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Forest Fire Zone Identification and Susceptibility Hazard Mapping of Gandaki Province, Nepal

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Abstract

Forest fires are the most frequent hazards in Gandaki Province, Nepal, and have deeply affected its unique physiography, vegetation, and human activities. This study focuses on identifying the main factors that cause forest fires and develops a susceptibility map using the MaxEnt model. Satellite image data and field observation across the province; topographical variables such as physiography, elevation, slope, and environmental variables such as temperature and precipitation, and anthropogenic variables such as land use were analyzed to deduce fire risk. The results indicate that the Myagdi, Gorkha, and Baglung have the largest share of fire-prone areas, representing 44% of the total area falling within the fire-risk zone. Myagdi is the most hazardous district, which covers 17.35% of this fire-susceptible area, followed by Gorkha with 16.56%, and Baglung with 10.59%. Their rugged topography, steep slopes, shrubland, and high density of forests are these districts are so prone to susceptibility. Contrasting this, Parbat and Manang present very low fire hazard conditions because of cool climates, less vegetation cover, and river and snow barriers. These account for only 1.56% and 2.39% of the total fire-prone area. Principles of effective forest fire management emphasize the targeting of high-risk districts with appropriate measures concerning sustainable land-use practices, community participation, and enhancing monitoring activities within the province.

Keywords: Forest fire susceptibility, Hazard mapping, Risk factors, MaxEnt modeling, Gandaki province

Introduction

Forest fires are a rising global concern, destroying millions of hectares of forest areas yearly. These have caused massive ecological losses by disrupting the balance of nature, causing a loss of biodiversity, human life, and socioeconomic development (Gao & Liao, 20170). The alarming trend has linked forest fires to a combination of anthropogenic activities and climate change (Robinne, 2021). Most of the terrible events in recent decades have been blamed on poor local forest management practices among other causes, exacerbated by climate change factors such as unprecedented protracted droughts and rising temperatures. The devastating wildfires in both Australia and the Amazon rainforest have been blamed on poor local forest management practices exacerbated by the impacts of climate change, including exceptionally prolonged droughts and increasing temperatures (Shukman, 2020). These come with serious repercussions, mostly irreversible damage to the ecosystems, habitat loss among innumerable species, and very heavy financial losses among the local communities and nations alike.

In recent years, forest fires have become a crucial factor in the deterioration of Nepal's forest ecosystems and, consequently, pose a variety of environmental problems. The main cause of this is human activities; it has been recorded that about 89% of forest fires usually originate during the dry season, specifically during March, April, and May (Bhujel et al., 2017). This peak fire season, characterized by prolonged low rainfall and high temperatures, seriously threatens the country's natural vegetation, besides causing massive damage to public and private properties. These fires have very depressing ecological consequences, including severe vegetation damage, threats to biodiversity, and disruption of ecosystem services that include soil fertility and water regulation. Moreover, forest fires destroy Non-Timber Forest Products (NTFPs) and promote invasive species, as well as pose great risks to human life and infrastructure, which is why the management of forest fires is an urgent priority for both national and local authorities (Uys et al., 2018).

This is evident in the rising tide of research works on understanding the factors that underpin forest fires in Nepal, as incidents have increased over time. Indeed, more than 35,000 fire incidents reportedly occurred between 2000 and 2016, with estimated economic losses of over $107,000, 11 fatalities, and several injuries (Bhujel et al., 2017). It denotes human-induced fires, whether due to deliberate land-clearing practices or accidental ignitions, as the main cause of disturbance to Nepal's forest ecosystems and biodiversity. With the call for addressing the risks of forest fires in Nepal becoming increasingly important, modern technologies have been utilized to model the fire risk and map hazard zones. Recent developments in remote sensing, GIS technology, and statistical approaches have enhanced the understanding of the dynamics of forest fires, thus enabling the formulation of appropriate management strategies (Parajuli et al., 2020). In this respect, the present study examines the risks associated with forest fires and determines hazard zones in Gandaki Province, Nepal, thereby contributing to the development of a better framework of forest fire risk assessment and its management in the region.

Literature Review

On a global scale, forest fires are a significant contributor to anthropogenic greenhouse gas emissions and have negative impacts on the integrity of wildlife and ecosystems. Robinne (2021) estimates that between 2001 and 2018, about 7.2 billion hectares burned at an average of roughly 400 million hectares per year. This number is staggering and represents the growing need for good fire management practices. Although the total area burned during the period 2013-2018 was below the long-term average, according to FAO (2020), the risk associated with forest fires is already 1.1 times higher in contemporary climate conditions compared with that in pre-industrial times, and under future climate scenarios may double.

The situation is not different when it comes to Nepal. Some studies estimated that about 40,000 hectares of forest are burned every year, most in the dry seasons between February and May of each year. This is the period with low rainfall and high temperatures; hence, a period of high fire spread. The 2009 disastrous fires, which affected most people and caused immense destruction, indicate the severe effects of forest fires on human habitations as well as on the natural ecosystem. Land clearing, careless behavior of people, and deliberate ignition for land management on account of anthropogenic causes have been identified as the key factors (Parajuli et al., 2015).

The occurrence and magnitude of forest fires are increasing, and thus there is an urgent need for better tools to assess risk. Parajuli et al. (2020) developed fire risk models for two major landscapes in Nepal using remote sensing and GIS technologies to develop risk maps for early warning. This method is supported by the works of Jaiswal et al. (2020) and Erten et al. (2004), where fire risk zones were defined as areas with a high possibility of potential fire spread. Precise threat mapping may be thus considered as a tool not only to minimize negative impacts resulting from forest fires but also to provide input for resource allocation in fire management.

