Susceptibility Modeling for Potential Fire Risk Zone in Semi-Urban Area

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KEYWORDS

Spatial Modeling, Multi-criteria evaluation, Analytical hierarchy process, Fuzzy Membership Function

ABSTRACT

Fires inflict major losses in global forest resources as well as human lives and property. Forest fires and their tendencies have increased in recent years in Nepal that, necessity for adequate management actions. The fire risk zone is identified with the origin of the ignitions and the pattern of their occurrence, as well as by shared environmental variables that translate into the same risk potential. To reduce the detrimental impacts of fire, several strategies for preventing and combating fires have been implemented based on identified potential fire risk zone. The work is carried out in Shambhunath Municipality, Saptari. In this study, spatial modeling with integration of MCE, fuzzy and AHP is applied for susceptibility assessment for identifying the potential fire risk zone. In fire risk assessment index map shows that 21.14 percent of municipality extent land occurred in the fire risk in which the distribution of the high risk occupied 0.01 percent, medium risk, 0.49 percent, low risk 20.64 percent and remaining 79 percent land free from fire risk. The high risk of potential fire zone were identified along the east west highway surrounding to the high voltage transmission route and petrol pump location. Likewise, potential high risk of forest fire also found in the dense forest area in elevation greater than 400m.

1. INTRODUCTION

Fires cause significant losses in worldwide forest resources as well as human lives and property. It impacts on the global ecological balance and gained substantial (Zhang *et al.*, 2019). In recent years, the frequency and severity of fires have increased considerably in many countries with global warming, industrialization, and human interference (Crimmins, 2006; Running, 2006; Hantson *et al.*, 2015) mainly in forest region. Nepal predominantly faces forest fires and its trends increasing in the recent years that need proper management interventions (Ranabhat *et al.*, 2022). Fire incidence has generally occurred during the summer season (March-June) and caused the loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, and environmental damage. It took place in the village houses made of thatched grasses as well as building through poor management of fire and randomly occurred from the electric circuit malfunction and high voltage transmission line circuit breakdown. Smokes due to burnings of houses, forest leaf litters and aerial parts have created the hazy environment and drab surrounding to the forest and adjoining villages. So, fire incidence damaged mainly the beautiful natural resource as forest and related other forest resources that resulting the loss of biodiversity and deterioration of forest condition. The spatial scale of fire occurrence analysis could provide new information to assist planning efforts and reduce fire risk (Yang *et al.*, 2007). Controlled burning is commonly used by rural landowners in developing nations to prepare pasture for renewal. However, improper planning and execution of controlled burns can lead to fire incident (FAO, 2006).

Several measures for preventing and combating fires have been adopted to minimize the negative effects of fire. Fire risks are a recurring problem in worldwide, and information on the spatial distribution of fires is necessary to improve fire prevention strategies and tactics (Tian *et al.*, 2013). A fire risk zone is identified based on the cause of ignitions and pattern of their occurrence, and it is identified by common environmental characteristics that translate into the same risk potential (Eugenio *et al.*, 2016). It is very important in the land use planning to manage forest resources sustainably and support in planning and management of forest for increasing environmental protection. Several measures that utilize information obtained from risk maps may help reduce fire occurrence, including higher surveillance in the at-risk areas, restricted access to these sites, construction of firebreaks, reorganization of management practices, and aid in firefighting, which includes the construction of roads for faster access to at-risk sites and resource allocation for firefighting at strategic points (Ferraz & Vettorazzi, 1998).

