FOREST FIRE RISK MAPPING USING GEOGRAPHIC INFORMATION SYSTEM AND ANALYTIC HIERARCHY PROCESS IN RASUWA DISTRICT, NEPAL

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DECLARATION

I hereby declare that the thesis presented herein is based on the original research and the thesis has not been published or submitted elsewhere for the requirement of any other degree program. Any literature and data cited within this dissertation have been given due acknowledgment and listed in the reference section.

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Sudeep Jogi Kanwar

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This research report entitled "**FOREST FIRE RISK MAPPING USING GEOGRAPHIC INFORMATION SYSTEM AND ANALYTIC HIERARCHY PROCESS IN RASUWA DISTRICT, NEPAL**" prepared and submitted by Mr. Sudeep Jogi Kanwar, under Learning Entrepreneurial Experience Program as an integral part of Bachelor of Science in Forestry.

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LETTER OF ACCEPTANCE

This is to certify that this project paper report entitled, **"FOREST FIRE RISK MAPPING USING GEOGRAPHIC INFORMATION SYSTEM AND ANALYTIC HIERARCHY PROCESS IN RASUWA DISTRICT, NEPAL"** submitted in partial fulfillment for the award of the degree of Bachelor of Science in Forestry to Faculty of Forestry, Agriculture and Forestry University is a record of real field and social based research work carried out by **Mr. Sudeep Jogi Kanwar** under my guidance and supervision. No part of this research report has been submitted for any other degree or diploma. The assistance received by him during the course of the investigation has been fully acknowledged.

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LETTER OF ACCEPTANCE

This is to certify that **Mr. Sudeep Jogi Kanwar**, B.Sc. Forestry final year (2075-2079) student at Agriculture and Forestry University, Faculty of Forestry, Hetauda has prepared the LEE report entitled **"Forest Fire Risk Mapping using Geographic Information System and Analytic Hierarchy Process in Rasuwa District, Nepal"** under my supervision. This entire work is based on the fieldwork performed by the candidate and this work brings out useful findings in the concerned field.

I congratulate him for the success.

…………………………..

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Sincerely,
Sudeep Jogi Kanwar

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ABBREVIATIONS

%	Percentage
AHP	Analytic Hierarchy Process
AUC	Area Under Curve
DFO	District Forest Office
FAO	Food and Agricultural Organization
FFRI	Forest Fire Risk Index
FIRMS	Fire Information for Resource Management System
FR	Frequency Ratio
GIS	Geographic Information System
GPS	Global Positioning System
ICIMOD	International Centre for Integrated Mountain Development
LP DAAC	Land Processes Distributed Active Archive Center
LST	Land Surface Temperature
MCDM	Multi-Criteria Decision-Making
MCD45	MODIS Combined Data
MFSC	Ministry of Forest and Soil Conservation
MODIS	Moderate Resolution Imaging Space Spectro-radiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
ROC	Receiver Operating Characteristic
TWI	Topographic Wetness Index
UN OCHA	United Nations Office for the Coordination of Humanitarian Affairs
USGS	United States Geological Survey

UTM	Universal Transversal Mercator
VIIRS	Visible Infrared Imaging Radiometer Suite
WGS	World Geodetic System

ABSTRACT

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Forest fire is one of the leading causes of forest degradation in high mountain environments. Forest fires are common near anthropogenic areas; about 80% of fire events occurred in Rasuwa district from January to April. The rugged topography makes forest fire control actions in the High Mountains extremely tough. In this work, we used GIS and the AHP approach to predict the forest fire risk in Rasuwa district. The forest fire risk index model was created by combining abiotic and biotic factors such as Land Use Land Cover, Land Surface Temperature, Slope, Aspect, Elevation, Distance from Road, and Distance from Settlement utilizing the AHP approach. This study validated the developed AHP model and forest fire risk map. The results revealed that 20.49%, 68.15%, and 11.36% of historical fire incidents occurred at very high, high, and medium risk, encompassing an area of about 7.27%, 44.79%, and 21.35% respectively. The consistency ratio was 0.07, indicating that the created AHP model was valid, and the Area Under Curve value was 0.867, indicating that the generated forest fire risk map was acceptable. The produced forest fire risk index model could be utilized in similar study areas, and the Division Forest Office, Rasuwa, Langtang National Park, and other concerned stakeholders could use the risk map for prioritizing, preparedness, and resource allocation for fire management and mitigation.

Keywords: GIS, AHP, forest fire, fire risk zone, Land Use Land Cover

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Asst. Prof. Ramesh Silwal Sudeep Jogi Kanwa

Major Advisor Author

शोध सार

नाम: सुदिप जोगी कवँर दर्ता नम्बर: ३-१-१२८-२०१८

सेमी र वर्ष भर्ना: पहिलो, २०१८ डिग्री: स्नातक वन विज्ञान

प्रमुख सल्लाहकार: उप प्राध्यापक रमेश सिलवाल

उच्च पहाडी वातावरणमा वन विनाशको प्रमुख कारण वन डढेलो हो। मानविय क्षेत्रहरू नजिक वन आगो सामान्य छ; रसुवा जिल्लामा गत जनवरीदेखि अप्रिलसम्म आगलागीका ८० प्रतिशत घटना भएका छन् । असहज भुगोलले उच्च पहाडहरूमा वन आगो नियन्त्रण कार्यहरू अत्यन्तै कठिन बनाउँछ। यस कार्यमा, हामीले रसुवा जिल्लाको जंगलमा आगलागीको जोखिम अनुमान गर्न भौगोलिक सूचना प्रणाली र विश्लेषणात्मक उत्तराधिकारी प्रक्रिया दृष्टिकोण प्रयोग गरेका छौं। वन डढेलो जोखिम सूचकांक मोडेल अजैविक र जैविक कारकहरू जस्तै भूमि उपयोग भूमि आवरण, भूमिको सतहको तापक्रम, ढलान, पक्ष, उचाइ, सडकबाट दूरी, र बस्तीबाट दूरीको गतिलाई संयोजन गरेर विश्लेषणात्मक उत्तराधिकारी प्रक्रिया दृष्टिकोण प्रयोग गर्दै सिर्जना गरिएको थियो। यस अध्ययनले विकसित विश्लेषणात्मक उत्तराधिकारी प्रक्रिया मोडेल र वन आगो जोखिम नक्सा प्रमाणित गर्यो। यस अध्ययनको नतिजा अनुसार २०.४९%, ६८.१५%, र ११.३६% ऐतिहासिक आगलागी घटनाहरू अत्यन्तै उच्च, उच्च र मध्यम जोखिममा भएका छन्, जसमा क्रमशः ७.२७%, ४४.७९%, र २१.३५% क्षेत्र समेटिएको छ। स्थिरता अनुपात ०.०७ थियो, जसले सिर्जना गरिएको विश्लेषणात्मक उत्तराधिकारी प्रक्रिया मोडेल मान्य थियो भनेर सङ्केत गर्‍यो, र वक्र अन्तर्गत क्षेत्र मान ०.८६७ थियो, जसले उत्पन्न गरिएको वन आगलागी जोखिम नक्सा स्वीकार्य छ भनी संकेत गर्दछ। उत्पादित वन आगलागी जोखिम सूचकाङ्क मोडेललाई समान अध्ययन क्षेत्रमा प्रयोग गर्न सकिनेछ र डिभिजन वन कार्यालय, रसुवा, लाङ्टाङ राष्ट्रिय निकुञ्ज र अन्य सम्बन्धित सरोकारवालाहरूले आगलागी व्यवस्थापन र न्यूनीकरणका लागि प्राथमिकता, तयारी र स्रोत विनियोजनका लागि जोखिम नक्सा प्रयोग गर्न सक्नेछन्।

मुख्य शब्दहरु: भौगोलिक सूचना प्रणाली, विश्लेषणात्मक उत्तराधिकारी प्रक्रिया, वन डढेलो, अग्नि संकट क्षेत्र, भूमि उपयोग भूमि आवरण

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उप प्राध्यापक रमेश सिलवाल सुदिप जोगी कवँर

प्रमुख सल्लाहकार लेखक

CHAPTER 1: INTRODUCTION

1.1 Background

Fire is a chemical reaction involving the rapid oxidation of combustible material, typically accompanied by the release of heat, light, and various gases. In simpler terms, a fire occurs when a substance burns in the presence of oxygen, producing heat and light. It requires three essential elements known as the "fire triangle": fuel, oxygen, and heat (Pyne et al., 1996). Heat is the energy required to initiate and sustain the reaction. When the fuel is heated to its ignition temperature, it begins to break down chemically, releasing flammable gases that react with oxygen in a self-sustaining chain reaction. Fire can spread rapidly if there is a continuous supply of fuel, oxygen, and heat.

Forest fire risk may be considered at different spatial and temporal resolutions: global and local; short-term and long-term. Both types of risk assessments are very important for fire management. The health of the world is greatly influenced by forests, which also assist the environment and human society in a variety of ways. A wide variety of plant and animal species, many of which are unique and found nowhere else on Earth, may be found in forests. Forests are essential for regulating the Earth's climate, functioning as carbon sinks, maintaining the water quality, managing the water cycle, conserving soil, bringing socioeconomic advantages to local people, providing recreational, and tourism opportunities, and many more.

Forests, on the other hand, are degrading day by day globally due to various factors. Forest fires, agriculture, infrastructural development, urbanization, the grazing of animals, the gathering of fuelwood, mining, logging, etc. are the leading causes of deforestation and forest degradation (Kissinger et al., 2012).

A forest fire, commonly referred to as a wildfire, is an uncontrolled fire that rapidly spreads over wooded or wilderness regions. Although forest fires are essential for the sustainability of forest ecosystems due to their ability to recycle nutrients, control the density and species mix of trees, and build and modify habitats for wildlife (Noss et al., 2006), forest fires have been shown to be a significant uncontrolled natural catastrophe that disrupts ecosystems and threatens biodiversity by depleting the variety of plants and animals. The most frequent threat to forests is fire, which has an adverse effect on the long-term sustainability of ecosystems and fauna (Sivrikaya et al., 2014). Deforestation (Giri & Shrestha, 2000), modifications in the physical properties of the soil (Ekinci et al., 2006), and the release of greenhouse gases (such as CO2, N2O), CO, non-methane organic compounds (NMOC), nitrogen oxides, NH3, and SO2 (Urbanski, 2014) are additional detrimental effects of forest fires that have an impact on both human and animal health. The loss of plants and animals as well as global warming are two more effects of forest fires. Additionally, it modifies aspects of the carbon cycle, the type of vegetation, and its structure (Alkhatib, 2014; Harper et al., 2018).

Particularly from November to June each year, when it is dry, it appears that there is an uneven pattern in the frequency of forest fires in Nepal (Bhujel et al., 2017). Several environmental factors, such as fuel availability, weather, topography, and the source of ignition, interact to cause forest fires. When conditions like low humidity, high wind, advantageous terrain, and the direction of the wind are present, a fire can spread quickly if the amount and availability of fuel are suitable (Wen et al., 2018; Teodoro et al., 2013). One of the most crucial steps in today's disaster management at the national level is identifying the spatial distribution of forest fire susceptibility. The prospective forest fire hazard area for various locations may be reliably predicted using the integration of fieldwork, RS data, GIS tools, and statistical methodologies. Geospatial technology can provide the geographical and temporal information needed for complicated fire models in a timely and accurate manner (Ganteaume et al., 2013; Modugno et al., 2016; Vallejo-Villalta et al., 2019). A novel approach for evaluating fire risk zones is also provided by the integration of multi-criteria decision-making (MCDM) in the spatial domain (Rasooli et al., 2018; Novo et al., 2020). One of the most popular MCDMs is the AHP technique (Rahmati et al., 2015). In various regions of the world, AHP and GIS approaches have been used to successfully identify the highest risk zones (Pourghasemi et al., 2016; Van Hoang et al., 2020; Nuthammachot et al., 2021).

1.2 Forest Fire Driving Factors

<u>Land Use Land Cover (LULC)</u>

The most crucial element for facilitating the spread of a fire is thought to be land cover. The area is particularly vulnerable to forest fires because of the vast quantity of degraded land, the steeper slope, and human activity like grazing (Chuvieco & Congalton, 1989; Smith et al., 2016; Shumilovskikh et al., 2021). The vegetation serves as fuel for the fire, and the kind of plant cover, the distance between the fuel sources, and other factors all affect how quickly the fire spreads. Because flames spread fast if fuels are near together, forests with dry, dense foliage are more likely to have forest fires (Veena et al., 2017).

Land Surface Temperature (LST)

High temperatures are closely correlated with fuel moisture content and relative humidity (Hussin et al., 2008). LST affects the temperature of the fuel to be burned, hence changing the amount of energy required to get the fuel to ignition point.

Slope

The slope is a significant element that affects the intensity of flames. More fuel preheating results from the steeper slopes (Estes et al., 2017). Fire spreads more quickly uphill than it does downward (Jaiswal et al., 2002). In comparison to places with shallow slopes, locations with steeper slopes are exposed to higher rates of surface runoff, making these areas drier. Greater slopes contribute significantly to the development of regional winds and hasten the upward movement of fire (Ajin et al., 2017).

Aspect

The quantity of sun radiation and moisture availability, as well as variations in the vegetation's composition and density, all have an impact on a location's aspect, which in turn affects how a fire behaves (Estes et al., 2017). Greater sun radiation is directed toward the southern aspects, while more warmth is generated toward the western aspects. As a result, fires tend to occur more frequently in the southern and western areas (Setiawan et al., 2004).

Elevation

Many topographic, meteorological, and hydrologic variables, including wind and direction, temperature, precipitation, humidity, and runoff, are influenced by the elevation factor, which has an impact on the spread and intensity of forest fires (Tiwari et al., 2021; Falkowski et al., 2005). Additionally, at the level of patterns and kinds of plant cover and soil qualities, elevation creates a significant regional variance in the spread of forest fires (Hong et al., 2019; Satir et al., 2015).

Distance from road

Road presence is a significant factor in the occurrence of human-induced fires (Ricotta et al., 2018). Fires may start intentionally or unintentionally by moving people and vehicles along the road (Veena et al., 2017). Wildfire can start from sparks from cooking close to forest roads, campfires started by tourists close to forest roads, and coal tar heating for road construction or from renovating and repairing existing roads (Satendra & Kaushik, 2014).