In this regard, quantitative evaluation models, including the Maximum Entropy Model (MaxEnt), are among the popular applications for the assessment of risks from forest fires (DoF, 2022). MaxEnt would preferably be applied since it requires merely a minimum amount of data and can predict the spatial distribution of fire risk with environmental variables. It has already outperformed a few other machine-learning methods in a couple of comparative studies, which makes it the most preferred by researchers who are focusing on forest fire prediction (Vilar et al., 2016; Kim et al., 2019). Geospatial models, now increasingly use satellite data to map fire risk indices, allowing researchers to pinpoint high-risk areas and strategize accordingly for fire management (Bowman & Murphy, 2010; Nelson & Chomitz, 2011).

Understanding the causes and dynamics of forest fires is rather an important aspect of developing effective mitigation strategies. The studies on the temporal-spatial pattern of fire occurrences will help classify areas that are prone to high risk, something which is important in implementing preventive measures and managing sources of ignition. They further help incorporate biophysical and human elements in their forest fire risk models to enhance their accuracy and relevance. Matin et al. (2017) pointed out that much of the research relating to district-specific fire patterns and risk mapping lacks district-level risk mapping, on which resource allocation should be based. Second, the management of fires needs to be made more inclusive of the resident's local communities; after all, their traditional knowledge of the local conditions will enrich the preventive measures for fires.

The various technological advancements have increased the availability of remotely sensed data to study forest fires; hence, helping in fire monitoring, risk assessment, and understanding of causes and effects that include (Bowman & Murphy, 2010; Nelson & Chomitz 2011). Common tools that are normally used to predict fire risks for forest fire modeling include MaxEnt, random forest, and regression tree analysis. This is especially effective, being simple yet accurate, outperforming many of these other models in many comparative studies (Phillips et al., 2006; Vilar et al., 2016; Kim et al., 2019).

Study Area

This study focuses on Gandaki Province, which is centrally located in Nepal and lies between 27° 26' 15" N - 29° 19' 15" N and 82° 52' 45" E - 85° 12' 01" E. It consists of 11 districts, namely Nawalpur, Tanahun, Gorkha, Lamjung, Kaski, Syangja, Parbat, Baglung, Myagdi, Manang, and Mustang. It has 85 local bodies comprising one Metropolitan City, 26 Municipalities, and 58 Rural Municipalities (MoITFE, 2018). It covers an area of 21,976.34 km² and constitutes 14.93% of the total land territory area of Nepal. According to the census 2021, the population of the province is 2,466,427; there are 662,480 households. The male population is 1,170,833, while the number of females is 1,295,594 (NSO, 2021).

Elevation varies from 104 meters at the southern part of Nepal (India border) on the Gandaki Canal of the Narayani River to 8,167 meters at Dhaulagiri, the highest peak. A lot of such geomorphological and physiographical features come within this varied topography of the province, which controls the pattern of forest fire susceptibility across the province.

Around 37.1% area of the province is covered by forest. Major tree species of the province are Sal, S*issoo, Khair, Rani salla, Chilaune*, *Katus*, *Utis* and G*obre salla*. The major forest management models exercised in the provinces are community forest management, collaborative forest management, and block forest management. A scientific forest management program has been launched in all these forest areas through the Nepal government. *Chiraito, Kutki, Panchaule, Lokta, Ban lasun, Satuwa, Atis, Nirmansi* are major Non-timber forest products (NTFPs) (MoITFE, 2018).

