0.06 – 0.02), Moderate (0.02 – 0.1), Low (0.1 -0.18), and the value of NBR greater than 0.18 is Very low burn severity (Fig. 4.11). The findings of this study showed that the extent of burn severity as the very high, high, moderate, low and very low levels of fire extents covered 17.314%, 21.105%, 28.089% 25.644% and 7.848% respectively. From these results, it can be observed that the majority of the study area is classified as having moderate burn severity, covering approximately 28.089% of the total area. This is followed by areas with high burn severity, which cover approximately 21.105% of the study area. Furthermore, when combining the areas with very high and high burn severity, it is found that they collectively cover approximately 38.419% of the study area. These areas are represented by red and yellow colors on a map or visualization (Table 4.11 and Fig. 4.11).

Table 4.11: Fire detection using NBR and covered area of Asebot forest area

No	NBR Value	Risk level	Area (Ha)	Area (%)
1	<-0.06	Very high	1164.247	17.314
2	-0.06 – 0.02	High	1419.166	21.105
3	0.02 – 0.1	Moderate	1888.792	28.089
4	0.1 -0.18	Low	1724.383	25.644
5	>0.18	Very low	527.724	7.848
Sum			**6724.312**	**100.000**

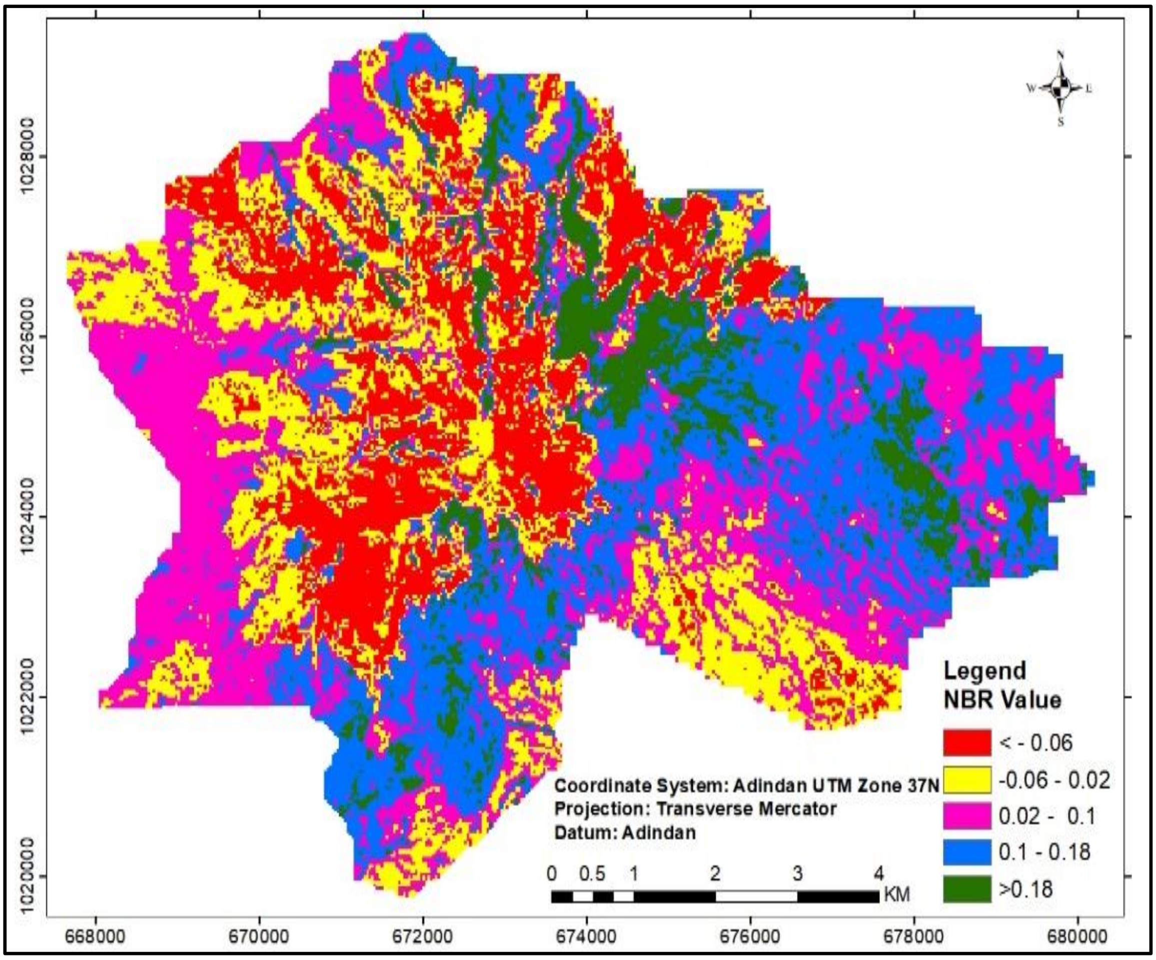

Fig 4.11:Re-classified Normalized Burn Ratio (NBR) map

4.2.2. Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index, or NDVI, is a commonly used method for monitoring and identifying potentially fire-prone areas in forests. As per the current research area, the study's results indicate that the very high, high, moderate, low, and very low levels of fire extents covered 22.869%, 29.408%, 24.631%, 18.295%, and 4.797%, respectively, in terms of burn severity. From the total of the study area, very high (red color) and high burn severity (yellow color) covered 52.277% (Table 4.12 and Fig. 4.12).