Distance from settlement

One of the most important human spatial indicators that measure how much human activity is putting strain on forest ecosystems is the distance to settlements (Jaafari et al., 2018). As a result of cooking, cigar butts, and coaling, forest people might start unintentional or intentional fires during dry seasons (Geng et al., 2020).

1.3 Analytic Hierarchy Process (AHP) method

The AHP approach is a mathematical method for analyzing complicated decision issues with many criteria, which aids decision makers in prioritizing their tasks in order to make the optimal decisions (Saaty, 1980).

1.4 Objective

1.4.1 General objective

The general objective of this study is to prepare the fire risk zone map using Geographic Information System (GIS) and Analytic Hierarchy Process (AHP).

1.4.2 Specific objective

The specific objectives of this study are:

- To generated required geospatial database such as LULC, road, settlement index map, LST, terrain data (aspect, slope, elevation) using DEM, etc.
- To map forest fire risk zone using GIS and AHP and validate using in-situ data.

CHAPTER 2: LITERATURE REVIEW

Risk zone mapping had been done utilizing RS data, GIS techniques, the AHP and FR methodologies, as well as factors such as land cover types, NDVI, NDWI, slope angle, slope aspect, and distance from the settlement (Pradeep et al., 2022). The AHP approach was discovered to be more effective in this investigation than the FR method. Moreover, ROC curve analysis was used to validate the fire risk map, and once more, the AHP approach provided a reasonable value while the FR method fell short.

For the mapping of the fire risk zone in Aalital rural municipality, Dadeldhura, the following factors were taken into consideration: land cover, land surface temperature, slope, distance from the road, proximity to a settlement, aspect, and elevation (Subedi et al., 2022). Data analysis involved the use of GIS and remote sensing. Analyzing and converting the descriptive parameters for the forest into a rating system and risk index for the forest fire. Land cover, land surface temperature, slope, road network, proximity to settlement, elevation, and aspect were examined and ranked in order of significance. The numerous category classes of a person's forest fire risk factor were given the proper ratings when the impact of that component was determined. The forest fire risk index (FRI) model was used to integrate the variables and generate the forest fire risk index.

Using GIS and the AHP method for forest fire risk zonation, Nikhil et al. (2021) conducted research at the Parambikulam Tiger Reserve in Kerala, India. The parameters included were land cover types, slope angle, aspect, TWI, distance from settlement, distance from road distance from popular tourist attractions, and distance from the anti-poaching camp shed. The parameters were examined using GIS and AHP techniques, ROC curve analysis was used to confirm the results. According to the study, neither the kind of land cover nor the slope angle significantly affect the likelihood of a fire. Surface moisture, meanwhile, was essential for the occurrence of fires. The majority of fire incidents, it was observed, took place close to human made structures including road, settlement and camp sheds.

Lamat et al. (2021) carried out the research, which investigated the use of geospatial technology and the AHP approach to evaluate fire risk in the Ri-Bhoi district of Meghalaya, India. The variables utilized were population, LULC, slope, aspect, elevation, temperature, rainfall, and wind speed. After data processing, the outcome was verified using MODIS data, and it was discovered that the defined fire risk zones and the fire locations derived from MODIS fire data were closely aligned.

Matin et al. (2017) conducted study to understand forest fire risk in Nepal using factors such as land cover, land surface temperature, distance from settlement, distance from road, slope, and elevation as well as MODIS hotspot data to understand the forest fire pattern.

The findings demonstrated that the construction of reliable fire risk maps in the study in NW Vietnam was made possible by the integration of GIS technology and multi-indicator analysis tools (MCA) with layers of information related to forest fire risk, such as humidity, wind direction, forest type, slope, slope direction, stream density, slope, distance to the residence, main roads, trails, etc. (Van Hoang et al., 2020). The system's accuracy and dependability were validated by comparing model findings with prior data. It was determined that using the semi-quantitative AHP method and the expert systems approach in the assessment was a useful addition. This was especially useful for creating a real-time early warning system. The outcomes of the district- and commune-level forest fire danger maps enable effective fire prevention in Son La.

The historical fire incidences detected by field data, MODIS, and SNPP-VIIRS satellite products were used to verify the forest fire risk map. The findings showed that geoinformatics-based forest fire zones established using the MCDA-AHP approach are in excellent agreement with past instances of forest fires and may be applied to fire planning and mitigation in forest regions (Kumari & Pandey, 2020).

Adequate logistics, infrastructure, financial resources, and complete knowledge of wildfire risk zones, including fire characteristics, are necessary for wildfire preventive and control management (Sharma et al. 2015). Western nations such as Australia, the United States, and Canada use wildfire danger maps for effective wildfire preparedness efforts; however, such practices are absent in Nepal (Ghimire et al. 2014). In this context, the production and dissemination of wildfire risk zonation maps might be extremely beneficial for disaster preparedness actions in Nepal (Sharma 2006; Sharma et al. 2015).

Because of the alpine pastures, there is a high frequency of fire incidents in the high mountains, as local herders purposely set fire to obtain new succulent grass for livestock (Parajuli et al., 2015). The wildfire incidence was found 0.03 per km2 in High Mountain and Himalayan region

(Bhujel et al., 2018). Forest fire, open grazing, indiscriminate product extraction was found as the main causes of deforestation and forest degradation in the High Mountain (Baral et al., 2012). About 10-15% of all forest fire incidents in the country happened in high altitude regions, and they lasted at least three to four days on average (Baral et al., 2012). (Rahman & Chang, 2017) established the reliability and robustness of MODIS data in mapping fire severity and the seasonality of vegetational response.

2.1 Global forest fire scenario

Annual forest fires destroyed over 67 million hectares (1.7%) of land between 2003 and 2012, predominantly in tropical South America and Africa (van Lierop et al., 2015). The 2019-2020 Australian bushfire burned an estimated 24.3 million hectares (Binskin et al., 2020) as of October 28, 2020, damaged over 3,000 structures, (including 2,779 residences) (Tiernan & O'Mallon, 2020), and left at least 34 people dead (Henriques-Gomes, 2020; ABC News, 2020). Three billion terrestrial creatures, the most majority of which were reptiles, were allegedly harmed, and certain rare species were allegedly pushed to extinction (Slezak, 2020). The United States had 44,647 wildfires that had consumed 5.6 million acres of land as of September 14, 2021, according to the National Interagency Fire Center (NIFC, 2021) since the beginning of 2021. In a similar vein, 2021 was also Canada's worst year for forest fires, according to the Canadian Interagency Forest Fire Centre (CIFFC, 2021), which stated that 6,317 wildfires burned across 10.34 million acres .

2.2 Forest fire scenario of Nepal

According to the study, intentional reasons accounted for 58.06% of all forest fire causes overall, followed by negligence (22%) and accidental causes (20%) (Kunwar & Khaling, 2006).More than half of the forest areas in Nepal experience frequent fires during the dry season, and active fire incidents and burning days have been rising annually (Parajuli, Chand, …, et al., 2015). The majority of forest fire events and impacted areas are documented between March and May, and according to Nepal's historical dataset, over 40,000 hectares of forest land burns throughout each year (Matin et al., 2017). In the year 2021, Nepal experienced the worst-case scenario for forest fires, with at least 60 wildfires burning in 22 different districts, causing 5 fatalities as well as the destruction of a significant number of wildlife, planted crops, and domestic animals (Chitrakar, 2021). Around 172 040.65 hectares of Nepalese forest were destroyed by fires between the years 2001 and 2020, resulting in a loss of biomass of 7.07 million tons (40.84 t/ha/yr) and 71 human casualties, with the highest incidence of forest fires

(10,658) and burned areas (5,95,875 ha/yr), followed by 2014 (4,488 incidents with 2,38,777 ha/yr burnt area), and 2009 (4,080 incidents with 2,07,799 ha/yr burnt area with the highest number of 49 lives lost) (Bhujel et al., 2022).

2.3 AHP and GIS in fire hazard modelling

For the purpose of predicting the forest fire zone, the evaluation of each thematic layer's weight is crucial since the output depends heavily on the choice of weight. The most significant weighting approaches, such as fuzzy sets (Bellman & Zadeh, 1970), linguistic variables (Chen & Hwang, 1992), and AHP (Saaty, 1980), were used to identify the fire risk zone. However, the most used technique for identifying the highest risk zone is AHP (Vadrevu et al., 2010; Sharma et al., 2014). Saaty's AHP was a decision-added technique for producing relative ratio scales for paired comparisons (Saaty, 1980).

Table 1: The relative importance values

Intensity of importance	**Definition**	**Explanation**
1	Equal	Two factors contribute equally to the objective.
3	Somewhat more important	Experience and judgement slightly favour one over the other.
5	Much more important	Experience and judgement strongly favour one over the other.
7	Very much more important	Experience and judgement very strongly favour one over the other
9	Absolutely more important	The evidence favouring one over the other is of the highest possible validity.
4,6,8	Intermediate values	When compromise is needed.

By breaking down difficult decisions into a series of comparable pairs and combining the outcomes, this technique determines the optimum course of action (El Jazouli et al., 2019). The AHP technique is one of the most extensively used approaches with trustworthy outcomes for determining the geographical vulnerability of natural hazards, such as forest fires (Kayet et al., 2020; Busico et al., 2019; Akbulak et al., 2018; Setiawan et al., 2004).

CHAPTER 3: MATERIALS AND METHODS

3.1 Study Area

The Rasuwa district, which has a size of 1514 square kilometers and is situated between 614 and 7227 meters above mean sea level, is situated between $27^0$2’ and $27^0$10’ degrees north latitude and $85^0$45’ and $85^0$08’ degrees east longitude. 31.43% of the area is covered in forests, while 16.63% is perpetually covered in snow. There are 46,689 people living in this district, according to the census of 2021 A.D., with the majority of them being Tamang (69.6%) followed by Hill Brahmin (15.2%) and Gurung.

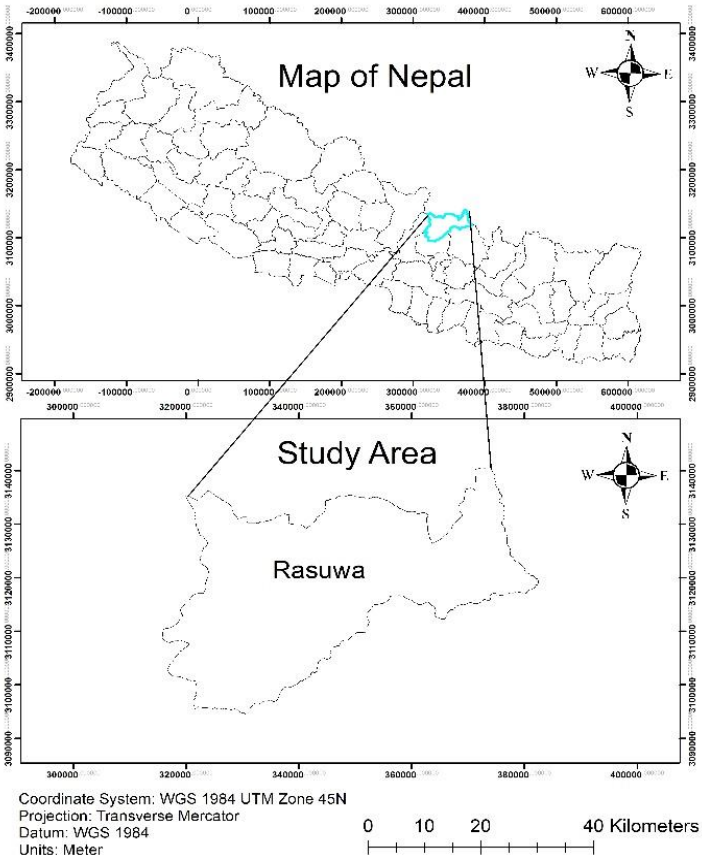


Figure 1: Study area

The average annual rainfall and temperature are 361.57 mm and 19.76 ^{0}C respectively (Rasuwa Garhi Climate).

The climate of Rasuwa ranges from subtropical to temperate and alpine, however the majority of the region is temperate and alpine in nature.

Majority of the area of Rasuwa district falls under Lamgtang National Park. Topography and geology have resulted in a rich biodiversity and unique vegetation patchwork. The major species found in this area are *Pinus roxburghii, Pinus wallichiana, Taxus baccata, Larix himalaica, Zanthoxylum armatum, Rhododendron arboretum, Rhododendron cowanianum* Davidian*, Alnus nepalensis, Quercus spps., Abies spectabilis, Picea smithiana, Abies pindrow, Castanopsis indica, Cedrus deodara, Choerospondias axillaris, etc.* and various medicinal plants like *Asparagus racemosus, Dactylorhiza hatagirea, Paris polyphylla, Vitex negundo, Valeriana jatamansi, Swertia chirayita, Cordyceps sinensis,* etc.

3.2 Methods of data collection

The literature review and experts' opinions were taken to assign a relative weightage to each factor. The Nepal government lacks data on the location and timing of forest fires, making monitoring difficult. In Nepal, ICIMOD offers forest fire data, however because this data is closely connected with NASA, the historical data were obtained via NASA's Fire Information for Resource Management System (FIRMS).

ICIMOD provided land cover 2010 for LULC categorization. USGS Earth Explorer was used to get SRTM 1 Arc-Second Global for the generation of slope, aspect, and elevation maps. The road network and settlement cluster were gathered from UN OCHA. The monthly day and night LST maps were created using MODIS MOD11C3 V6.1 data from LP DAAC Earthdata.

Various literatures connected to the study theme's purpose were also investigated in order to get information as well as to enhance understanding in giving relative weightage to the forest fire impacting elements via pairwise comparison.

The factors used as a thematic layer for the forest fire risk mapping are provided in Table 2.