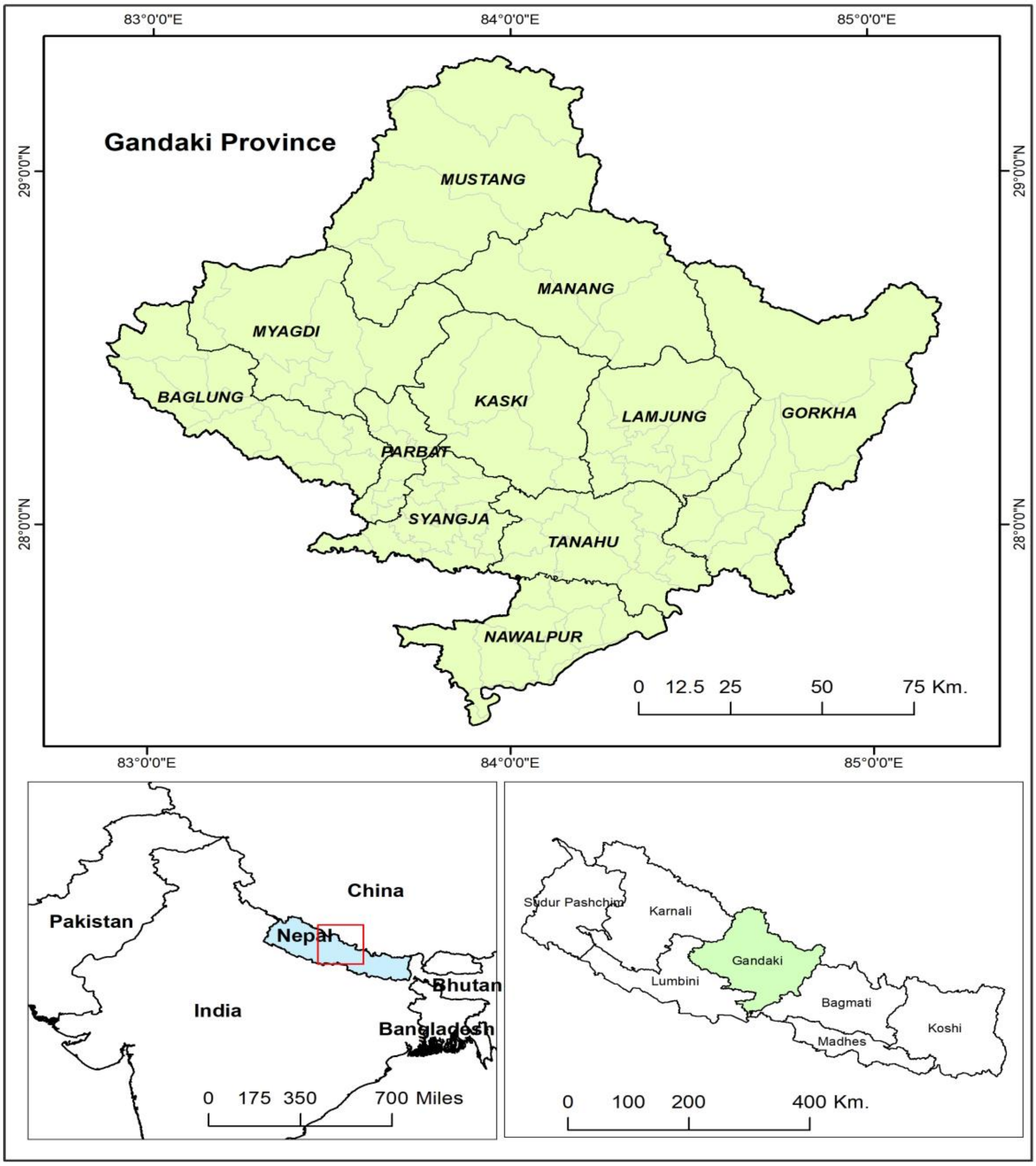

Figure 1: Location Map of the study area

The diversified geological and geographical features of Gandaki Province make it very prone to different kinds of natural hazards. Unplanned settlements, steep terrain, rapidly flowing rivers, and large areas of uncultivated land contribute greatly to their occurrence in that region. Human intrusion into these natural settings brings even higher risks, enhancing the frequency and intensity of disasters related to forest fires, among others. These combined factors make the hazard landscape complex, and management needs to be closely considered.

Materials and Methods

Materials

Key informants' interviews and focus group discussion for the current study was carried out in 2019. Preliminary consultations were carried out with government officials, including staff from the district administration office, district police office, district coordination committee, and representatives from municipalities and rural municipalities. Members of the Red Cross Society and elected community leaders from all 11 districts of Gandaki Province were also consulted to identify potential risk zones and locations prone to hazards. The following environmental variables were derived from free available databases, as shown in Table 1, before their processing with ArcGIS 10.8 to make their format uniform in ASCII format and their resolution in 30 m. Also, some of the variables whose data formats are vectorial (points and lines) were transformed to raster data with the same resolution.

Table 1: Environmental variables used for the study

Category	Variables	Source	Unit
Topographic	Aspect	(USGS, 2019)	degree
	Elevation		m
	Slope		degree
	Distance to water	(Geofabrik, 2019)	km
Climatic	Mean precipitation	(WorldClim, 2019).	cm
	Mean temperature		degree
	Mean solar radiation		
Vegetation Related	Mean EVI	(MODIS, 2019)	dimension less
	Forest	Global forest change (Hansen, et al., 2013)	dimension less
Anthropogenic	Land use land cover	(ICIMOD, 2010)	type
	Distance to road	(Geofabrik, 2019)	km
	Distance to path		km
	Distance to settlement	Department of Survey, Nepal	km

Methods

MaxEnt, or Maximum Entropy, is a software tool that models species distributions using geo-referenced occurrence data along with environmental variables to predict the suitable habitat of a species (Phillips et al., 2006). It was firstly designed for ecological studies and then used in the prediction of the distribution of various plants and animals (Guisan, et al., 1998; Pearce & Ferrier, 2000; Gillespie & Walter, 2001; Phillips et al., 2006). It also has recently been used to predict natural hazard risks such as forest fire, flood, and landslide events (Goetz, et al., 2011). Environmental variables presented in Table 1 and hazard occurrence data were input in MaxEnt version 3.4.1 to model the potential disaster risk zones of this work. The model used 1000 maximum iterations, as suggested by Barbet-Massin et al. (2012), and was run for ten replicates. A data split was performed technique where 70% goes to training, while the remaining 30% goes to the validation of the models. Based on the findings of Liu et al. (2013), the MaxSSS threshold was chosen for changing continuous probability maps into binary maps. To prepare the forest fire susceptibility map of the present study area, this threshold was applied.

Accuracy Assessment

An accuracy assessment was carried out to establish the reliability of the susceptibility map using both threshold-independent and threshold-dependent methods. The threshold-independent method AUC has been utilized to evaluate model performance, measured by the area under the ROC curve. An AUC score of <0.7 indicates poor performance, 0.7-0.9 denotes moderate usefulness, while >0.9 suggests excellent performance (Pearce & Ferrier, 2000). The threshold-dependent method utilized the True Skill Statistics, computed as TSS = Sensitivity + Specificity − 1, within a range between −1 and 1 (Allouche et al., 2006). The TSS value less than 0 reflects unsatisfactory model performance, whereas 1 represents a perfect fit. The TSS was averaged over 10 model outputs, and the threshold used to maximize the TSS was used to transform the continuous susceptibility map into a binary map (Liu et al., 2013; Jiang et al., 2014).

Findings and Discussions

Factors determining the forest fire risk zone

In this study, the most important contribution was the determination of the contributing factors to forest fire susceptibility, focusing on those core variables that dictate fire risk. The results given by the MaxEnt model allowed one to perceive the relative importance of different environmental factors assessed through regularized training gain. This latter term measures how much better the model fits the occurrence data compared to a uniform distribution. The description of model performance includes all the variables, "with only variable" refers to the performance of the model on the removal of a certain variable, whereas "without variable" refers to a model run only when that particular variable is included as per Phillips (2017). Here, lower regularized training gain for only one variable contributes to indicating a higher contribution to forest fire susceptibility; and a higher value contributes to a lower effect.