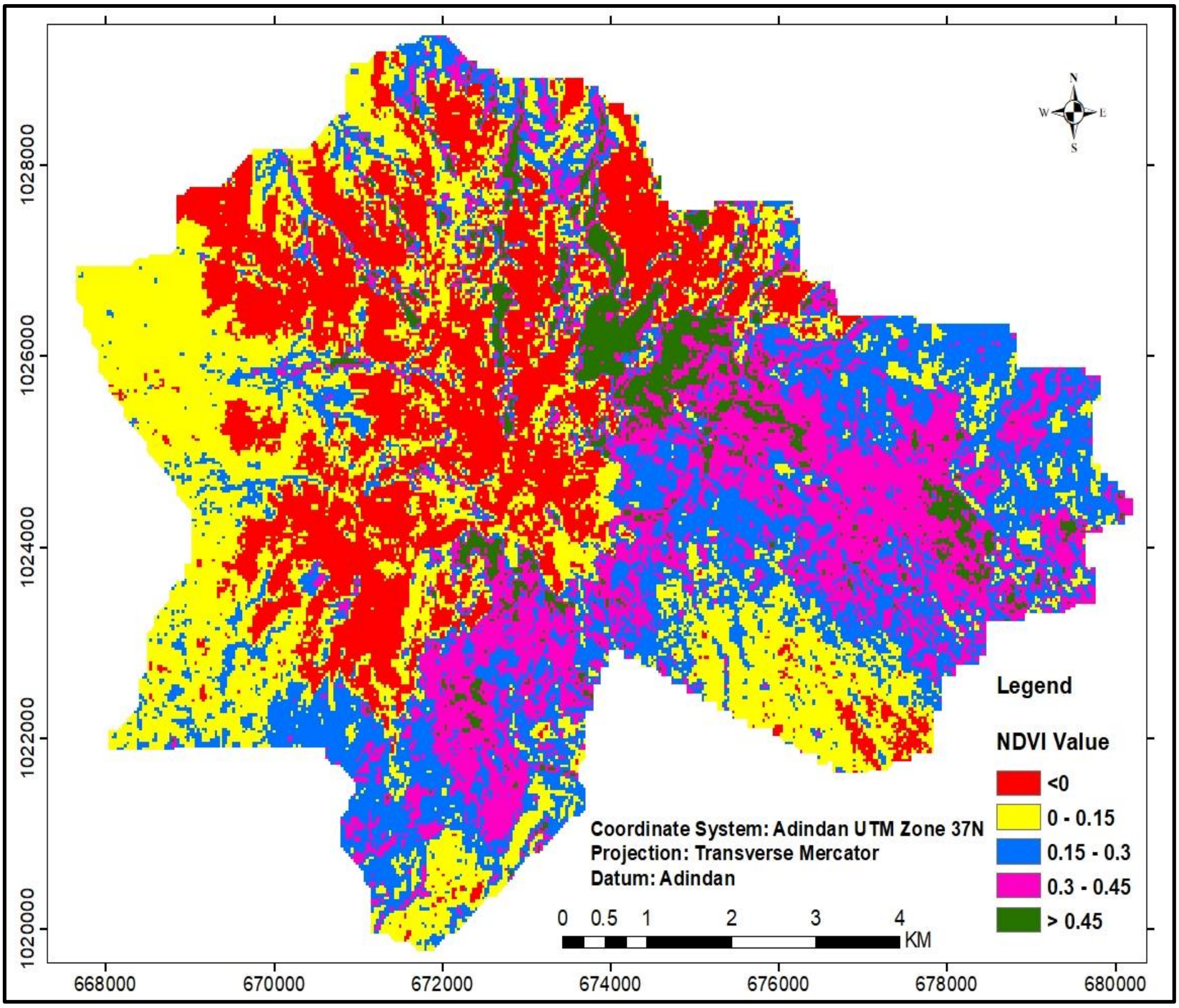

Fig 4.12: Re-classified Normalized difference vegetation index (NDVI) map

Table 4.12: Fire detection using NDVI and covered area of Asebot forest area

No	NDVI Value	Fire risk level	Area(Ha)	Area (%)
1	<0	Very high	1537.732	22.869
2	0 -0.15	High	1977.380	29.408
3	0.15 - 0.3	Moderate	1656.195	24.631
4	0.3 - 0.45	Low	1230.136	18.295
5	>0.45	Very low	322.556	4.797
Sum			**6723.999**	**100.000**

4.3. Modeling Forest Fire Susceptibility area of the study

The final forest fire risk model was created by overlaying the twelve dataset layers: Slope, Normalized Difference Vegetation Index (NDVI), Normalized Burn Ratio (NBR), Land Surface Temperature (LST), Normalized Difference Moisture Index (NDMI), Elevation, Rainfall, Aspect, Distance from Settlement, Wind Speed, Topographic Wetness Index (TWI), Dist. from Road. Thus, the final forest fire risk model indicated that the land is divided into three fire risk zones: very high (red color) covering 226.314 Ha (3.366%), high (orange color) covering approximately 1317.905 (19.599%), and moderate (yellow color) covering 2948.08 (43.842%). The remaining 1898.226 Ha (28.229%) and 333.791 Ha (4.964%) of the park categorized under Low-risk and very low risk zone respectively. Overall, the final forest fire risk model map shows that there are considerable regions that fall into the very high and high fire risk zones, covering about 1544.219Ha (22.965%) (Table 4.13). As indicated in the map, most of the central part of the study area is under very high and high level of fire risk (Fig 4.13).

Table 4.13: The final forest fire risk model of the study area

No	**Fire sensitivity**	**Area(Ha)**	**Area (%)**
1	Very low risk	333.791	4.964
2	Low risk	1898.226	28.229
3	Moderate risk	2948.080	43.842
4	High risk	1317.905	19.599
5	Very high risk	226.314	3.366
	Sum	**6724.315**	