Table 2: Remote Sensing and GIS Datasets

Factors	Sources	Data format	Resolution
LULC	International Centre for Integrated Mountain Development ((ICIMOD)	Raster	30 m
LST	MODIS MOD11C3 V6.1 (LP DAAC - Data (usgs.gov))	Raster	5.6 km
Slope	SRTM DEM (https://earthexplorer.usgs.gov/)	Raster	30 m
Aspect			
Elevation			
Distance from road	UN OCHA (OCHA (unocha.org))	Vector	1:25000

Distance from settlement			
MODIS fire hotspot	Fire Information for Resource Management System (NASA | LANCE | FIRMS)	Vector	1 km

3.3 Data analysis

3.3.1 Software and Tools

ArcGIS 10.8 was used to create maps of various thematic layers by analyzing various satellite data, analyzing fire hotspot identification, and lastly creating fire risk zone mapping. MS-Excel 2019 was utilized for data input, analysis, and visual representation of the explored data in the form of tables and charts. The Google Earth engine was also utilized to analyze various satellite pictures in order to create maps of some of the thematic layers.

Table 3: Software and Tools

Software and Tools	Use
ArcGIS 10.8	Geospatial analysis (LULC, elevation, aspect, slope, distance from road, distance from settlement, reclassify, and overlay analysis)
Google earth engine	LST analysis
MS-Excel 2019	Statistical analysis
MS-Word 2019	Thesis writing

3.3.2 Generation of thematic layers

Criteria assessed in Table 7 was referred to generate thematic layers as following:

Land Use Land Cover 2010 map obtained from ICIMOD was used for the classification of land use land cover using ArcGIS 10.8 through the spatial analyst tools.

LST was estimated using MOD11C3 V6.1 image through google earth engine.

The ArcGIS spatial analyst tools using SRTM DEM was used to prepare slope, aspect, and elevation map.

Distance from settlement and distance from road layers were generated using ArcGIS spatial analyst tool (Euclidean Distance).

3.3.3 Assigning weightage to the AHP model

The AHP approach is a mathematical method for analyzing complicated decision issues with many criteria, which aids decision makers in prioritizing their tasks in order to make the optimal decisions (Saaty, 1980). The relative importance of two criteria was then calculated using a numerical scale from 1 to 9 (Table 1) and employed to establish a weight for each criterion using decision makers' pairwise comparisons.

The parameters are sorted in according to their relevance, and therefore their weights may be calculated. Their weights were assigned through the literature review, expert's opinion and self decision making process. To offer a flexible hierarchy, each element has been assigned a preliminary weight based on its influence on forest fire risk. For the purpose of predicting the forest fire zone, the evaluation of each thematic layer's weight is crucial since the output depends heavily on the selection of weight. The major steps involved in the AHP method are constructing a matrix for pair-wise comparisons (Table 5), eigenvector and weighting calculation, and consistency ratio calculation (Table 6) (Saaty, 1980).

We determined the consistency ratio (CR) by using the following formulae in order to confirm the consistency of our comparison estimations.

The Eigen vector (V_p) was calculated using Eq.1

$V_p = \sqrt[k]{W1 * \ldots Wn}$ ………………………… (1)

Where, n is number of factors and W is rating of factors.

The weighting coefficient (C_p) was calculated using Eq.2

$C_p = V_P/(\ V_{P1} + \ldots . V_{Pn})$ ………………………… (2)

The sum of weighting coefficient (C_p) of all parameters of a matrix must be equal to 1.

The matrix is normalized by dividing each element by the sum of the column. By averaging each row, the priority vector, [C], is calculated. The overall priority, [D], is calculated by multiplying each column of the matrix by the corresponding priority vector. The rational priority, [E], is determined by dividing each overall priority by the priority vector.

The eigenvalue (λ_{max}) was calculated using Eq.3 as follows:

λ_{max} = E/n ………………………… (3)

The consistency index (CI) was calculated using Eq.4 as follows:

CI = (λ_{max}-n)/(n-1) ………………………… (4)

The consistency ratio (CR) was calculated using Eq.5 as follows:

CR = CI/RI ………………………… (5)

where RI is the random index (inconsistency).

Table 4: Random Inconsistency values

Number of criteria	1	2	3	4	5	6	7	8	9	10	11
Random Inconsistency	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

According to Saaty (1980), CR should be less than 0.1; else, the exercises should be redone and the judgments should not be accepted.

3.3.4 Preparation of Forest Fire Risk Map

After the calculation of final weights for each factor through the AHP method, weighted overlay method was used to prepare the forest fire risk map in ArcGIS.

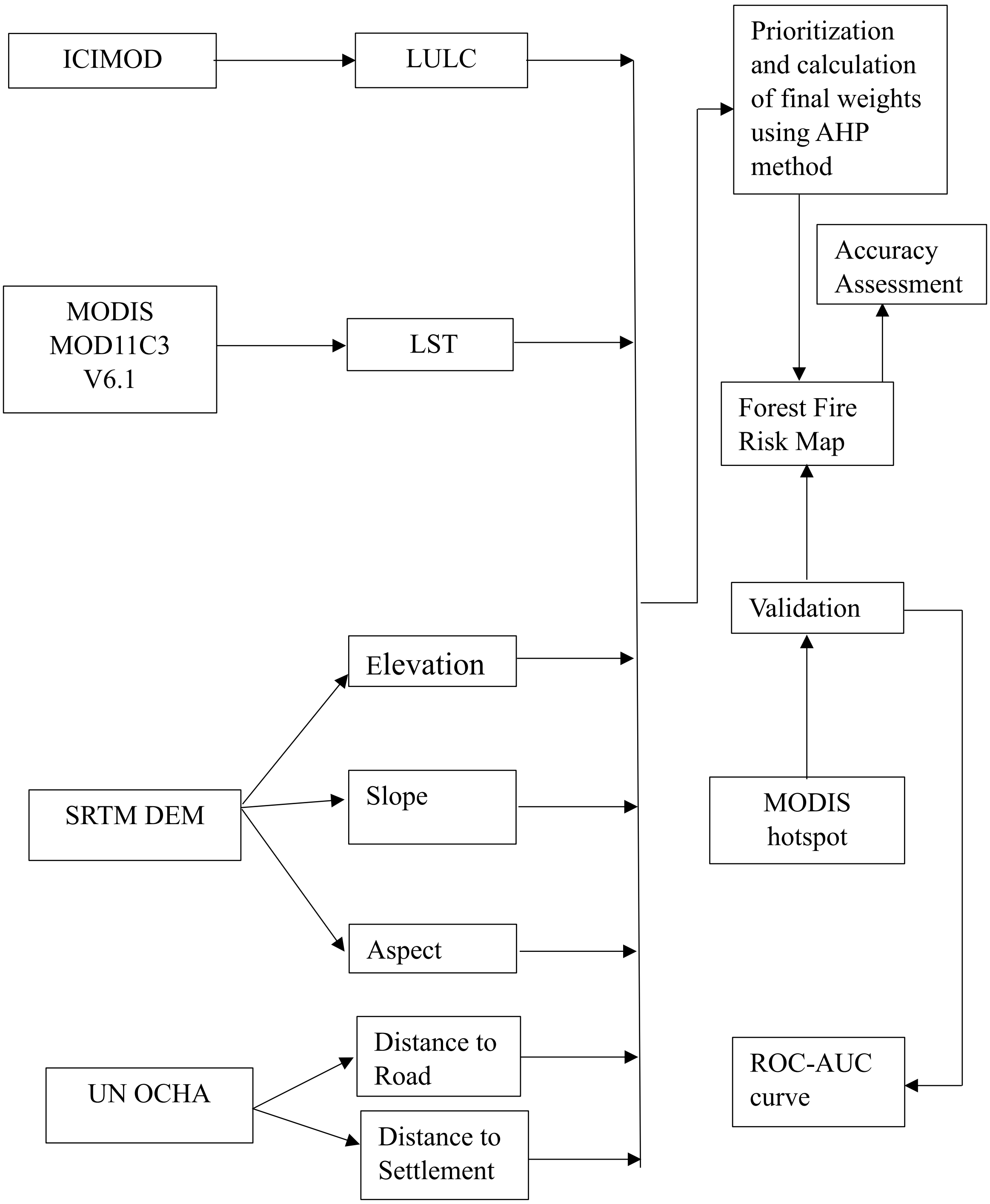
3.3.5 Accuracy Assessment

Evaluating the accuracy of prediction outputs is an important and complementary measure for maximizing the effectiveness of modeling research. Accuracy assessment was done using MODIS hotspot data having a date range from 2004-2023. High forest fire incidences should fall on the high-risk class followed by the medium and low-risk classes.

3.3.6 Validation of the Result

The ROC-AUC curve was used to validate the generated forest fire risk map. The ROC analysis analyzes the connection between a binary classifier's sensitivity (true positive rate) and specificity (true negative rate) (Flach, 2016). The AUC is a single scalar measure that measures a binary classifier's overall performance (Hanley & McNeil, 1982). When the AUC equals 0.5, it is certainly random chance, and when the AUC equals 1.0, it represents flawless accuracy. 2007 (Zou et al., 2007). The AUC was determined to be outstanding for values more than 0.9, good for values greater than 0.8, acceptable for values greater than 0.7, bad for values greater than 0.6, and failed for values less than 0.5 (Lüdemann et al., 2006).

3.4 Methodological Framework



CHAPTER 4: RESULTS AND DISCUSSION

4.1 Results

The major steps involved in the AHP method were constructing a matrix for pair-wise comparisons (Table 5), normalized pairwise comparison, eigenvector, weighting calculation, and consistency ratio calculation (Table 6) through the expert's opinions and peer reviewed journal articles (Pradeep et al., 2022; Nikhil et al., 2021; Lamat et al., 2021; Van Hoang et al., 2020; Novo et al., 2020; Pourghasemi et al., 2016)

Table 5: Pairwise comparison matrix by AHP method

Factors	LULC	LST	Slope	Aspect	Elevation	Distance from road	Distance from settlement
LULC	1	3	3	3	3	2	2
LST	1/3	1	3	2	3	1/4	1/4
Slope	1/3	1/3	1	2	1/2	1/3	1/3
Aspect	1/3	1/2	1/2	1	1/3	1/4	1/4
Elevation	1/3	1/3	2	3	1	1/3	1/3
Distance from road	1/2	4	3	4	3	1	1/2
Distance from settlement	1/2	4	3	4	3	2	1

Table 6: Normalized pairwise comparison matrix and computation of weights

Factors	LULC	LST	Slope	Aspect	Elevation	Distance from road	Distance from settlement	Criteria weight
LULC	0.30	0.23	0.19	0.16	0.22	0.32	0.43	0.26
LST	0.10	0.08	0.19	0.11	0.22	0.04	0.05	0.11
Slope	0.10	0.03	0.06	0.11	0.04	0.05	0.07	0.07
Aspect	0.10	0.04	0.03	0.05	0.02	0.04	0.05	0.05
Elevation	0.10	0.03	0.13	0.16	0.07	0.05	0.07	0.09

Distance from road	0.15	0.30	0.19	0.21	0.22	0.16	0.11	0.19
Distance from settlement	0.15	0.30	0.19	0.21	0.22	0.32	0.21	0.23
λmax = 7.62								
n = 7								
CI = 0.103								
RI (n=7) = 1.32								
CR = 0.07								

The final model obtained through the AHP method is given in Eq.6:

Forest Fire Risk Index (FFRI) = (0.26*LULC) + (0.11*LST) + (0.07*S) + (0.05*A) + (0.09*E) + (0.19*DR) + (0.23*DS) ……………. (6)

Where, LULC=Land Use Land Cover, LST=Land Surface Temperature, S=Slope, A=Aspect, E=Elevation, DR= Distant from road, DS=Distance from settlement

4.1.1 Weightage of the parameters

Weightage of the parameters were generated based on peer reviewed journal articles (Pradeep et al., 2022; Subedi et al., 2022; Nikhil et al., 2021; Qadir et al., 2021; Parajuli et al., 2020; Matin et al., 2017; Parajuli et al., 2020; Sibanda et al., 2011; Vadrevu et al., 2006), expert's consultations, and field verifications.

Table 7: Weightage to the parameters

Factors	Sub-Factors	Number of fire incidents	Score	Forest Fire Risk Potential	AHP weight
LULC	Forest	191	5	Very High	0.26
	Shrubland	27	4	High	
	Grassland	125	3	Medium	
	Agriculture area	59	2	Low	
	Barren area	3	1	Very Low	
	Water body	0	0	No	
	Snow/glacier	0	0	No	
LST (°C)	20-25.75	133	5	Very High	0.11
	15-20	108	4	High	
	10-15	128	3	Medium	
	5-10	34	2	Low	
	<5	2	1	Very Low	
Elevation (m)	606-1000	10	5	Very High	0.09
	1000-2200	171	4	High	
	2200-3500	141	3	Medium	
	3500-5000	83	2	Low	
	5000-7223	0	1	Very Low	
Aspect	Southeast	77	5	Very High	0.05
	South	83	5	Very High	
	Southwest	56	4	High	
	West	43	4	High	
	East	51	3	Medium	
	Northeast	27	2	Low	
	Northwest	43	2	Low	
	North	25	1	Very Low	
	Flat	0	1	Very Low	
	60-81	8	5	Very High	0.07

Slope (degree)	45-60	66	4	High	
	30-45	190	3	Medium	
	15-30	125	2	Low	
	<15	16	1	Very Low	
Distance from road (m)	0-1200	375	5	Very High	0.19
	1200-2500	29	4	High	
	2500-5000	1	3	Medium	
	5000-8000	0	2	Low	
	8000-17960.19	0	1	Very Low	
Distance from settlement (m)	0-1500	244	5	Very High	0.23
	1500-3000	97	4	High	
	3000-4500	39	3	Medium	
	4500-7000	23	2	Low	
	7000-17960.19	0	1	Very Low	

4.1.2 Thematic layers

Thematic layers such as LULC (Figure 2), LST (Figure 3), elevation (Figure 4), aspect (Figure 5), slope (Figure 6), distance from settlement (Figure 7), and distance from settlement (Figure 8) were generated using criteria given in Table 7.