The results show that the most contributing factors to forest fire risk, according to the MaxEnt model, are related to elevation, temperature, distance to water bodies, and rainfall. These factors are those that most greatly affect the spatial pattern of areas prone to fire, where lower elevation, higher temperature, and reduced distance toward water sources are highlighted as principal factors increasing fire susceptibility in the area under investigation. The resultant output in ranking order presents the various environmental variables that best explain the zoning of fire risk in the forests of Gandaki Province, Nepal. These results also tend to indicate that while some variables have a very significant influence on fire risk prediction, others contributed moderately or minimally.

The top-scoring variables according to the highest regularized training gain are mean precipitation, mean temperature, and elevation. These are seemingly some of the most important factors to consider during the risk modeling process. Mean precipitation simply indicates that the lower precipitation areas are at a higher danger of experiencing fires because low rainfall simply sets the stage for ignitions and propagations to occur easily and efficiently. The mean temperature is a similarly important factor and the regions that are usually hotter tend to have a higher proclivity for fire since the proclivity for dryness and the actual weather of the location are right for the propagation of a fire. Probably due to changes in elevation, temperature, vegetation types, and moisture change significantly with altitude variations; it is an essential factor for fire. Elevation is another important factor.

The Mean solar radiation and land use/land cover, including forest cover, realize considerable increase, thus proving that they are very influential in fire risks, but at a slightly lower level than the ones of climatic origin. This is because land use or land cover is important in that areas with dense vegetation are more prone to fire since fuel is readily available. Mean solar radiation impacts surface temperatures and contributes to vegetation drying, thus increasing the chances of fire. On a similar thought, forest cover has to do with highly forested areas developing bigger and more destructive fires due to the abundance of material to burn.

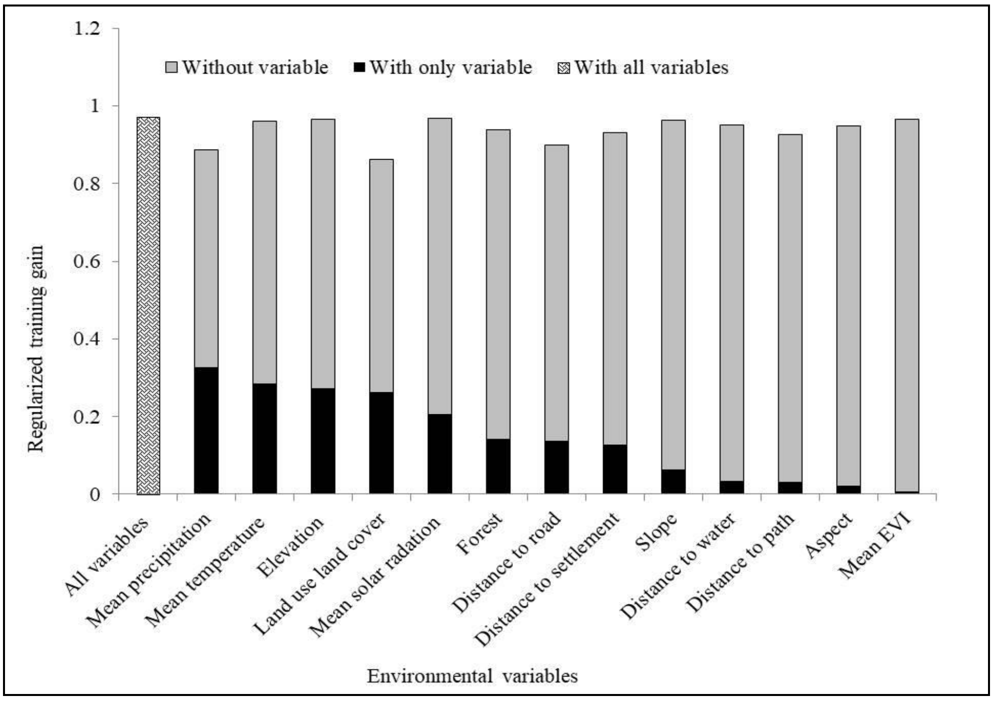

Figure 2: Importance of variables to train the forest fire risk model

Other factors-distance to roads, distance to settlement, slope, and distance to water-show a more moderate impact on fire risk. Although each of these variables taken individually contributes less, they are relevant in their joint consideration for the analysis of fire risk. These might include distance to road and settlement, which features the proximity of humans, raising the danger from human-caused fires, such as those from the clearing of land or other unintentional ignitions. The slope is one-factor affecting fire spread; in general, fires travel uphill faster. Distance to water sometimes serves as a natural firebreak that may reduce the spread of a fire in those areas near the body of water.

The last three factors, which have less individual influence yet are still a part of the overall risk model, are aspect, distance to path, and mean Enhanced Vegetation Index. Aspect influences a slope's received solar radiation, which again controls vegetation dryness and, therefore, fire susceptibility. Mean EVI is an indication of vegetation health and density and would therefore be indicative of fire susceptibility but seems in this case to have less direct influence on this model.