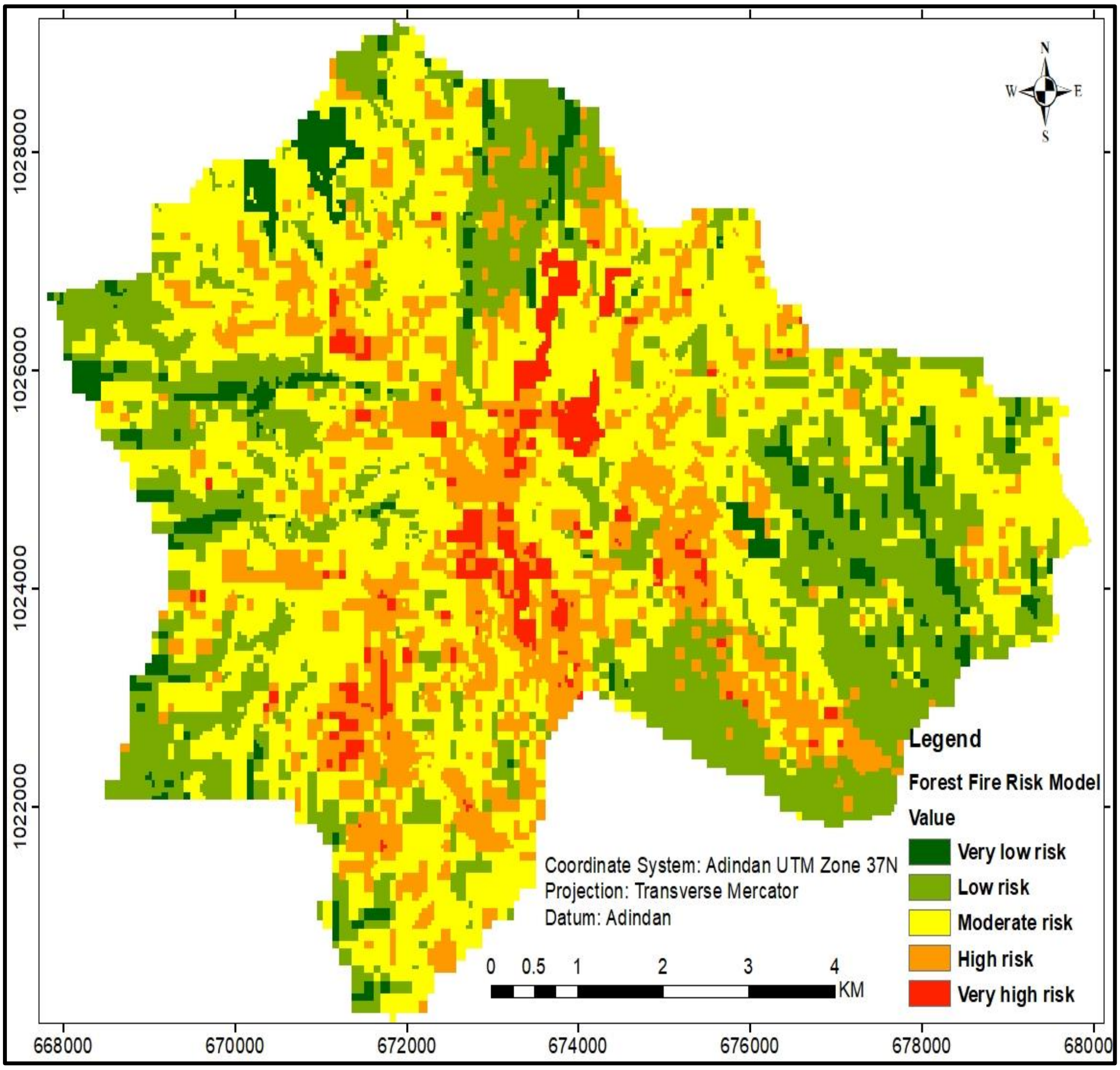

Fig 4.13: The final forest fire risk model map of the study area

4.4. Model Validation

The forest fire risk model of the study area was validated using 106 collected and used coordinate points on the previously burned areas. 91.51% of the 106 sample points fall within the first two forest fire danger zones, which are classified as very high and high-risk. Consequently, most of the points were overlapping with those areas under very high and high fire risk zones of the final risk model map. Therefore, it is possible to conclude that the model performance is very good and illustrative (Table 4.14).

No	Degree of fire risk	Validation points	Percent
1	Very high	49	46.23
2	High	48	45.28
3	Moderate	9	8.49
Total		106	100.00