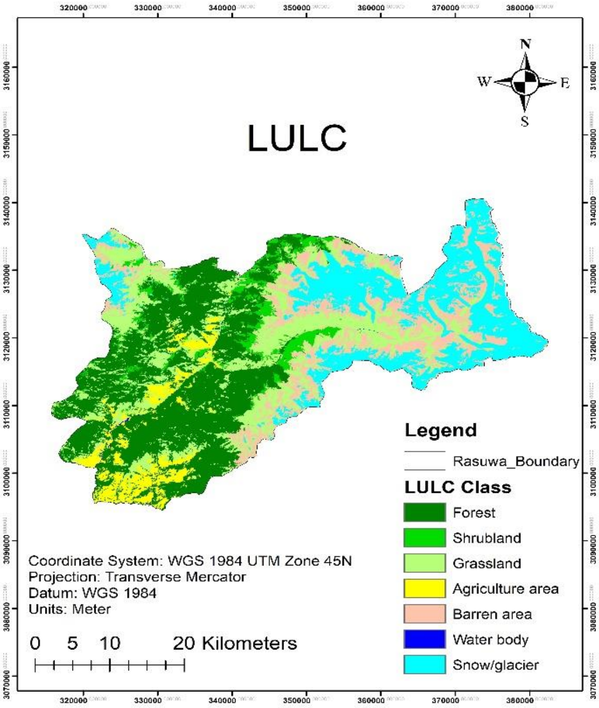


Figure 2: LULC

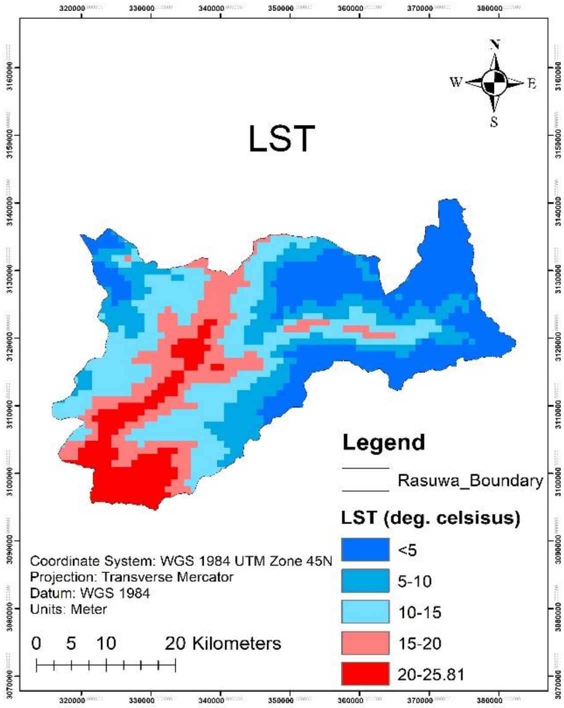


Figure 3: LST

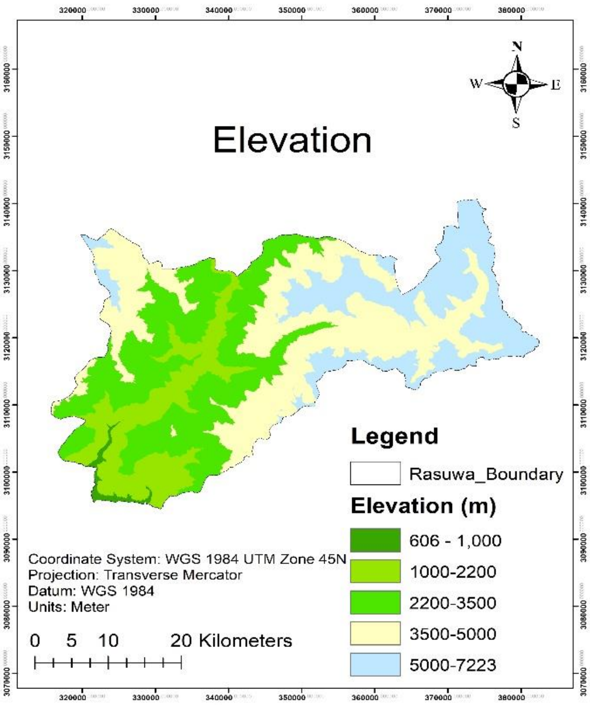


Figure 4: Elevation

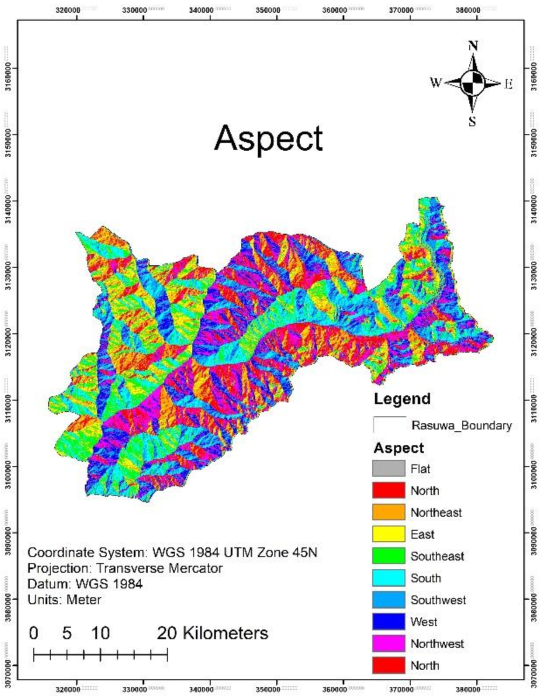


Figure 5: Aspect

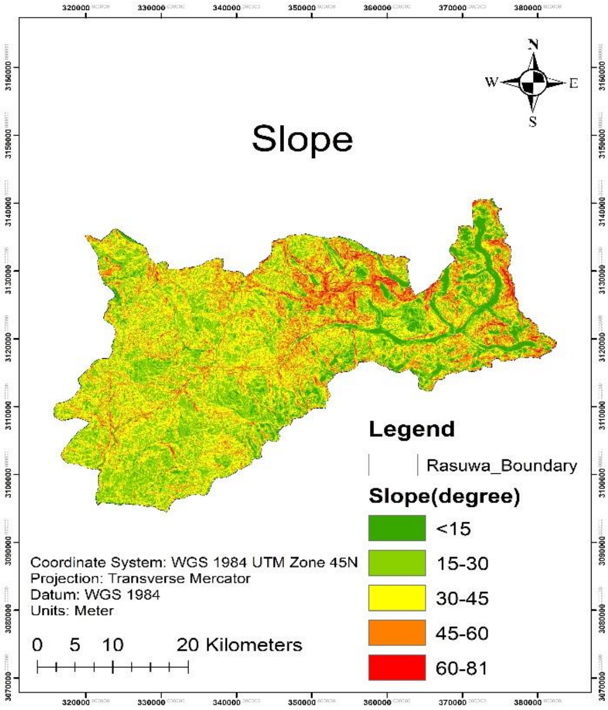


Figure 6: Slope

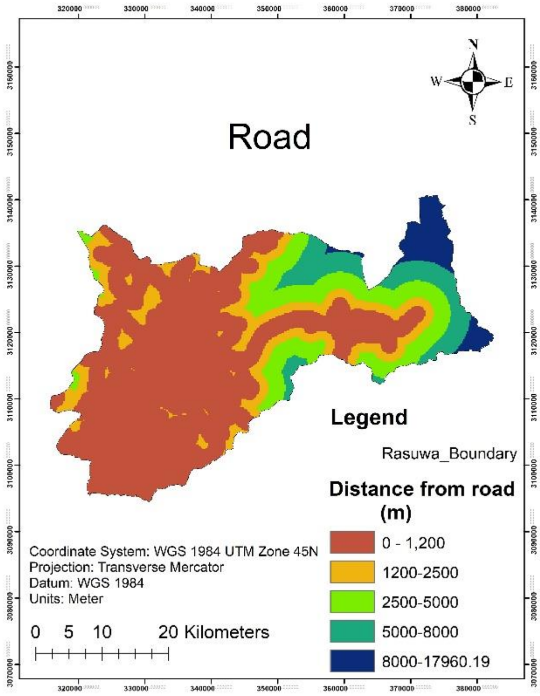


Figure 7: Distance from road

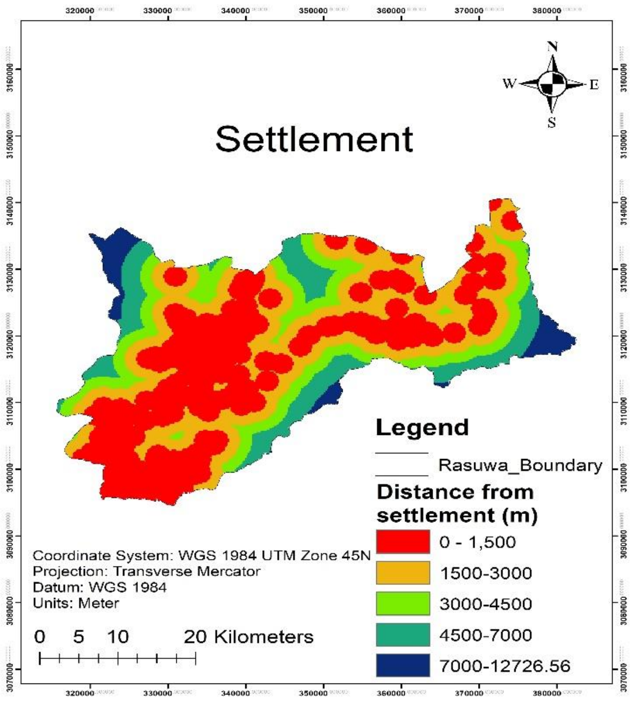


Figure 8: Distance from settlement

4.1.3 Historical forest fires, LST and precipitation

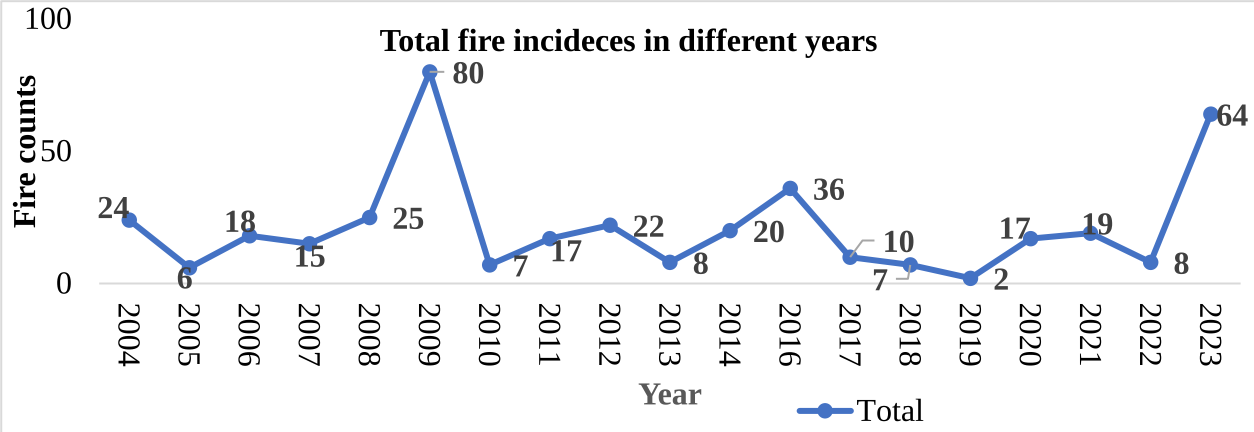


Figure 9: Total fire incidences in different years (MODIS fire hotspot)

Figure 9 indicated that the most fire events happened in 2009, with a total of 80, followed by 2023, with 64, despite just 5 months of data being included and less fire events happened in 2019 with a total count of only 2.

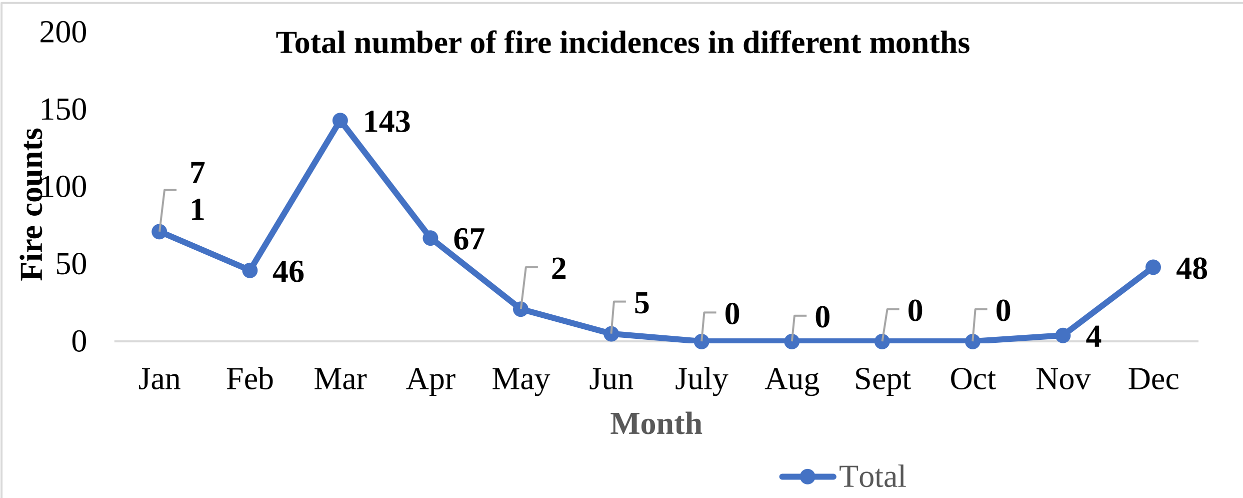


Figure 10: Total number of fire incidences in different months (MODIS fire hotspot)

According to Figure 10, the month of March had the highest fires, with 143, followed by January and April, which had 71 and 67, respectively. No fire incidences were recorded from the month of July to October.