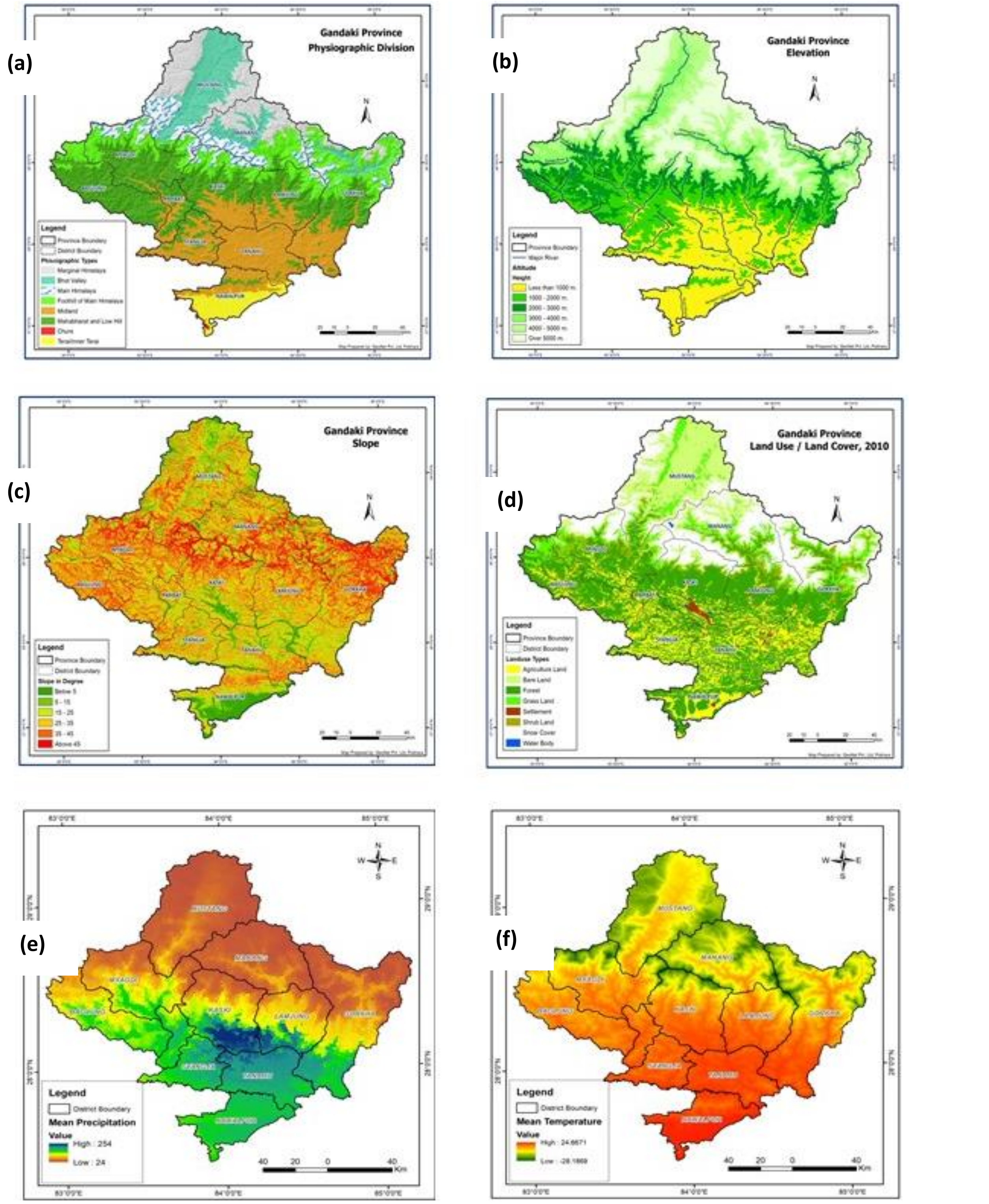

Figure 3: Factors determining the forest fire risk

Source: USGS, 2019 of (a) Physiography (b) Elevation (c) Slope; ICIMOD-2010 of (d) LULC; and WorldClim - 2019 of (e) Mean Precipitation (f) Mean Temperature

The risks of forest fire in Gandaki Province are primarily governed by physiography, elevation, slope, LULC, precipitation, and temperature (Figure 3). Generally, areas of low elevation, particularly the Terai and mid-hills, are considered at risk due to high vegetation and dry conditions; whereas, high-altitude regions such as Mustang and Manang fall into a low-risk category due to the scarce density of vegetation and colder climatic conditions. Steep slopes, as illustrated in the slope map, accelerate fire spread, especially in the mid-hill and mountainous regions since slopes above 45° pose greater risks. In the LULC map, forests in mid-hill and low mountains are very vulnerable to fires, especially during dry seasons. Human activities related to agriculture near forests also enhance the risk of fire.

Precipitation and temperature fluctuations also affect the vulnerability of land to fire. Southern regions with relatively high temperatures and irregular rainfall have much more propensity to catch fires because vegetation tends to dry up. In northern areas, temperatures are cooler, and the quantities of rainfall are lower, where the risk of such fire is lesser; however, small-scale fire is likely to happen when it is extremely dry.

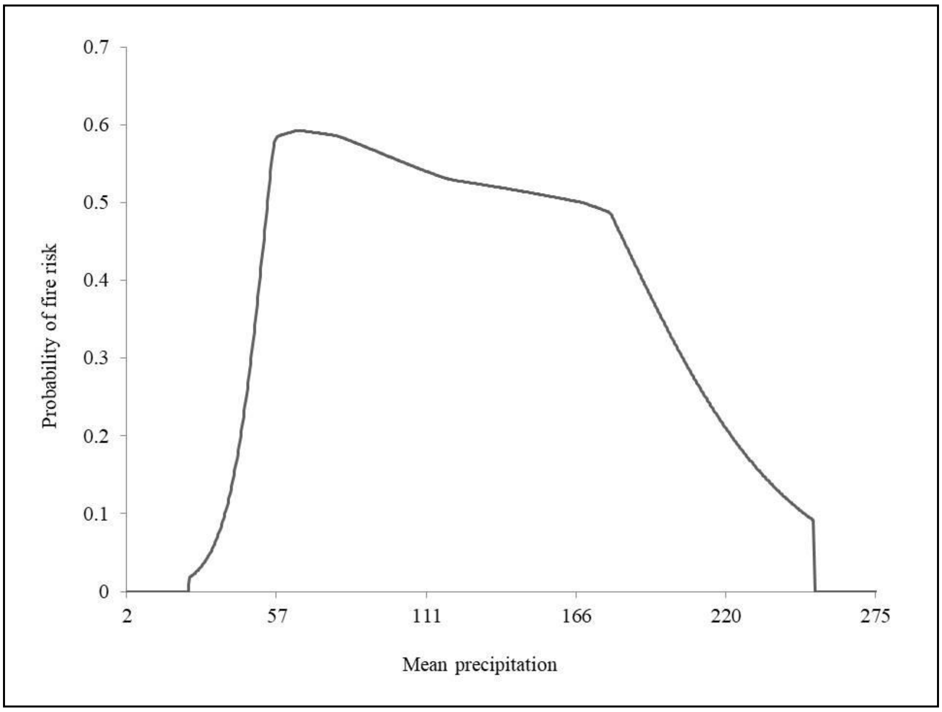

Figure 4: Response of fire risk to mean precipitation

In the graph at left, the curve depicts the relationship between mean precipitation and the probability of fire risk (Figure 4). This curve follows roughly a bell-shaped pattern. Starting from low precipitation, fire risk increases with rising precipitation, then peaks around a precipitation value of about 57 mm. past this peak, the probability of fire risk decreases linearly with increased precipitation.