Table 4.14: Distribution of validation points

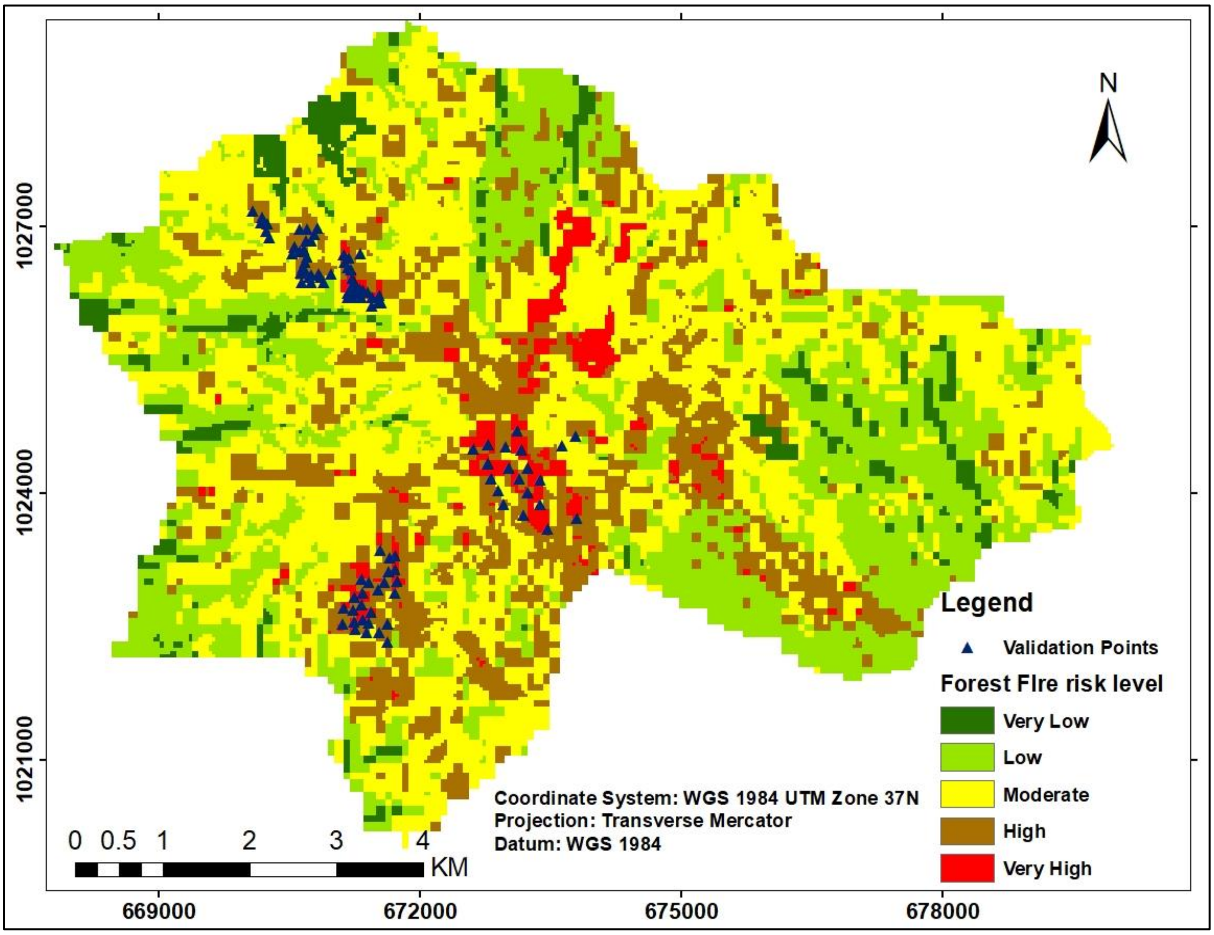

Fig 4.14: Validation model map of the study area

CHAPTER FIVE

5. DISCUSSION

As indicated in the findings of the current study, the identified influential factors of forest fires are topographic, meteorological and human activity factors. Topographic features such as slope, aspect, elevation and TWI can greatly influence the occurrence and behavior of forest fires. Steep slopes can accelerate the spread of fires due to increased wind speed and difficulty in accessing the affected areas. Similarly, aspects (the direction a slope faces) can affect fire behavior by influencing sun exposure and moisture levels. South-facing slopes tend to be drier and more susceptible to fire compared to north-facing slopes. The occurrence of forest fires is also influenced by elevation.

The likelihood of fires can be decreased since higher elevations often experience cooler temperatures and higher humidity. However, the climate may be drier at lower elevations, which increases the risk of fire ignition and spread. The current study's findings on the influential factors of forest fires are consistent with existing literature in several aspects. A number of studies have established the primary causes of forest fires are topographic, meteorological, and human activity.

Geographical features like elevation slope, aspect, and TWI have been identified as influencing factors because they increase the likelihood of a fire occurring (Zhao et al., 2021). Uphill movement of fire is fastest, while downhill movement is slowest (Kanga et al., 2012). Furthermore, the occurrence and spread of wildfires are significantly influenced by the topographic moisture index. While it is harder to start fires in moist environments, dry places are more likely to catch fire and do so quickly (Zhao et al., 2021). Agee et al. (2001) conducted one of the most comprehensive reviews of forest fire causes, and identified topographic, meteorological, and human factors as the main causes of forest fires. They found that topographic factors such as slope, aspect, and elevation contribute to the likelihood and severity of forest fires, especially in areas with complex terrain. Similarly, the current study found that topographic factors were significant predictors of forest fire occurrence.

Meteorological factors, such as temperature, humidity, and wind, have also been identified as important causes of forest fires in existing literature. For example, a study by Lawson et al. (2015), found that high temperatures, low humidity, and strong winds were associated with an increased risk of forest fires in the western United States.