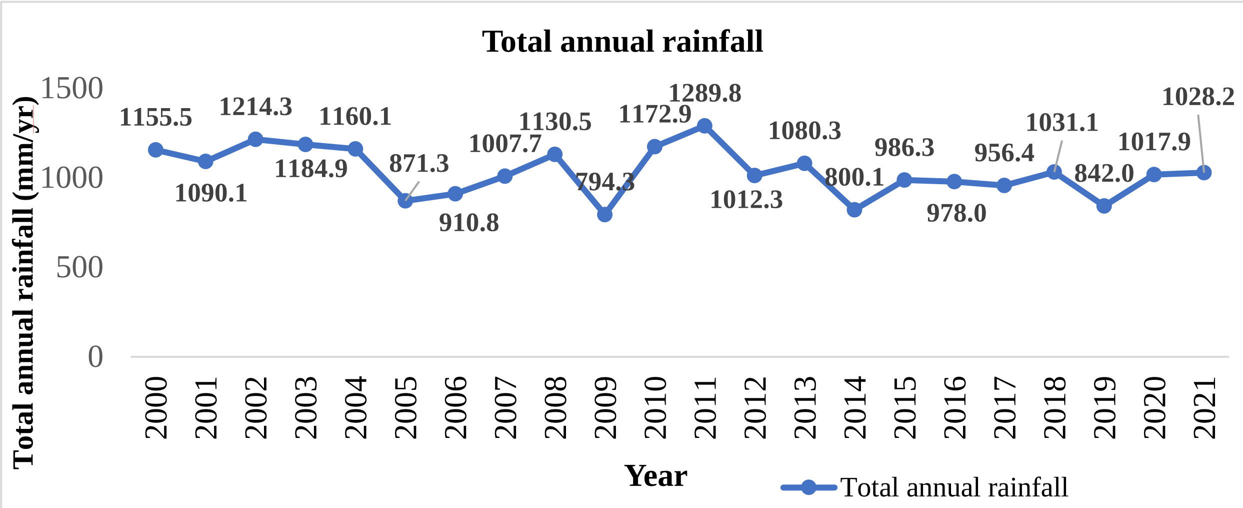


Figure 11: Total annual rainfall in different years

Figure 11 indicated that the highest annual rainfall was occurred in 2011 (1289.98 mm), followed by 2002 (1214.3 mm) and 2003 (1184.9 mm). Very low annual rainfall was occurred in 2009 (794.3 mm).

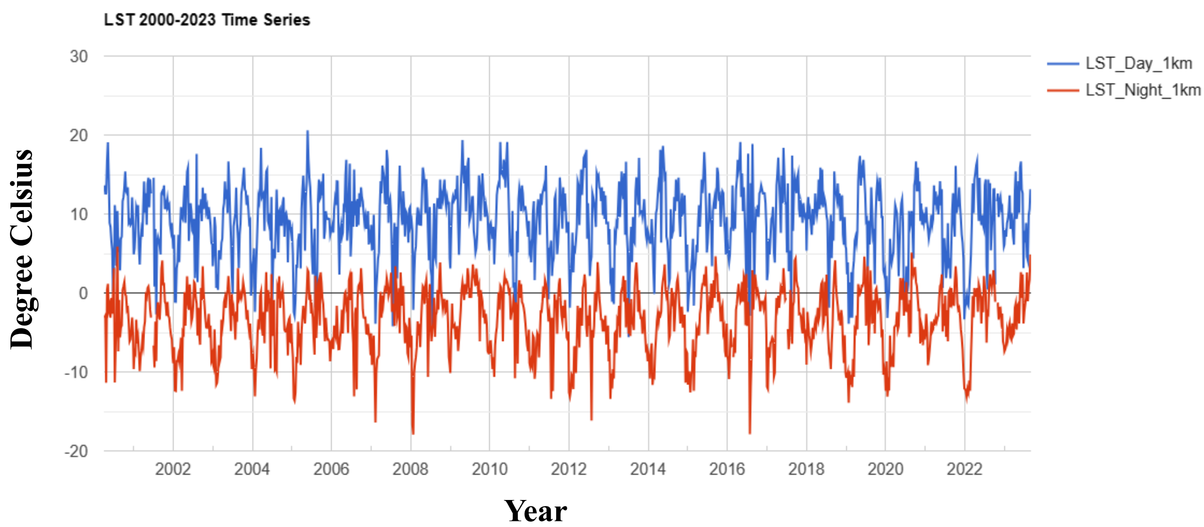


Figure 12: Average monthly LST in different years

Figure 12 indicated that the highest LST day was seen in year 2005 and LST night in year 2001 and lowest LST day in year 2019 and LST night in year 2008.

4.1.4 Fire incidences

MODIS hotspot data from 2004-2023, having confidence level greater than equal to 30 % were used to evaluate the fire incidences occurred in different local bodies.

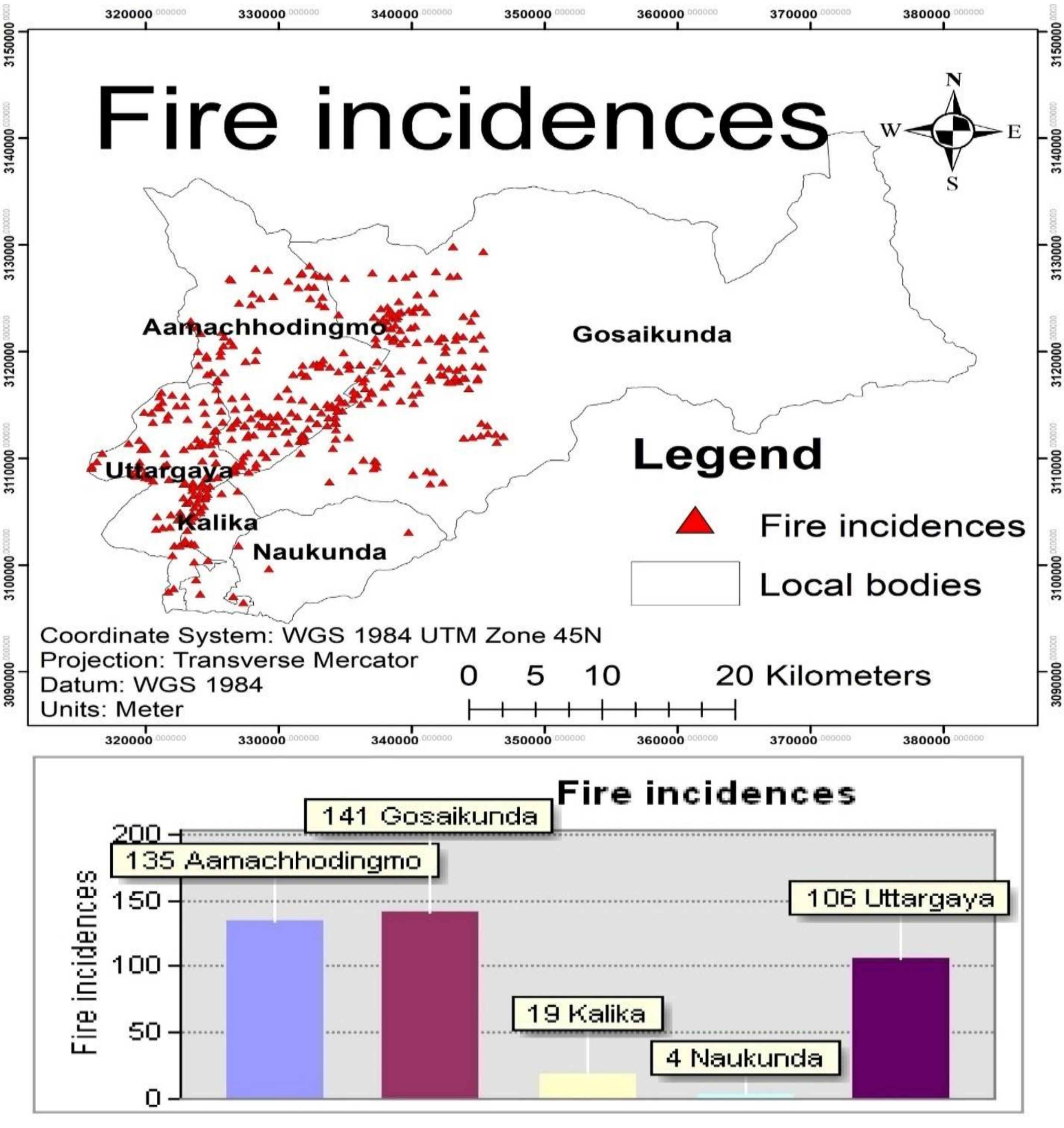


Figure 13: Fire incidences in different local bodies

Figure 13 indicated that the highest fire incidence occurred in Gosaikunda (141), followed by Aamachhodingmo (135), Uttargaya (106), Kalika (19), and Naukunda (4) rural municipality.

4.1.5 Fire Incidences in different classes of each predictive variable

MODIS hotspot data from 2004-2023, having confidence level greater than equal to 30 % were used to evaluate the fire incidences occurred in different classes of each factor.

LULC

One of the major forest fire influencing factor is LULC. The type of land cover influences the intensity, magnitude and spread extent of fire. Figure 14 indicated that high frequency of fire occurred in forest category, 47.16% followed by grassland, 30.86%. About 80.69% fire occurred in forest land in the study area.

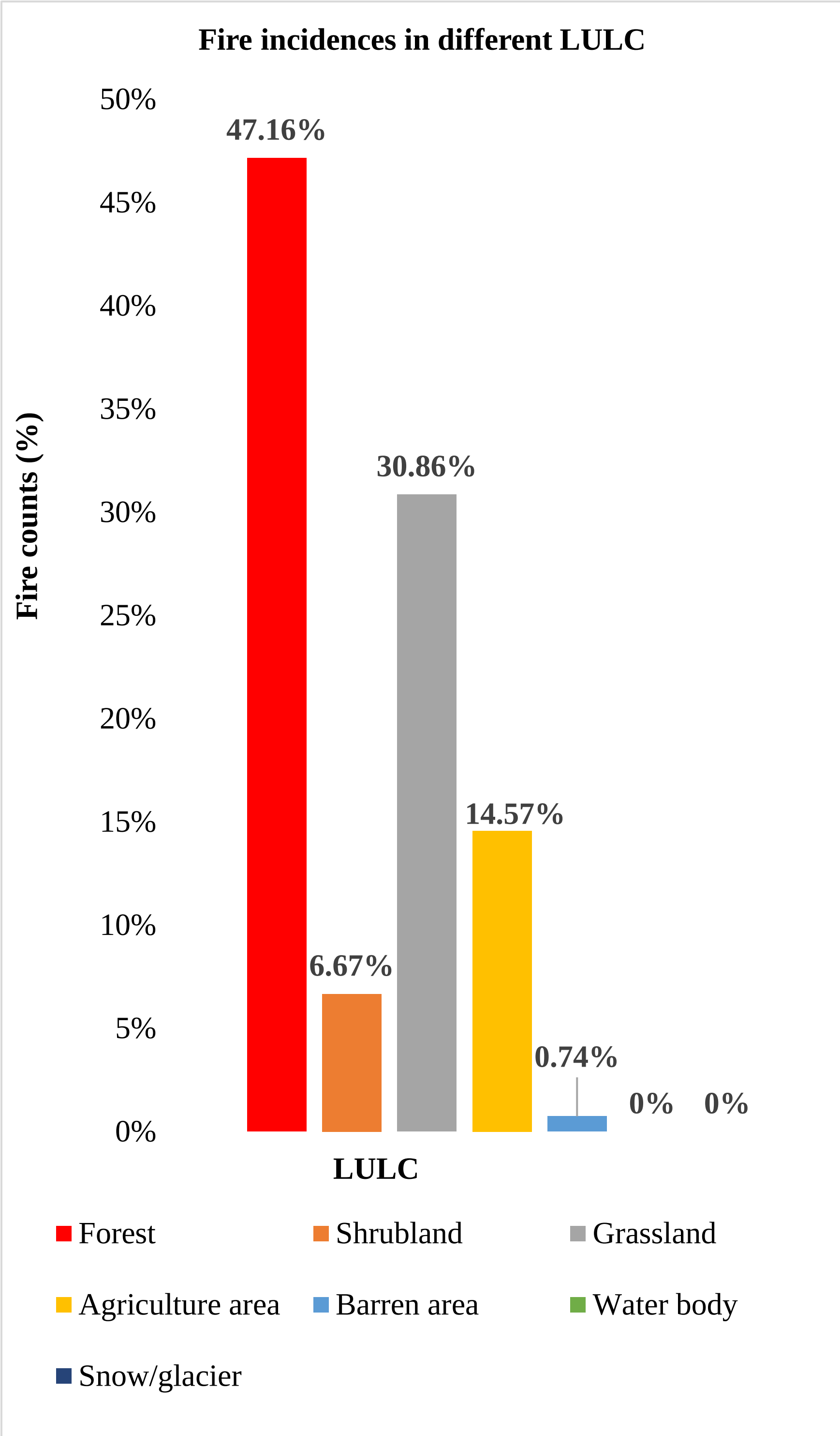


Figure 14: LULC versus fire incidences

LST

When temperatures rise, the moisture content of the forest systems decreases, making them more prone to fire. Figure 15 indicated that the highest frequency of fire incidents, about 32.84% occurred in between 20-25.575 °C, followed by 31.60% and 26.67% occurred in between 10-15 °C and 15-20 °C temperature respectively. Very less fire incidents about 0.49% occurred in less than 5 °C.