This would suggest that moderate precipitation creates conditions that are opportune for forest fires. In such periods, adequate moisture prevails for vegetation to grow, while it could be used as fuel for fires. On the other hand, rainfall is not high enough to keep biomass moisture high, and so the region becomes prone to ignition. When the precipitation value exceeds a threshold value of 111–166 mm, the environment becomes relatively wet, decreasing the likelihood of fires due to higher moisture levels that may impede the easy firing of vegetation.

In other words, low and extreme precipitation both reduce fire risk, while fire danger is highest for moderate levels of precipitation. This pattern shows that for ecosystems, there is a narrow window of precipitation where fire hazards increase greatly. This conclusion also agrees with global patterns, where large fire outbreaks occur usually during dry seasons or after a moderately wet year because of the amount of dry, combustible material available and due to the favorable weather toward ignition and fire propagation.

The result shows the probability of fire risk concerning land cover types; it can be shown that different land covers perform differently concerning fire hazard (Figure 5). Shrub land, broadleaved open forest, and needle-leaved open forest have high probabilities of fire risk, while rivers, snow/glacier areas, and built-up areas have the lowest probabilities.

Shrubland and open forests are less dense compared to other vegetation classes, thus being highly vulnerable to fires. Areas in such categories may have vegetation that is arid and of lowlands nature and may be characterized as light fuel to the spread of fire for a period of a dry season or in areas with moderate rainfall. The region catches fire easily because the area has combustible materials, accompanied by heat and wind exposure. Broadleaved closed forests and needle-leaved closed forests, on the contrary, have lower risks from fire as compared to their open categories of woods. This probably is due to the more humid microclimate created by a close canopy, thereby decreasing the possibility of the fire reaching the forest floor. The canopies also contribute to holding moisture within their cover, hence making the overall forest even less flammable.

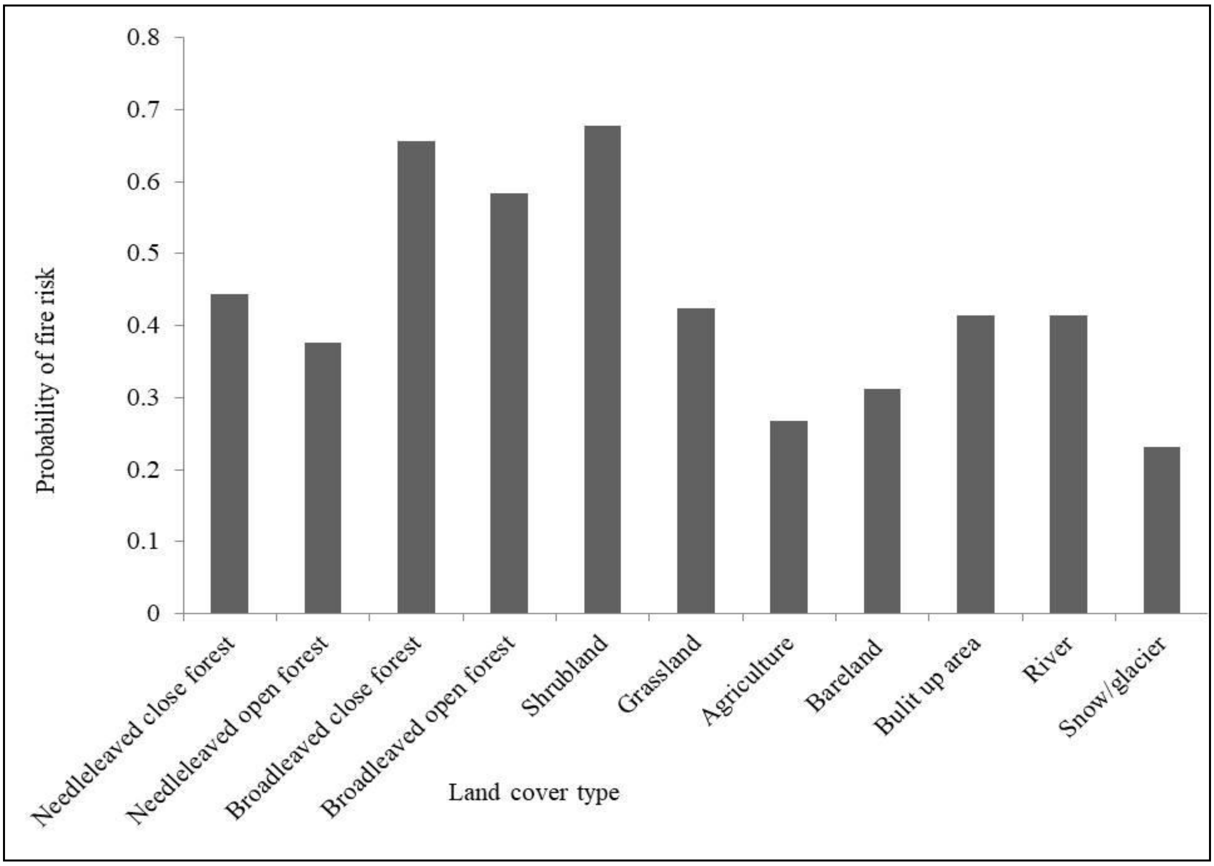

Figure 5: Probability of landslide risk to land use land cover type

Grassland also has a high fire hazard since grasslands are known to dry off quite rapidly, therefore offering considerable fuel for wildfires. With less vegetation, the similar-looking landscapes over vast expansions make grasslands more prone to widespread fires, especially in periods of dry weather. Agricultural land presents a medium fire hazard, probably because fire is used in land clearing for agriculture. The risk is still smaller, however than in natural sceneries, where broad vegetation cover makes such areas more flammable. Intuitive enough, the lowest fire risk is demonstrated by built-up, rivers, and snow-covered areas. Large built-up areas generally have fire management systems in place and less combustible material, whereas rivers and snowy regions act like natural firebreaks that prevent the spread of a fire.