The current study also found that meteorological factors were significant predictors of forest fire occurrence. Existing literature has also identified human activity factors as significant forest fire causes, including land use practices and human-caused ignition sources. For example, a study by Bradshaw et al. (2017) found that human-caused ignition sources, such as arson and unattended campfires, were responsible for the majority of forest fires in a region of Australia. The current study also found that human activity factors were significant predictors of forest fire occurrence.

Human activities have a significant impact on forest fire occurrence. These factors include both intentional and unintentional actions by humans. The affected area is higher than roads because of the frequent activities of the residents in the populated areas (Zhao et al., 2021). The majority of forest fires are caused by human activity, such as people throwing cigarettes or leftover fires after sacrifices (Eugenio et al., 2016). Human activity in populated areas or destinations for tourists can produce fire sources that start forest fires (Tien Bui et al., 2016). Most forest fires are related to human behavior, cigarette butts thrown by people, or residual fires from sacrifices may cause forest fires (Eugenio et al., 2016). Human activity is a major source of fire sources that start forest fires in populated areas and tourist spots (Tien Bui et al., 2016). Thus, it is possible to consider populated areas and roads to be igniting factors. The affected area is higher than roads because of the frequent activities of the population in the crowded areas (Zhao et al., 2021).

The result showed that a significant area is under high fire severity. Therefore, this study helps to decrease forest fire risk in the future and to monitor post-fire management by identifying the hotspot area. In the current study, NDVI (Normalized Difference Vegetation Index) and NBR (Normalized Burn Ratio) are two commonly used remote sensing indices for estimating burn severity in vegetation. The study found that approximately 38.419% of the area had very high and high burn severity, as classified by the Normalized Burn Ratio (NBR) index. The NBR values were categorized into five classes: Very low, Low, Moderate, High, and Very high burn severity. The findings of this study have important implications for fire management and ecosystem conservation in the study area.

The identification of areas with severe fire damage can inform strategies for fire suppression and restoration, as well as the development of management plans to mitigate the impacts of future fires.

To identify and model specific areas within the study area that are potentially at risk of forest fires, the researcher employs various factors to produce forest fire risk models by overlaying layers of twelve factors. These factors are Slope, normalized difference vegetation index (NDVI), normalized burn ratio (NBR), land surface temperature (LST), normalized difference moisture index (NDMI), Elevation, Rainfall, Aspect, distance from Settlement, Wind speed, topographic wetness index (TWI), and Distance from road were overlaid to create the final forest fire risk model.

The study reveals that most of the central part of the study area is particularly prone to very high and high levels of fire risk. This concentration of high-risk zones in the central region suggests a potential hotspot for forest fires and emphasizes the need for targeted preventive measures and management strategies in this area. To model the fire risk area, the researchers in several study areas used these factors. Suryabhagavan et al., (2016b), employ Slope, Aspect, Elevation, Settlement proximity and Road proximity to producing fire risk models by giving weights high to low respectively for each layers. Moreover, to produce forest fire risk model, Tiwari et al. (2021) was used Slope, NDVI, Temperature, Elevation, Aspect, and distance to settlement, distance to road, NDMI, TWI, Rainfall and Wind speed. Accordingly, the current study also used the above listed factors to perform the forest fire risk model.

CHAPTER SIX

6. CONCLUSION AND RECOMMENDATION

6.1.CONCLUSION

This study developed a forest fire susceptibility model using 12 factors, including topographical, spectral, climate, and human activity factors. These factors were chosen based on their potential impact on forest fire risk and their availability in satellite imagery. Forest fires can be more likely to occur in areas with steep slopes due to the increased risk of debris accumulation and the difficulty of accessing the area. Higher elevations can also have colder temperatures and lower humidity, making forests more susceptible to fires.

Additionally, certain slope aspects, such as west, north-west, south-west, and flat facing slopes, tend to be drier and warmer, increasing the risk of forest fires. Moreover, factors such as low moisture content in soil and vegetation (indicated by low NDMI values), high land surface temperatures (LST), strong wind speeds, low rainfall levels, and proximity to settlements and roads all contribute to an increased risk of forest fires.

The research conducted in this study aimed to estimate post-fire degradation by using post-fire satellite images based on NDVI and NBR values. The findings indicate that a significant portion of the study area is at high or very high risk of fire outbreaks, with limited vegetation cover. On the other hand, there are also areas with moderate, low, and very low fire risk levels, characterized by varying degrees of vegetation density.