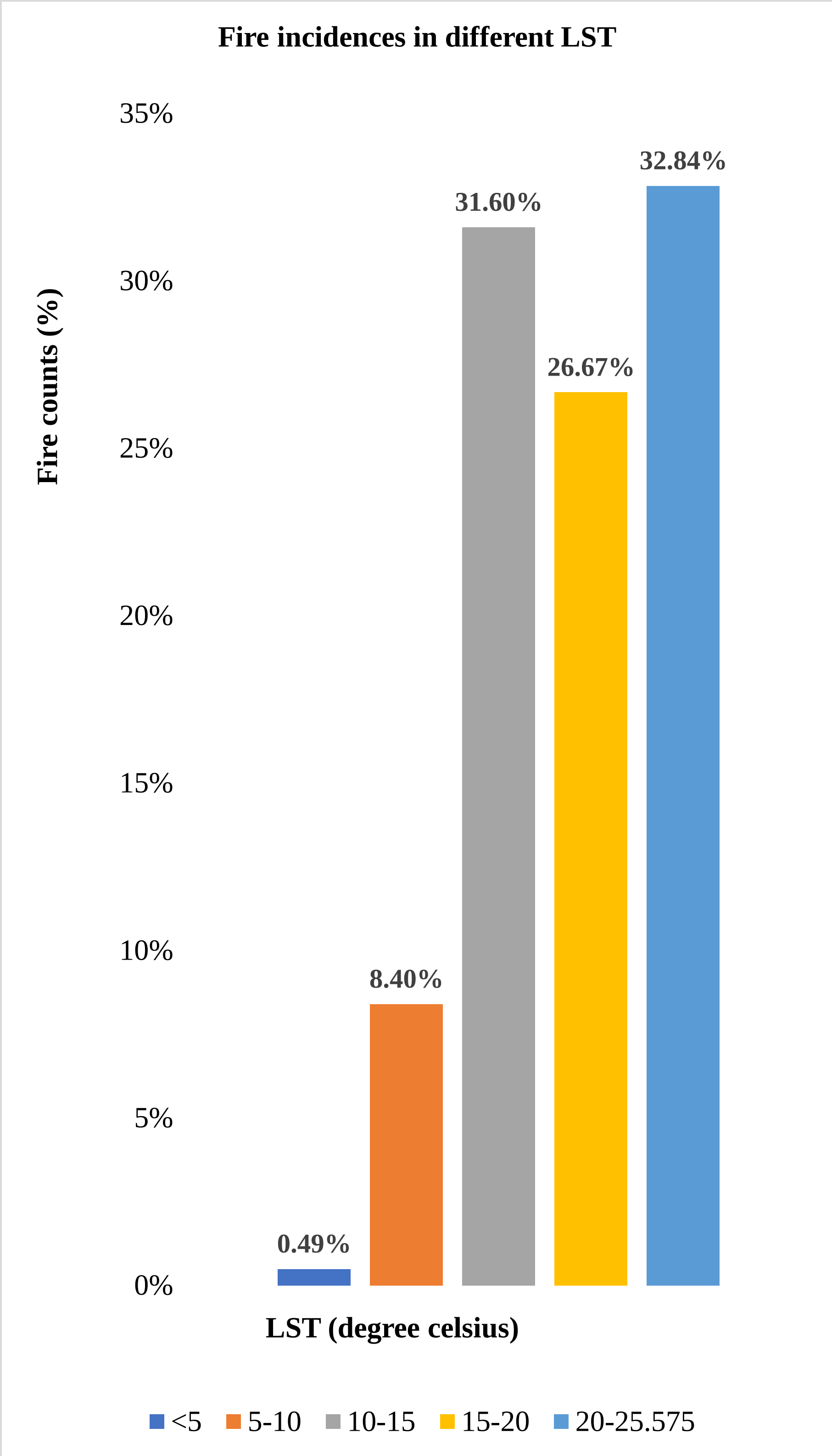


Figure 15: LST versus fire incidences

<u>Elevation</u>

Figure 16 indicated that highest frequency of fire incidences, 42.22% occurred in 1000-2200 m elevation range, followed by 34.82% and 20.49% in 2200-3500 m and 3500-500 m elevation range respectively. Very few frequency of fire incidences occurred in 606-1000 m and no incidences observed in aove 5000 m elevation.

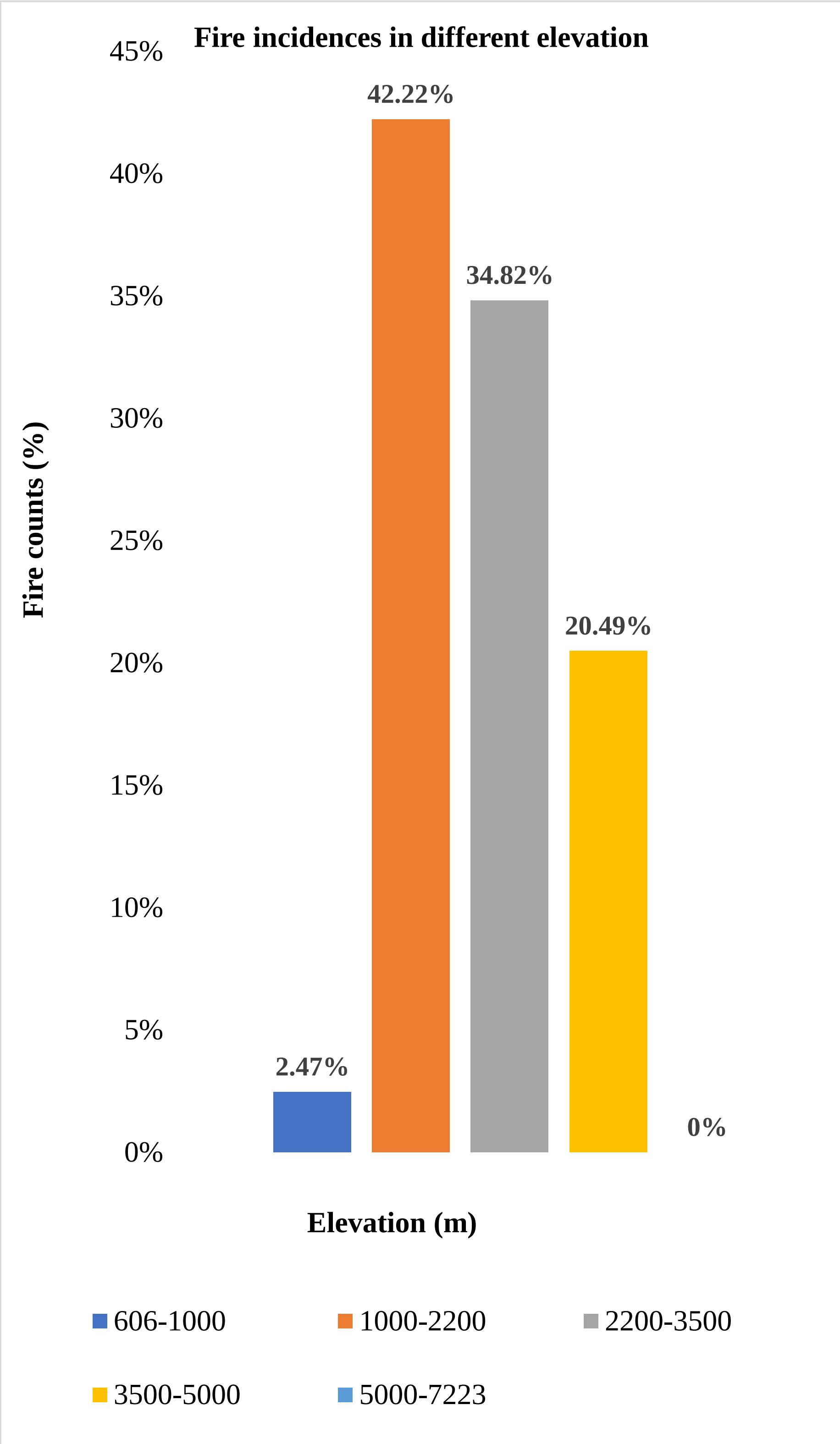


Figure 16: Elevation versus fire incidences

<u>Aspect</u>

Figure 17 indicated that high frequency of fire incidences, 20.49% occurred in South aspect, followed by 19.01%, 13.83%, and 12.59% occurred in Southeast, Southwest, and East respectively. Very less frequency of fire incidences occurred in North aspect and no fire incidences observed in flat aspect.

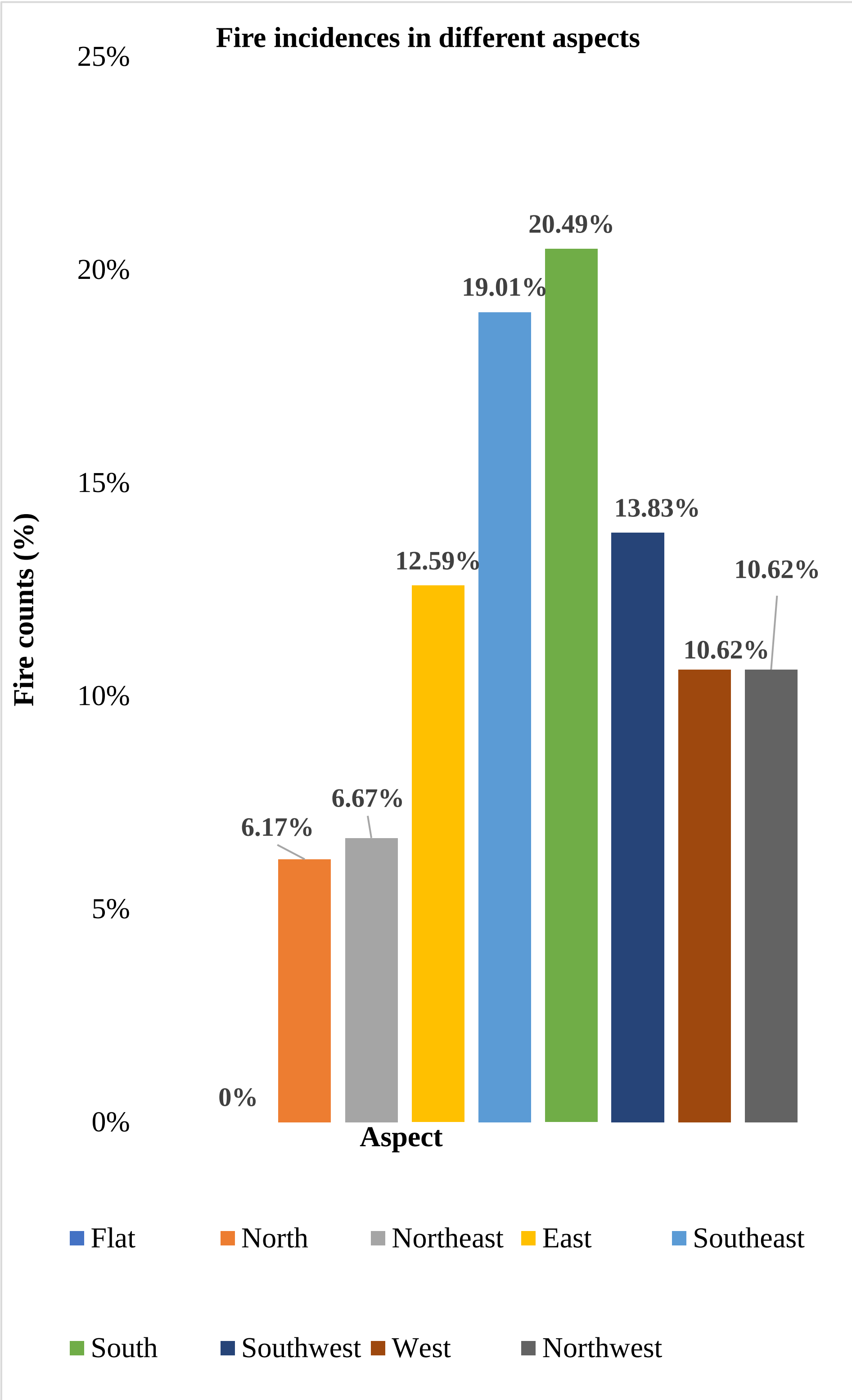


Figure 17: Aspect versus fire incidences

Slope

Figure 18 indicated that the highest frequency of fire incidences, about 46.91% occurred in between 30-45 degree slope, followed by 30.86% and 16.30% occurred in between 15-30 and 45-60 degree slope respectively. Very less fire incidences occurred in above 60 degree slope (1.98%) and less than 15 degree slope (3.95%).

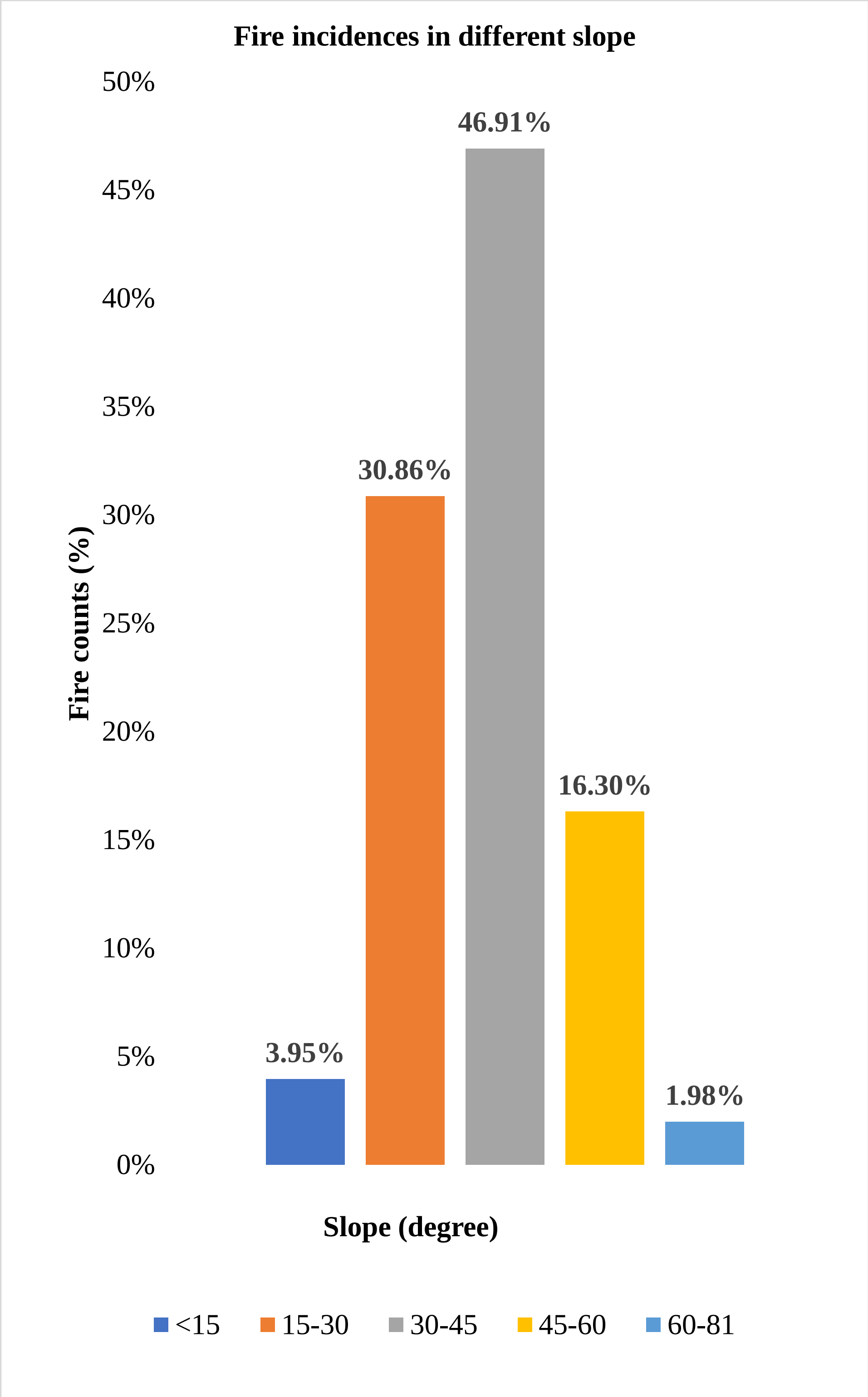


Figure 18: Slope versus fire incidences

Distance from road

Figure 19 indicated that highest frequency of fire incidences, 92.59% occurred at distance of about 0-1200 m from the road, followed by 7.16% occurred at distance of about 1200-2500 m from the road. Very few fire incidences were occurred in distance of 2500-5000 m from road and no fire incidences were observed above distance of 5000 m from road.