The presented analysis of precipitation and land cover types underlines a very complex interplay of natural and human-modified landscape factors that determine fire risk. On one hand, moderate precipitation favors vegetative growth that later will act as fuel for fires. At the same time, the territories of shrublands and open forests show high vulnerability to outbreaks of fires, drawing attention to special management interventions in these zones.

This will indeed be useful to understand while devising effective fire management strategies within Gandaki Province. Mitigation efforts should, therefore, target high-risk ecosystems such as shrublands and open forests, given the variability of precipitation patterns on fire risk. Local agricultural activities and land-use practices will also have to be carefully monitored, especially during periods of low rainfall when the fire hazard may be higher.

Forest Fire Susceptibility Mapping of Gandaki Province

Finally, this study predicted and mapped the forest fire risk zonation throughout the Gandaki province (Figure 6, Table 2). Shrubland, broadleaved close forests and other forests, and grassland are identified as major factors contributing to the forest fire risk zone.

The High Mountains and Terai regions are identified as major fire risk zones. A total of 6,349 km^2 area is identified as a fire risk zone in Gandaki province. A threshold (0.255) to maximize the sum of sensitivity and specificity was used to change the probabilistic map to binary risk-free zones. The high Himalayan and middle hills have low fire risk. In the middle hills there is more forest broadleaved close forests and shrubland so these regions have more fire-prone areas.

Out of 11 districts of the province Myagdi, Baglung, and Gorkha districts have more fire risk areas whereas Parbat and Manang districts have less fire risk areas (Table 2). Probably, these districts have more vegetation cover as a result they have more fire risk.

Table 2: District-wise fire risk area

S. No.	Districts	Fire risk area	
		Area (Km^2)	Percentage
1	Baglung	672.66	10.59
2	Gorkha	1051.23	16.56
3	Kaski	681.97	10.74
4	Lamjung	813.23	12.81
5	Manang	151.88	2.39
6	Mustang	376.76	5.93
7	Myagdi	1101.57	17.35
8	Nawalpur	787.98	12.41
9	Parbat	98.96	1.56
10	Syangja	208.21	3.28
11	Tanahun	404.55	6.37
	Total	**6349.00**	**100.00**

The district-wise data on the Gandaki Province, Nepal, regarding the forest fire potential area, shows considerable spatial variation of fire risk across the region. There is a large number of districts with higher conglomeration of fire-prone areas. Out of the total area of 21,976 km^2 of Gandaki province, the MaxEnt model derived that, there is area of the potential forest fire risk is 6349 km^2, which is distributed variably among 11 districts (Figure 6). Further, such data may be used in critical analyses to search for possible drivers of fire risk and inform appropriate fire management strategies.

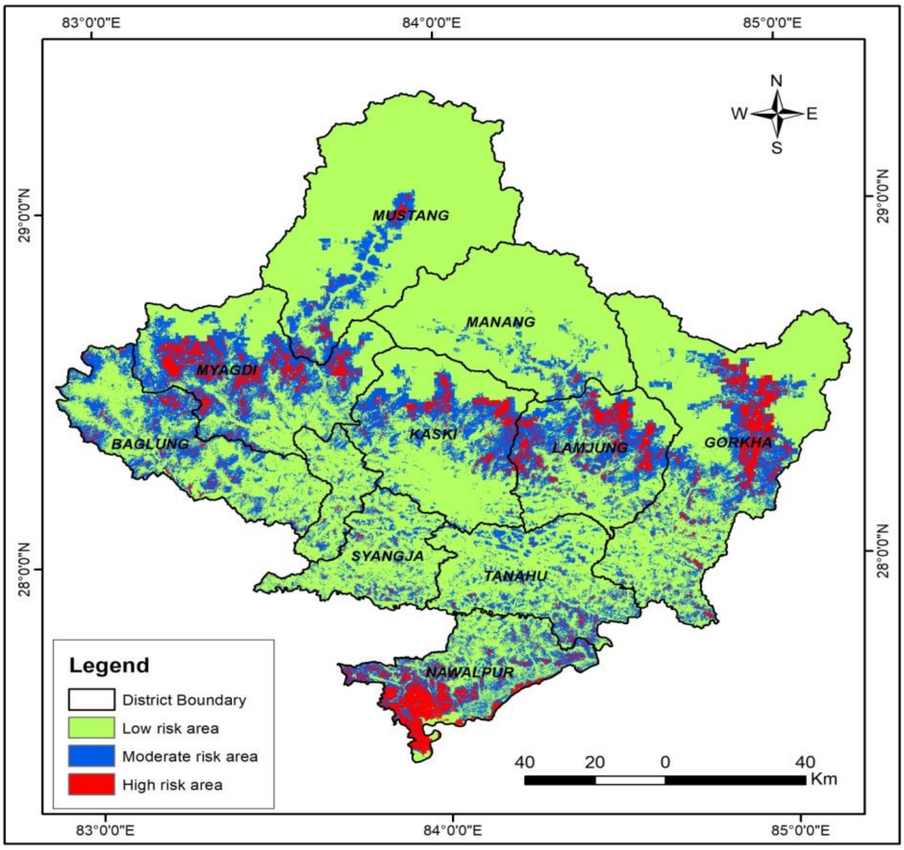

Figure 6: Forest fire susceptibility map of Gandaki Province

Among the districts, Myagdi, Gorkha, and Baglung have the largest proportion of forest fire risk areas, combining more than 44% of the total fire risk within the province. Myagdi alone has the largest area at risk with 1,101.57 km^2 (17.35%), but the second is Gorkha with 1,051.23 km^2 (16.56%), while the area covered by Baglung is 672.66 km^2