In recent, various methods and algorithm have been successfully applied in the production of forest fire risk maps using GIS based multi-criteria decision analyses (MCDA) with remotely sensed imaginaries. Fire analysis has carried out in GIS environment using MCE, fuzzy and AHP technique. In order to minimize the negative effects of fires, some measures have to be taken to prevent and combat fires. The preparation of a fire map can be a first, but important, step towards planning and managing the protection of forest regions. GIS based Multi-Criteria Decision Analysis (MCDA) techniques have become increasingly widespread in environmental modeling and natural hazard prediction. Combining GIS and MCDA is a powerful approach to forest fire risk mapping (Feizizadeh *et al.*, 2015). In order to model and assess forest fire risk and to identify the regions susceptible to fire, various studies have been carried out around the world. Among the methods that researchers have used for modelling forest fire risk are fuzzy logic (Pourghasemi *et al.*, 2016; Soto, 2012), analytical hierarchy process (AHP) (Pourghasemi *et al.*, 2016), fuzzy AHP (Sharma *et al.*, 2012), frequency ratio (Pourtaghi *et al.*, 2015), artificial neural networks (Bui *et al.* 2017), and logistic regression (Guo *et al.*, 2016; Pan *et al.*, 2016; Tien Bui *et al.* 2016). Likewise, machine learning (ML) approaches have the ability to provide better results for the spatial prediction of forest fires (Bar Massada *et al.*, 2013). In the last decade, various ML algorithms such as artificial neural networks (Dimuccio *et al.*, 2011; Bisquert *et al.*, 2012; Satir *et al.*, 2016), random forests (RF) (Oliveira *et al.*, 2012;

Arpaci *et al.*, 2014; Pourtaghi *et al.*, 2016), support vector machine (SVM) (Hong *et al.*, 2018), multilayer perceptron neural network (MLP) (Vasconcelos *et al.*, 2001; Satir *et al.*, 2016), kernel logistic regression (KLR) (Bui, Le, *et al.* 2016), naive Bayes (Elmas & Sonmez, 2011; Jaafari *et al.*, 2018), gradient boosted decision trees (Sachdeva *et al.*, 2018), and particle swarm optimized neural fuzzy (Tien Bui *et al.*, 2017) have been successfully developed and widely applied in susceptibility mapping of forest fire. In this study, fire analysis has carried out through spatial modeling with integration of MCE, fuzzy and AHP tools in GIS environment.

The performance of the proposed model was validated with benchmark methods using several statistical measure as receiver operating characteristic (ROC) curve, and area under the curve (AUC). Generally, ROC has used to quantify the quality of deterministic and probabilistic detections and to determine the accuracy of the spatial modeling (Akgun *et al.*, 2012). The ROC curve has drawn by plotting specificity on the X axis and sensitivity on the Y axis where sensitivity represents the false positive rate and specificity as the false negative rate based on the number of observed fire incident predicted accurately compare to the predicted fire risk zone. The AUC has used to identify the model accuracy based on the validation samples fire incident and ability in predicting future fire zone based on the training samples of fire incident. The range of the AUC ranges from 0.5 to 1 with the AUC of 1 representing perfect prediction and the closer the value of the AUC to this number, the better the performance of the model (Tehrany *et al.*, 2013). In general, AUC of range between 0.9–1.0 is excellent, 0.8–0.9 is good, 0.7–0.8 is fair 0.6–0.7 is medium and 0.5–0.6 is poor (Kantardzic, 2011). In the model evaluation by AUC, there has two evaluation process based on the success rate and the prediction rate. The results for the success rate have achieved on the basis of training data and the prediction rates has attained by a set of validation data. The results of the success rate have represented the fitness of the model for the training data; used in model building and not useful in assessing the predicting power of the model (Nohani, *et al.*, 2019).