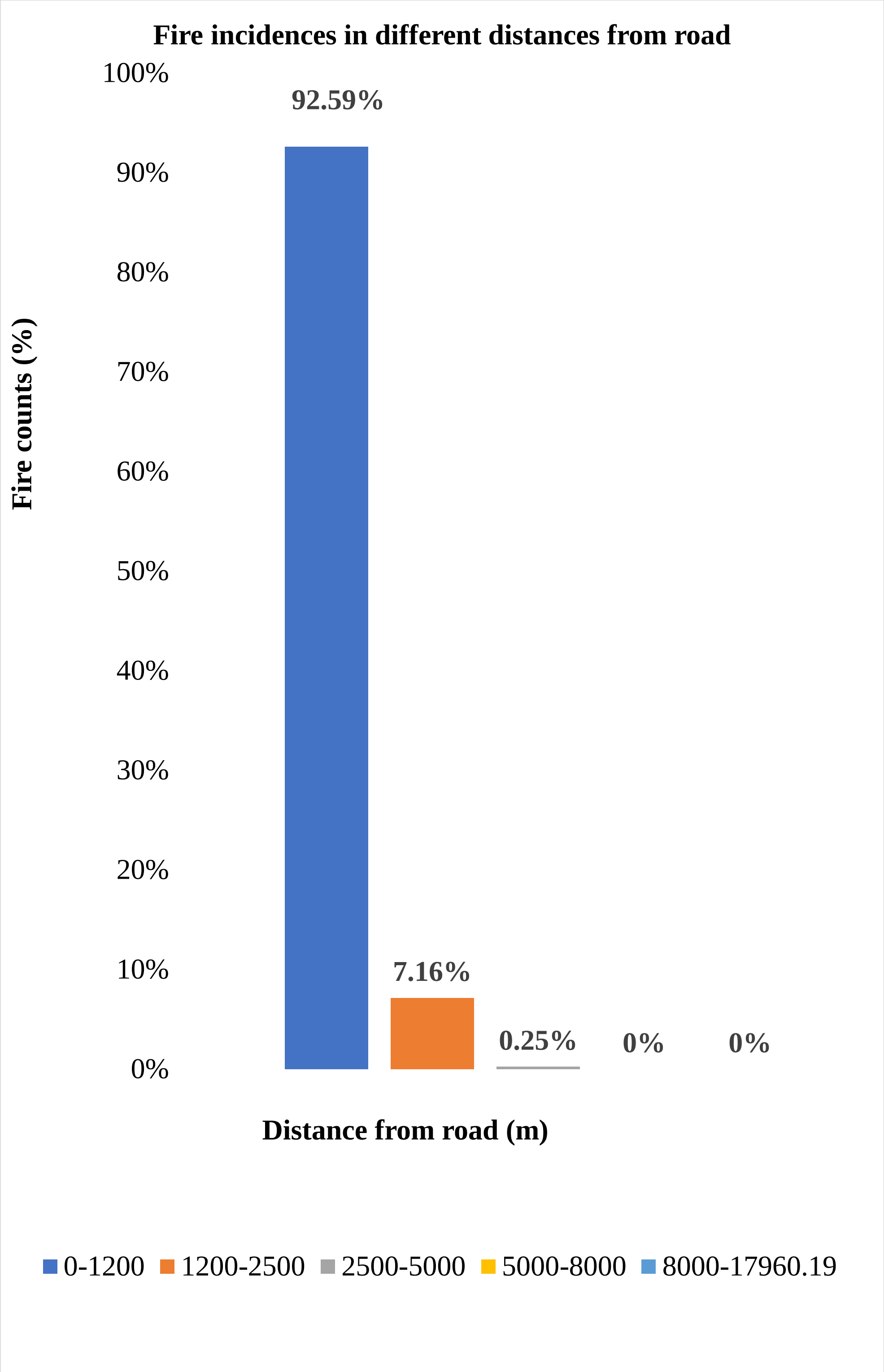


Figure 19: Distance from road versus fire incidences

Distance from settlement

Figure 20 indicated that highest frequency of fire incidents, 60.25% occurred at distance of 0-1500 m from settlement, followed by 23.95% at distance of 1500-3000 m from settlement. As the distances from settlement increased fire incidences were decreased, 9.63%, 5.68%, and 0.49% fire incidences were observed in distance of 3000-4500 m, 4500-7000 m, and above 7000 m from settlement.

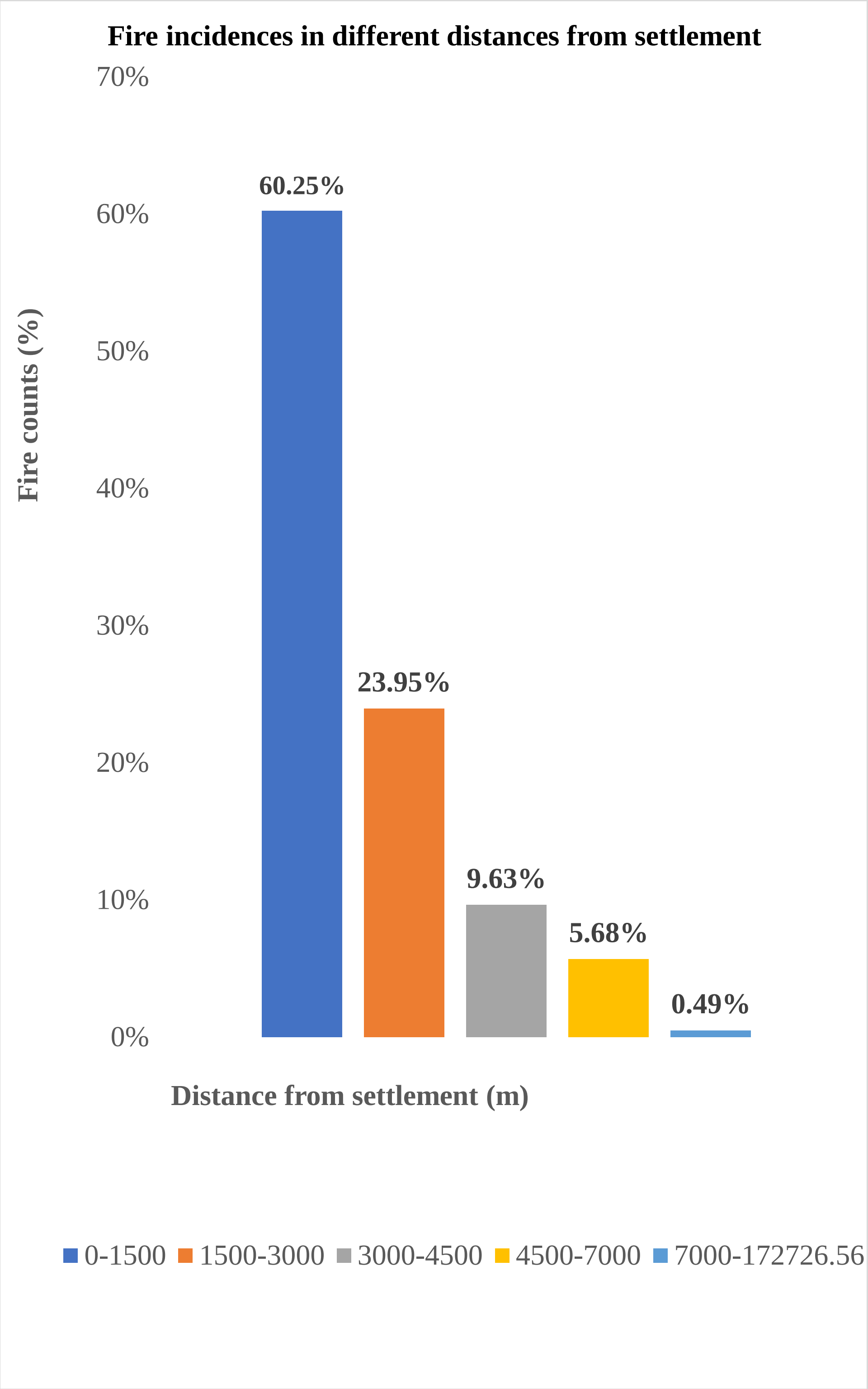


Figure 20: Distance from settlement versus fire incidences

4.1.5 Forest Fire Risk Zone

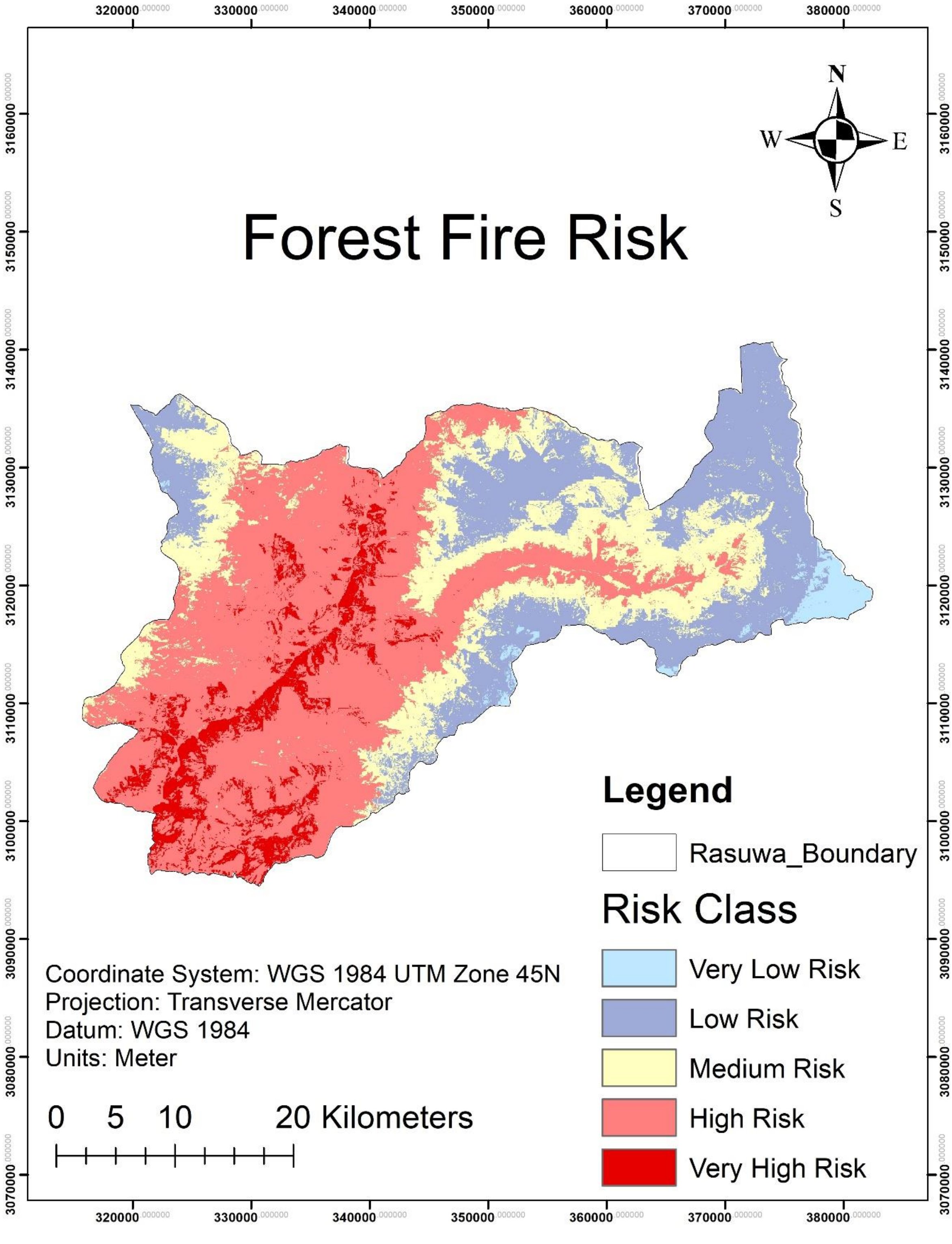


Figure 21: Forest Fire Risk

From Figure 21, for each risk classes the area covered was calculated. Highest area was covered by High risk class (44.79%), followed by low risk class (24.71%) and medium risk class (21.35%). Only 7.27% of total area was covered by very high risk class.

Table 8: Area covered by different risk classes

Risk Class	Risk Area (sq.km)	Risk Area %	Fire counts
Very High risk	108.15	7.27%	83
High risk	665.97	44.79%	276
Medium risk	317.5	21.35%	46
Low risk	367.32	24.71%	0
Very Low risk	27.84	1.87%	0

Very high risk area were fallen on all rural municipalities of Rasuwa district. Very high risk class's area was mainly on Gosaikunda rural municipality and also large area of medium risk class, low risk class and very low risk class were in this rural municipality. Low risk class was only in Gosaikunda and Aamachhodingmo rural municipality.

4.1.6 Accuracy assessment

MODIS hotspot data from 2004-2023, having confidence level greater than 30% were used.

Figure 22 indicated that the highest fire incidences occurred in high risk class (68.15%), followed by very high risk class (20.49%) and medium risk class (11.36%) encompassing an area of 44.79%, 7.27%, and 21.35% respectively. No fire incidences were seen in low and very low risk class encompassing an area of 24.71% and 1.87% respectively.