Remote sensing techniques play a vital role in monitoring and detecting forest fires. In the current study, both NDVI and NBR are used to detect forest fires. For identifying areas with healthy vegetation and assessing changes in vegetation density over time, NDVI is a better approach. It can be used to monitor vegetation health before and after a fire, providing information on the recovery process. However, NBR is made expressly to identify burned areas to assess the severity of fires. It is more sensitive to changes in burned vegetation and can provide a more accurate estimation of fire-affected areas. Both NDVI and NBR are useful for monitoring forest fires, but they have different strengths and limitations. NDVI is better suited for monitoring vegetation health and changes in vegetation density, while NBR is more sensitive to changes in burned vegetation and provides a more accurate estimation of fire-affected areas. Our understanding of the effects of forest fires and the recovery process can be expanded by integrating the two indexes.

The current study provides an overview of fire sensitivity areas categorized into five levels of risk: very low risk, low risk, moderate risk, high risk, and very high risk. The analysis indicates that a significant portion of the studied region falls under moderate-risk areas, while very low-risk and low-risk areas cover smaller proportions. High-risk and very high-risk areas have relatively smaller coverage but pose higher susceptibility to fire incidents. The significance of this study lies in its ability to provide a quantitative assessment of fire sensitivity areas, allowing stakeholders to make informed decisions regarding fire management strategies, land use planning, and ecological conservation efforts. By categorizing areas into different risk levels based on their size and percentage coverage, this study provides a comprehensive overview of the spatial distribution of fire sensitivity across the studied region. Continuous monitoring and analysis of fire sensitivity areas over an extended period are essential for assessing changes in risk levels.

Future research should focus on establishing long-term monitoring programs to track changes in vegetation composition, climate conditions, land use patterns, and fire occurrence rates. This will enable us to detect trends and patterns that may influence fire sensitivity over time and provide valuable insights for adaptive management strategies.

6.2. RECOMMENDATION

According to the research findings of the analysis, the following recommendations are forwarded to overcome the existing problems.

- Implement effective forest management practices: It is crucial to prioritize forest management practices in areas with steep slopes to reduce the risk of debris accumulation. Regular clearing of dead vegetation and debris can help minimize fuel sources for fires.
- Promote community awareness and preparedness: Educating local communities about the risks associated with forest fires is essential. Encouraging responsible behavior such as proper disposal of cigarette butts and campfire safety practices can significantly reduce the likelihood of accidental fires. Additionally, establishing community-based fire prevention programs and training residents in fire suppression techniques can enhance preparedness and response capabilities.
- Implement targeted fire management strategies: A significant portion of the study area is at high or very high risk of fire outbreaks with limited vegetation cover, it is crucial to implement targeted fire management strategies. This could include measures such as controlled burns, fuel reduction treatments, and creating defensible spaces around vulnerable areas. By proactively managing fire-prone areas, the risk of large-scale wildfires can be minimized, and the ecosystem's resilience can be enhanced.
- Enhance monitoring and early warning systems: To manage effectively fire risks, it is essential to establish robust monitoring and early warning systems. By regularly assessing changes in vegetation cover and identifying areas prone to fire outbreaks, authorities can take timely actions such as deploying firefighting resources, issuing warnings to communities at risk, and implementing preventive measures.
- Invest in research and technology for fire risk assessment: To manage effectively fire sensitivity areas, continuous research and technological advancements are necessary. Investing in GIS and advanced remote sensing technologies, satellite imagery analysis, and predictive modeling can provide valuable understanding to identify vulnerable areas and predict fire behavior.

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Appendix

Appendix 1: forest fire of the study area during 2021.

Source: https://www.youtube.com/watch?v=ghsIaPGRNF8

Appendix 2: Forest fire of the study area during 2021 at the nighttime.

Source: https://borkena.com/2021/03/24/asebot-monastery-experienced-another-fire-accident/

Appendix3: post fire degradation of the study area

Source: Worku, A., & Zewdie, W. (2008). *The 2008 Fire incidence in Asebot forest: Cause, impact and its implication for sustainable management of the ever-fragmented dry Afromontane forests in Ethiopia*.