2. STUDY AREA

Shambhunath municipality is declared by Government of Nepal on 18th May, 2014 which has formulated by integration of previous Village Development Committees (VDCs) of Khoksar Parbaha, Shambhunath, Mohanpur, Bhangha, Basbalpur and Rampur Jamuwa in Sapatari district. After formulation of new Nepalese Constitution, local level has reconstructed and Sambhunath municipality has expanded by emerging Arnaha VDC. It is connected with east west highway and located at the latitude from 26^{0}23’ 35” to 26^{0} 42’ 36” and longitude from 86^{0} 37’ 39” to 86^{0} 44’ 54”. It has elevation ranges from 81 m to 444 m above sea level. The total coverage of the municipality is 108.60 sq.km having 12 wards has its sub-units. The municipality headquarter office is located at Kathauna Bazar as previous headquarters of Mohanpur VDC. It had a population of 38018 people living in the municipality in 2017 according to Local Level Reconstruction Commission. The naming of the municipality as famous Shambhunath temple (main attraction for Nepal and Indian Pilgrims) is situated within the municipality. People are likely to come here in Bada Dashain. During month of Baisakh (The first month of Bikram Sambat) the people are celebrate here with joy and happiness. The study area of the work is shown in Figure 1.

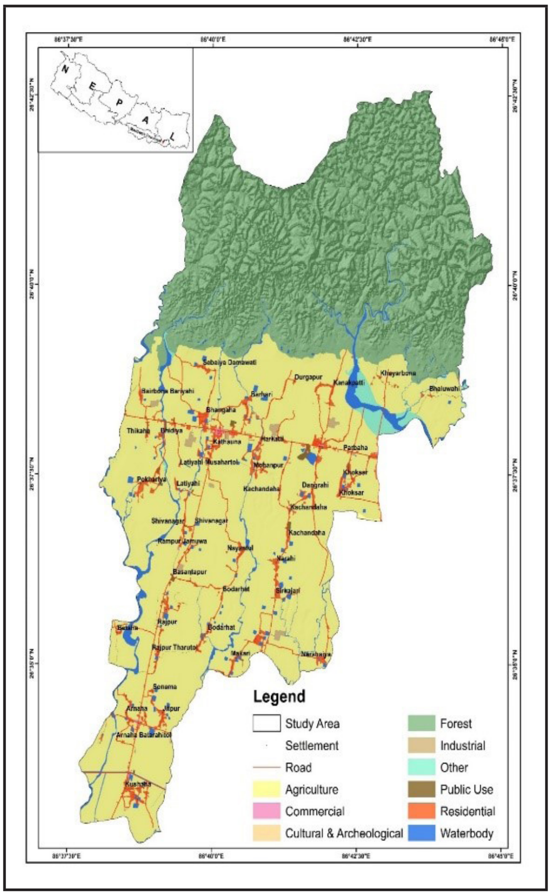

Figure 1: Study Area

3. METHOD & MATERIALS

3.1 Data used

The data collected from secondary source that utilized to create the influencing factors as criterion map and determine the potential site for susceptibility of forest fire (in Table 1).

Table 1: Data & data sources

Data Type	Compilation From	Year
World view satellite image, 2016	National land use project	2016
Land use map, scale 1:10000	National land use project	2017
Topographical map, scale 1:25000 & its digital layer	Survey department	1996
Climatic Data	Department of Hydrology and Metrology	2000-2017
Fire incident data	https://firms.modaps.eosdis.nasa.gov/download/create.php & District Disaster Committee	2000-2017

The previous fire locations were collected from the moderate-resolution imaging spectro-radiometer (MODIS) images for forest fire incident and house/building fire incidence from District Disaster Committee, Saptari.

3.2 Influencing Factor

The influencing factors used in fire risk analysis are: elevation, slope, aspect, annual precipitation (rainfall), wind speed, temperature, normalized difference vegetation index (NDVI), land use, distance from transmission line, and distance from petrol area from land use data, 2017. Three topographical related influencing factors were elevation, slope and aspect; which were derived from topographical contour of contour interval 10m. The climatic characteristics of an area affect the occurrence and intensity of forest fires (Moritz *et al.*, 2012). Three meteorologically related influencing factors were 17 years annual average precipitation, average wind speed, and maximum temperature from climatic data and secondary source. The climate related factors map has generated using the inverse distance weighted (IDW) interpolation method. The vegetation-related factor has NDVI which has identified as an important variable in forest fire modeling (Bajocco *et al.*, 2015) and reflected the vegetation's health and essentially the fuel load distribution (Yi *et al.*, 2013). The NDVI indices were derived from WorldView-2 satellite images. The human activities variables such as land use, distance from transmission line and distance from petrol area has used.