(10.59%). These districts are rugged in topography, steep slopes, and with diversified types of forests, and shrub land which may enhance the vulnerability of fire by accumulating dry biomass and being highly exposed to wind. This fire risk may be much more pronounced because of the interaction between these topographic factors and human activities such as deforestation or slash-and-burn agriculture.

Lamjung, Kaski, and Nawalpur also come under considerable fire-risk areas that share more than 36% of the total area. These three districts are almost identical in geographical and ecological conditions and therefore depict moderate fire-risk indicators. Lamjung shares 12.81%, Kaski 10.74%, and Nawalpur 12.41%. These places are very vital because they have high biodiversity, and any increment in occurrences of fires might have detrimental effects on the local ecosystems and efforts of biodiversity conservation. This requires moderate but fairly targeted fire prevention efforts against local vulnerabilities such as dry types of forests and agricultural burning practices that contribute to the total fire risk at the province level.

On the opposing, districts such as Parbat, Manang, Syangja, Mustang, and Tanahun contain areas prone to fires that contribute much less to the respective zone. With only 98.96 km² and 151.88 km² areas of fire risk, respectively, Parbat and Manang are the two districts with the least area of fire risk in the province. It could be explained by several factors including cooler climates and less vegetation in Manang. An arid environment keeps Mustang, despite that, contributing about 5.93 percent because of the highly vulnerable dry shrubland and grassland zones to wildfire.

This difference in fire risk across the districts conveyed that uniformity in approach may not work concerning fire management in Gandaki Province. High-risk districts such as Myagdi, Gorkha, and Baglung require immediate attention regarding fire prevention and control (Figure 6). Some initiatives regarding that would be community-based fire monitoring, improvement of fire management policies, and popularization of sustainable land-use practices.

Correspondingly, low-risk districts like Parbat and Manang may not need such a high level of concentration; still, precautionary measures should be provided in case there is an outbreak of a wildfire somehow. What's more, the general vegetation density in Mustang is pretty low, but the fire spreads fast in that type of landscape and destroys the local ecosystem.

Model accuracy of fire risk modeling

The accuracy metrics of the model are shown in Table 3. The threshold-independent method AUC has a value of 0.758±0.072, whereas the threshold-dependent method measured by TSS produced a value of 0.484±0.122. The optimal threshold value found was 0.255, for which the sum of sensitivity and specificity was maximum. This threshold was used for the calculation of TSS, and also for transforming the continuous risk map into a binary map of risk and non-risk zones.

Table 3: Accuracies of different replications of fire risk modeling

Replication	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Average**	**Std**
Threshold	0.360	0.190	0.080	0.600	0.070	0.210	0.460	0.240	0.230	0.110	0.255	0.172
AUC	0.802	0.700	0.678	0.649	0.702	0.847	0.850	0.822	0.763	0.762	0.758	0.072
TSS	0.606	0.384	0.381	0.276	0.414	0.574	0.662	0.584	0.468	0.495	0.484	0.122

Conclusion

The study on forest fire susceptibility in Gandaki Province, Nepal, infers that the risk of fire might be highly varied in space in its 11 districts, based on a complex interaction of environmental and climatic factors. Other than precipitation, the most contributing factors to forest fire risk by using a MaxEnt model are elevation, temperature, and proximity to water bodies. Low precipitation combined with high temperatures contributes to fire incidents, especially in regions with a high vegetation cover like forests and shrublands.

From the district-level data, Myagdi, Gorkha, and Baglung have the highest shares of fire risk zones, with about 44% of the total fire-prone area in the province. The fire risk area is very huge in Myagdi with an area of 1,101.57 km², adding 17.35% of the total area, followed by Gorkha with an area of 1,051.23 km² (16.56%), and then Baglung with an area of 672.66 km² (10.59%). These districts fall within rugged topography, steep slopes, and massive areas of forest cover. Besides this, the nature of the forest due to its dry biomass accumulation in the forest increases the rate of vulnerability towards forest fires.

In Lamjung, Kaski, and Nawalparasi districts, it is very high too, ranging between 10.74% and 12.81% of the total fire-prone areas. Due to similar ecological and geographical characteristics, they share every likelihood of catching fire, especially during dry periods. Targeted methods of fire management are effective measures against large-scale outbreaks and risks to ecosystems.

Therefore, places like the Parbat district, covering 98.96 km² and accounting for 1.56%, and the district of Manang, covering 151.88 km² and accounting for 2.39%, are those districts that have the least fire hazard. Such geographical features as cooler climates, less density of vegetation, and natural obstacles like rivers and snow-covered lands can act to establish a firebreak that will retard or stop fires from spreading in these areas.

In general, the findings of this study have established that fire risk in Gandaki Province is highly connected with environmental factors like precipitation, temperature, and elevation, and also land cover types such as shrublands and open forests, whereas the lowest fire risks were observed to be for built-up areas and those areas with important water bodies. The fire management strategies should henceforth give ample priority to the high-risk districts, especially Myagdi, Gorkha, and Baglung Districts while taking precautionary measures in relatively low-risk districts to protect against future potential outbreaks. Gravitating toward sustainable land-use practices, better fire monitoring systems, and community involvement are all keys to reducing fire risks and enhancing ecosystem resilience across Gandaki Province.

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