Appendix 4: Model validation GPS points collected in the study area

ID	**X**	**Y**	**Risk**		ID	X	Y	Risk
1	671413.3	1022541.04	Very High		63	670680.3	1026599.65	High
2	671337.1	1022585.49	Very High		64	670634	1026477.28	High
3	671260.9	1022471.19	Very High		65	670640.6	1026374.75	High
4	671394.3	1022439.44	Very High		66	670756.4	1026371.44	High
5	671527.6	1022439.44	High		67	670862.2	1026437.59	High
6	671622.9	1022325.14	High		68	670895.3	1026378.06	High
7	671622.9	1022528.34	Moderate		69	670978	1026467.35	High
8	671438.7	1022661.69	High		70	670832.5	1026467.35	High
9	671241.9	1022560.09	High		71	670756.4	1026464.05	High
10	671108.5	1022534.69	High		72	670683.6	1026503.73	High
11	671330.8	1022750.59	Very High		73	670660.5	1026543.42	High
12	671229.2	1022693.44	Very High		74	670700.2	1026659.18	High
13	671127.6	1022712.49	Moderate		75	670538.1	1026695.56	High
14	671241.9	1022839.49	Very High		76	670696.9	1026847.69	High
15	671337.1	1022877.59	High		77	670706.8	1026973.37	High
16	671407	1022998.24	Very high		78	670789.5	1026910.53	High
17	671330.8	1023042.69	Very high		79	670614.2	1026970.06	High
18	671521.3	1022915.69	Very High		80	670190.9	1027112.28	High
19	671718.1	1022877.59	Very High		81	670075.1	1027175.12	High
20	671730.8	1023010.94	Very high		82	670180.9	1027042.82	High
21	671718.1	1023144.29	Very high		83	670233.8	1026950.22	High
22	671718.1	1023296.69	Very high		84	670273.5	1026877.46	High
23	671648.3	1023277.64	High		85	671315.3	1026695.56	High
24	671641.9	1023125.24	High		86	671212.8	1026520.27	High
25	671231.3	1022998.24	Moderate		87	671226	1026417.74	High
26	671540.3	1023366.54	Very high		88	671229.3	1026298.68	Very high
27	673461.2	1023602.55	Very high		89	671295.5	1026249.07	Very high
28	673381.8	1023880.36	Very high		90	671232.7	1026206.08	Very high
29	673381.8	1024158.17	Very high		91	671166.5	1026258.99	Very high
30	672813	1024171.4	Very high		92	671166.5	1026209.39	Very high

31	672786.5	1024555.05	Very high		93	671222.7	1026255.69	Very high
32	672614.5	1024502.13	Very high		94	671325.3	1026209.39	Very high
33	673170.2	1024488.9	Very high		95	671341.8	1026285.45	Very high
34	673117.3	1024700.57	Very high		96	671272.3	1026328.45	Very high
35	673805.2	1023721.61	Very high		97	671236	1026358.21	Very high
36	673236.3	1024012.65	High		98	671523.7	1026146.55	Very high
37	673183.4	1023761.3	High		99	671536.9	1026235.84	Very high
38	672958.5	1023880.36	Moderate		100	671560.1	1026146.55	Very High
39	673143.7	1024171.4	Moderate		101	671444.3	1026113.47	Very High
40	673633.2	1024541.82	Moderate		102	671444.3	1026206.08	High
41	673791.9	1024647.65	High		103	671394.7	1026262.3	High
42	673024.7	1024290.46	Moderate		104	671302.1	1026308.6	Very High
43	672813	1024171.4	Very high		105	671136.7	1026599.65	Very High
44	672786.5	1024330.15	Very high		106	671176.4	1026546.73	High
45	672786.5	1024330.15	Very high					
46	673024.7	1024290.46	Moderate					
47	673236.3	1024290.46	Very high					
48	673236.3	1024012.65	High					
49	672905.6	1024039.11	Moderate					
50	672786.5	1024330.15	Very high					
51	673170.2	1024488.9	Very high					
52	672985	1024528.59	High					
53	672786.5	1024555.05	Very high					
54	670724.5	1026437.52	High					
55	670559.1	1026768.25	High					
56	670823.7	1026983.22	High					
57	670559.1	1026768.25	High					
58	670559.1	1026768.25	High					
59	670244.9	1027032.83	High					
60	670749.8	1026847.69	High					
61	670670.4	1026745.17	High					
62	670617.5	1026722.02	High					