3.3 Priority Ranking of Factor

These fire incident location were used as reference fire location to correlate with the influencing factor. Multicollinearity technique was applied to estimate the correlation between the forest fire locations with influencing factors. The priority values within the influencing factor was computed and normalized through the fuzzy membership function for ranking the classes of the influencing factor with the given relationship (Gheshlaghi *et al.*, 2019).

$$\mu_{i,j} = \frac{PR_{i,j}}{Max(PR_{i,j})} \quad \text{........................}(i)$$

Where, $\mu i,j$ is the fuzzy membership value of class, i of influencing factor, j and PRi.j is the priority value of class I of influencing factor j.

3.4 Computing weight of factor

In accordance with the advice of experts and local stakeholders, AHP a method is used to determine the weight of each criterion based on pairwise comparison with the scale of importance. Reciprocal pair-wise comparison were conducted based on the performance matrix. Each set of criteria in a pairwise comparison characterizes various attributes accordance with the specific qualities (Saaty, 1977; Shahabi & Hashim, 2015). The entries on the performance matrix use a 9-point rating system to rank each combination of criteria and relationship (Saaty, 1980). The rating scale's reciprocals represent the values in direct contrast to one another for each of the different criteria (Table 2). After comparing each interrelated combination of criteria pair-by-pair using the AHP approach, the criterion's weight is determined using numerical numbers. Consistency ratio is used to evaluate weight estimation. The performance matrix is thought to have a limited acceptance level if the consistency ratio is less than 0.1; otherwise, the pairwise relationship of the criterion is rejected (Karna *et al.*, 2021).

Table 2: Comparison rating scale

Intensity of importance	Description	Suitability class
1	Equal importance	Lowest suitability
2	Weak importance	Very low suitability
3	Moderate importance	Low suitability
4	Moderate to plus importance	Moderate low suitability
5	Strong importance	Moderate suitability
6	Strong to very strong importance	Moderate high suitability
7	Very strong importance	High suitability
8	Very strong to extreme importance	Very high suitability
9	Extreme importance	Highest suitability

(Source: Saaty, 1980)

3.5 Determination of potential fire zone

Based on the relationship between the acceptable performance matrix and the weight of the factor, the sum of the factor weights is maintained to be 1 in weighted linear combination (WLC) technique (Eastman, 2006). By dividing the weights supplied to each attribute factor by the scaled values given to the alternatives on those attribute classes of factor, then adding the results to get the total score for all attributes. Then, the weight and rank of influencing factors are converted into susceptibility index level in GIS using the weighted overlay function. According to the WLC result, the computed score categorizes the suitability susceptibility index level. The greatest score signified a class that was highly potential zone, and the lowest score indicated lesser potential risk zone.

4. RESULTS AND DISCUSSION

4.1 Influencing factor maps

The effective factors maps were created using geospatial methods and applied on the basis of their significance in which the result of some criterion maps are described below.