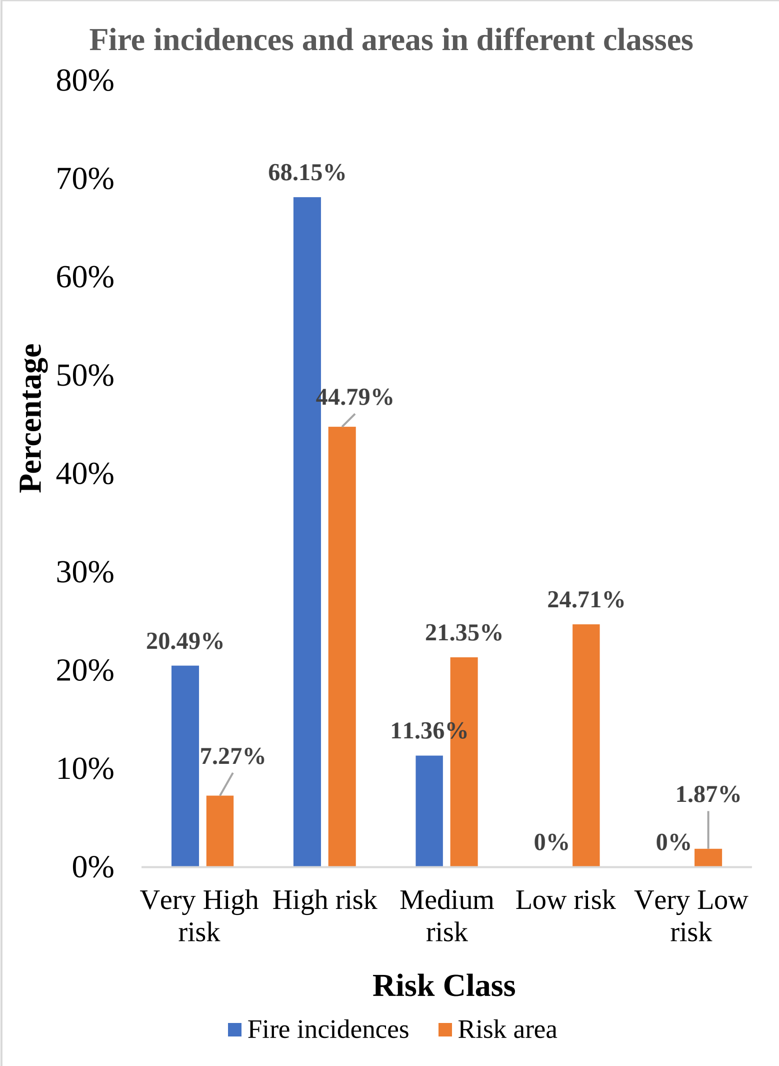


Figure 22: Total fire incidences and total area in different risk classes

4.1.7 Validation

- <u>AHP model validation</u>

The calculated consistency ratio value was 0.07, which means the FFRI model generated through the AHP method was valid.

- <u>Forest fire risk map validation</u>

The generated risk was validated using the ROC-AUC curve using MODIS hotspot data with confidence level >= 30% as true positive values.

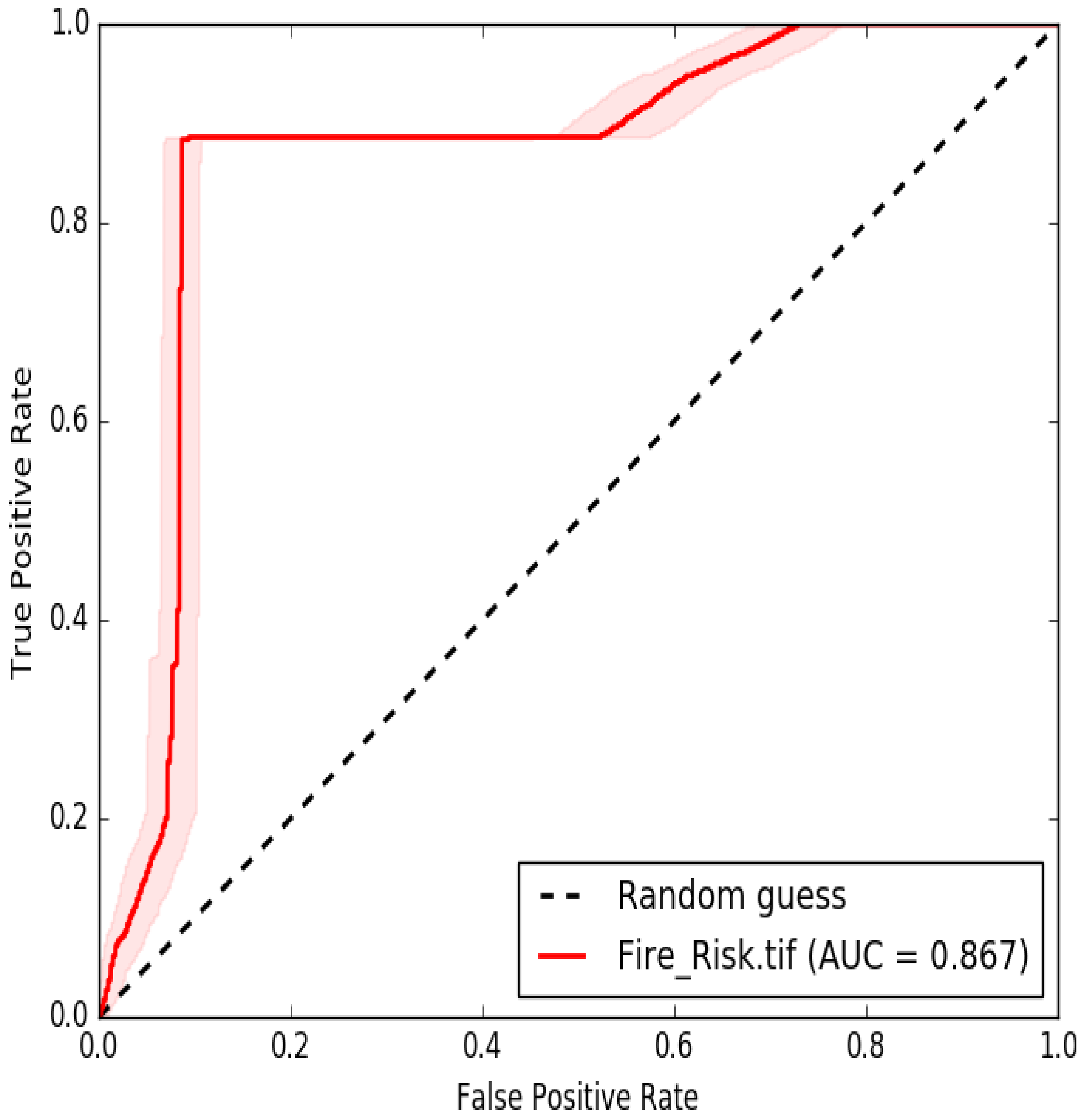


Figure 23: ROC curve

Figure 23 indicated the AUC value of generated forest fire risk map was 0.867, that means the generated map was good.

4.2 Discussion

Forest fires offer rising environmental concerns about ecological sustainability and ecosystem biodiversity across the world, particularly in light of climate change and the fast population increase. In this light, determining the geographical susceptibility of forest fires has become critical in the context of integrated global forest wealth management. A detailed geographical evaluation of the possible vulnerability of forest fires in Rasuwa was carried out in this study, utilizing a mix of GIS and AHP. Factors such as LULC, LST, slope, aspect, elevation, distance from road, and distance from settlement have been used for forest fire risk mapping.

Many earlier studies have emphasized the significance of land use land cover classes in assessing a specific area's risk of fire occurrences as it relates to fuel types and characteristics (Keane et al., 2001; Carmenta et al., 2001; Vadrevu et al., 2006). In my study, the result showed the highest number of fire incidents, about 47.16%, occurred in forest, followed by grassland, about 30.86%, which is consistent with the findings of Bhujel et al., (2018).

High LST impacts the danger of forest fire favorably. The maximum number of forest fire incidents, 32.84% happened in the highest LST range of 20-25.575 ^{0}C, followed by LST range of 10-15 ^{0}C, 31.60%, and LST range of 15-20 ^{0}C, 26.67%, which is similar with the result of (Subedi et al., 2022).

The risk of forest fires increases as the slope increases (Rothermel, 1983; Sibanda et al., 2011), but in my research area, forest fire incidences increase until 30-45 degrees and then drop since the bulk of vegetation is situated in this slope range. Slope of 30-45 degree had the most forest fire incidences (46.91%), followed by the 15-30 degree of slope (30.86%).

The majority of fire incidents occurred in the southern aspect, where more sunshine strikes and dries up the soil, hastening the igniting process (Alkhatib, 2014). In my study area also, the south aspect had the largest number of fire incidences (20.49%), followed by the southeast aspect (19.01%), and the southwest aspect (13.83%) consistent with the result of Bhusal & Mandal, (2020). Low-fire occurrences have been seen in the northern portion of the study area.

In general, forest fire occurrences decrease as elevation increases due to lower temperatures and more humidity compared to lower elevation (Rothermel, 1983). In terms of elevation, in my study are, the largest number of fire events (42.22%) occurred at 1000-2200 m elevation, followed by 2200-3500 m elevation (34.82%), and 3500-5000 m elevation (20.49%). The study region's most area is covered by 1000-5000 m elevation, and above 5000 m, there are no fire incidences due to lower temperatures and more humidity. Because lower altitudes cover a smaller area in the research region, fewer fires occur in lower elevation ranges (less than 1000 m) than in higher elevation ranges (1000-5000 m).

According to Matin et al. (2017) and Parajuli et al. (2020), rising forest fire incidence is caused by anthropogenic activity; however, other factors may be at play. The road network passing through the forest area and settlements near the forest influence the risk of forest fires. Sibanda et al. (2011) observed more fire incidents near roads, settlements, and agricultural areas. The number of fire incidents decreases with the increase in distance from roads and settlements (Matin et al., 2017). The highest number of fire incidents occurred at a distance of 92.59% from the road, followed by 7.16% at a distance of 1200–2500 m, and a gradual decrease in fire incidents was observed as the distance from the road increased. Similarly, the highest number of fire incidents occurred at a distance of 60.25% from the settlement, and a gradual decrease in fire incidents was observed as the distance from the settlement area increased: 23.95%, 9.63%, 5.68%, and 0.49% at a distance of 1500–3000 m, 3000–4500 m, 4500–7000 m, and above 7000 m from the settlement.

Forest fires are most common in South Asia from February to May (Reddy et al., 2019; Sahu et al., 2015; Upadhyay et al., 2022). There were a large number of fire events in 2009, which is in sync with Matin et al. (2017) findings, but contradicts Qadir et al. (2021) findings, which show that the highest number of fire incidents happened in 2016. In 2009, active fires were recorded in LNP and other national parks. Nepal received one of the most prolonged dry spells, nearly six months of no precipitation across most of the country. Winter has become increasingly drier recently (BBC NEWS, 2009). A large number of fire events occurred from January to May, which is consistent with the findings of Parajuli et al. (2015). The pre-monsoon season (Mar-May) has the largest number of forest fire events, followed by the winter season (Dec-Feb), which is similar to the findings of Bhujel et al., (2017).

The AHP weightings of the present study are consistent with the study by Pradeep et al. (2022) and Suryabhagavan et al. (2016), as higher weight was given to vegetation type, followed by settlement, and road. Land cover classes and anthropogenic factor influences accounted for roughly 68% of the AHP weight among the variables possibly explaining fire risk assessed in this study same as the result provided by Nikhil et al., (2021). Other research indicates that land cover and slope influence the occurrence of forest fires (Bhujel et al., 2017; Jaiswal et al., 2002;

Matin et al., 2017; Parajuli et al., 2020; Qadir et al., 2021; Sari, 2021). Unsurprisingly, the key factor defining forest fire in our analysis was land cover class, since it influences multiple variables crucial to the probability and intensity of a fire (Carmenta et al., 201; Vadrevu et al., 2006).

One of the most crucial components of fire risk maps' communication is validation; users must have confidence in the provided data in order to act on it (Pourghasemi et al., 2016). From the date 2004-01-01 to 2023-05-31, MODIS fire sites having confidence level greater than equal to 30% was overlayed on the final risk map. Rahman & Chang, (2017) established the reliability and robustness of MODIS data in mapping fire severity and the seasonality of vegetational response. The result reveals that about 68.15%, 20.49%, and 11.36% of documented occurrences occurred inside our map's high, very high, and medium-risk class respectively, and zero incidences occurred on low and very low risk class. Matin et al. (2017) conducted a similar procedure in Nepal for forest fire counts generated from MODIS hotspots and discovered that 80% of forest fires were in extremely high to high-risk zones. The AUC value was also calculated, same as given by Nikhil et al. (2021), in which LULC, slope, aspect, Distance from settlement, road, etc. were taken as forest fire influencing factors.

CHAPTER 5: SUMMARY AND CONCLUSION

5.1 Conclusion

In this study, we undertook a comprehensive analysis of forest fire risk in Rasuwa District, Nepal, employing a combination of GIS and the AHP using factors such as land cover, LST, slope, aspect, elevation, distance from road, and distance from settlement. The data used to prepare the geospatial database and MODIS hotspot data used in validation had coarse spatial resolution. The generated AHP model was valid. The validation of the forest fire risk map found an essential association between known fire incidents and our high and medium-risk zones, confirming the accuracy of our risk assessment. The ROC curve showed the validation of the generated fire risk map, which can serve as a practical decision support tool for local authorities, forest managers, and community stakeholders to improve forest fire management, lower the risk of forest fires, and boost the ecosystem's resilience.

5.2 Recommendations

The data can be used from other sources with different resolutions to increase the accuracy of the generated map. More experts can do the pairwise comparison to increase the efficiency of the AHP model. Other factors which influence in forest fire should be included for more precision. Surrounding districts can use the AHP model and applied methodologies to generate risk maps, which may be helpful for managerial purposes and decrease the chance of fire transfer in the Rasuwa district. VIIRS hotspot data have better spatial resolution and can be used to validate the result. Forest Fire Detection and Monitoring System, Nepal sends an alert message to different stakeholders of the concerned area about the real-time forest fire, which can be used to increase the efficiency of validation, and ground verification data can be highly appreciated.

APPENDICES

Photo Plates

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1	SLC	SLC, GON	A	2072 B.S.
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3	B.Sc. Forestry	FOF, AFU	-	Final year