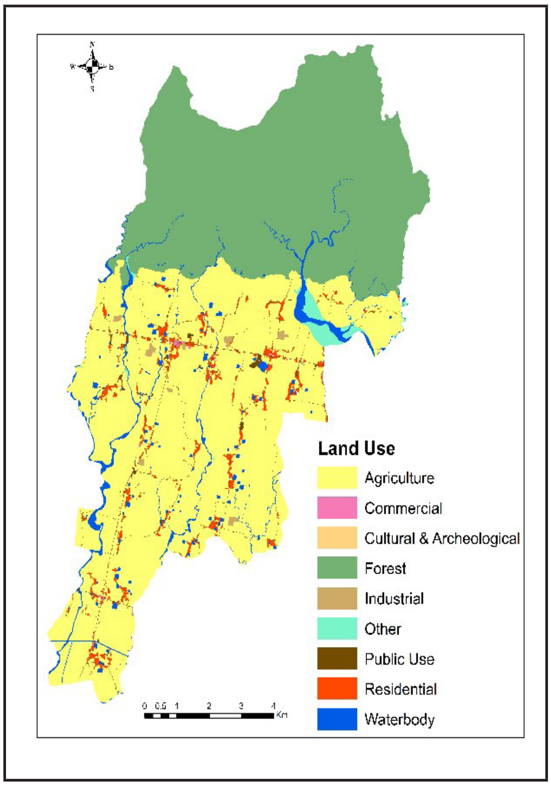

Figure 2: Land Use

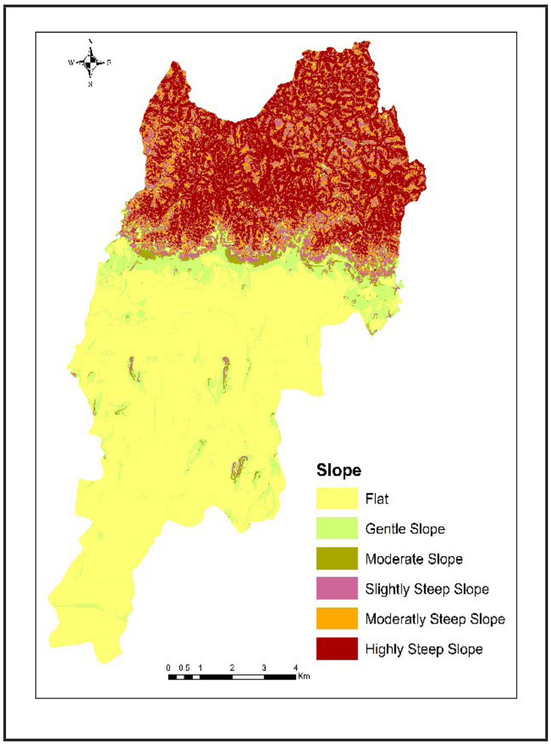

Figure 3: Slope

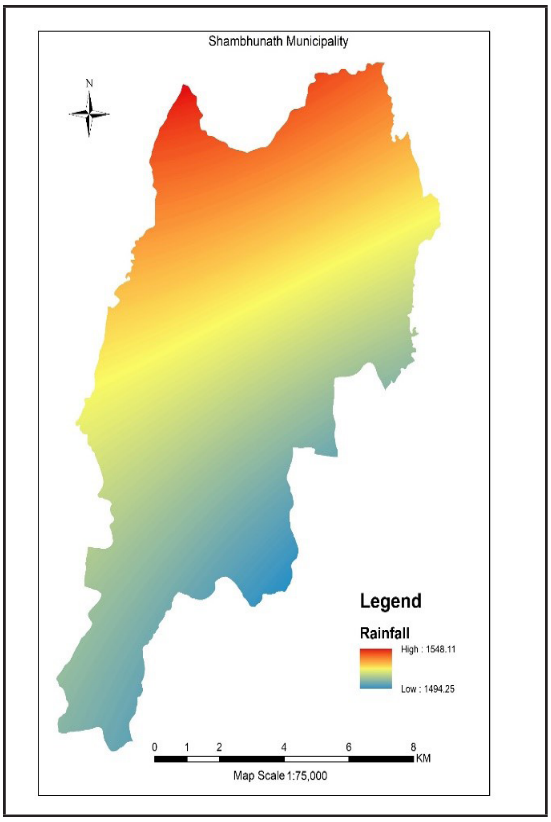

Figure 4: Annual Rainfall

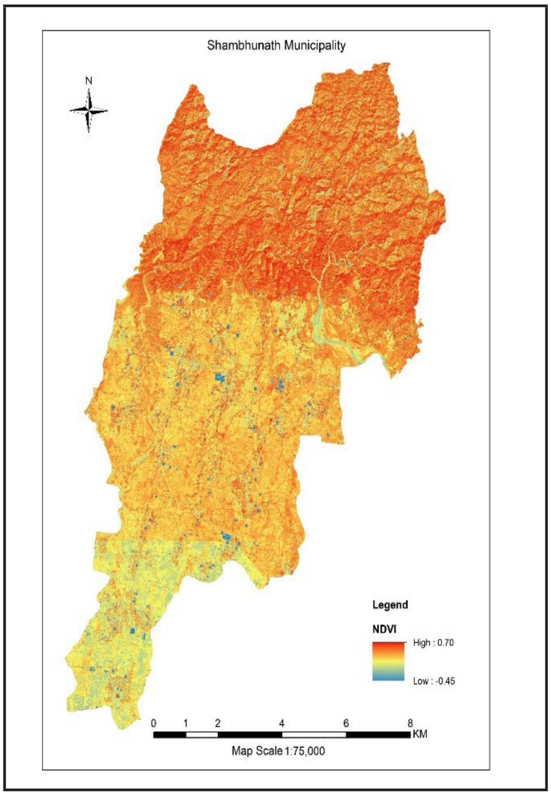

Figure 5: NDVI

Land use: About 3 percent having 251 hectares in the municipality is covered with residential areas. The pattern of land cover where residential practices are explained by human-related variables. It is crucial for residential use to manage infrastructure development operations, minimize development costs, improve socioeconomic condition, and increase the built-up area density in sustainable way.

Slope: Flat slope is occurred about 53 percent then highly steep slope area in Siwalik region in northern portion having 22 percent extent that are vulnerable area for residential use. Only 6 percent coverage belongs to moderate slope area having 5.74 sq. km. Similarly, moderately steep slope covers 8 sq. km having 7.72 percent; gentle slope covers 8 sq. km with 7.17 percent, and slightly steep slope covers 6 sq. km with 5.71 percent of municipality extent.

Precipitation: The average precipitation in terms of rainfall having more than 1500 mm per year area covers about 78.56 percent and remaining 21.45 percent area within the municipality occurs in average precipitation between 1000 to 1500 mm per year.

Normalized Difference Vegetation Index: The NDVI value less than 0 mainly waterbody or wetland area covered 1.25 percent, between 0 to 0.30 having bare soil, open area, built-up area, agriculture field, grass land etc. covered 32.55 percent, between 0.30 to 0.45 having shrubs, open forest area covered 38.88 percent and remaining 27.33 percent area having dense forest in the municipality.

4.2 Prioritized the factor

Based on its priority level, each factor data is ranked with risk level into subcategories of factors. The subcategories are normalized into uniformly ranking scales with fuzzy membership functions with priority rank and achieved in 1 to 4 values (in Table 2).

Table 2: Priority rank of factor

S.N.	Causative Factor	Classes	Risk	Rank
1	Slope (degree)	0-5	Very Low	0.00
		5-15	Low	0.25
		15-30	Moderate	0.50
		30-45	High	0.75
		< 45	Very High	1.00
2	Aspect	North	Low	0.25
		East	Moderate	0.50
		South	Very High	1.00
		West	High	0.75
3	Elevation (m)	< 200	High	1.00
		200-400	Moderate	0.67
		>400	Low	0.33
4	Wind Speed (km/h)	<21	Low	0.33
		21-23	Moderate	0.67
		>23	High	1.00
5	Temperature (^{0}C)	<35	Moderate	0.67
		>35	High	1.00
6	Annual Rainfall (mm)	<1500	Moderate	0.67
		>1500	High	1.00
7	NDVI	<0	Low	0.25
		0-0.30	Moderate	0.50
		0.30-0.45	High	0.75
		>0.45	Very High	1.00
8	Land Use	Water body	Very Low	0.00
		Built-up	High	0.75
		Agriculture	Moderate	0.50
		Open area	Low	0.25
		Forest	Very High	1.00
9	Dist. to Transmission Line (m)	<25	Very High	1.00
		25-50	High	0.75
		50-100	Moderate	0.50
		>100	Low	0.25
10	Dist. to Petrol Pump (m)	<100	Very High	1.00
		100-200	High	0.75
		200-500	Moderate	0.50
		500-1000	Low	0.25
		>1000	Very Low	0.00

4.3 Factor weight

In pair-wise relationships, various combinations of factor were created and examined according to the influencing factors. The weight of each influencing factor was determined by using the AHP technique. The calculated pairwise weights were assessed with consistency ratio and found to be the value of 0.08 which is within the acceptable threshold limit (0.10). The computed weight of the influencing factor is described in Table 3.

Table 3: Influencing factor weight

S.N.	Factors	Weight
1	Slope	0.1361
2	Aspect	0.0375
3	Elevation	0.0343
4	Wind Speed	0.1810
5	Temperature	0.1052
6	Rainfall	0.0377
7	NDVI	0.0528
8	Land Use	0.0588
9	Dist. to Transmission Line	0.1824
10	Dist. to Petrol Pump	0.1742

4.4 Potential fire risk zone

The potential fire risk assessment was carried out from the priority rank computed from fuzzy membership function and the weight computed from the AHP process using weighted overlay function in spatial analysis in GIS environment. The potential fire risk zonation map is shown in Figure 6.

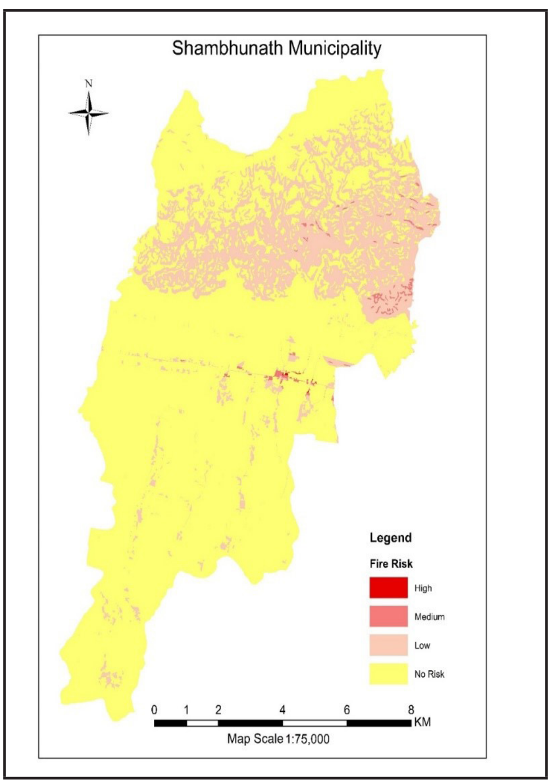

Figure 6: Potential Fire Risk Map

The municipality's fire risk assessment index map shows that 21.14 percent of municipality extent land occurred in the fire risk in which the distribution of the high risk occupied 0.01 percent, medium risk, 0.49 percent, low risk 20.64 percent and remaining 79 percent land free from fire risk. The high risk of potential fire zone were identified along the east west highway surrounding to the high voltage transmission route and petrol pump location. Likewise, potential high risk of forest fire also found in the dense forest area in elevation greater than 400m.

4.5 Validation of susceptibility model

The designed model was validated through ROC curve, and AUC through successive and prediction rate. The area under the curve of the success rate was found as 0.88 and prediction rate as 0.89 showing 89.5% prediction accuracy of the model. So, the produced susceptibility model of fire risk potential is reliable showing with all satisfactorily validation rates having good accuracy (in Figure 7).

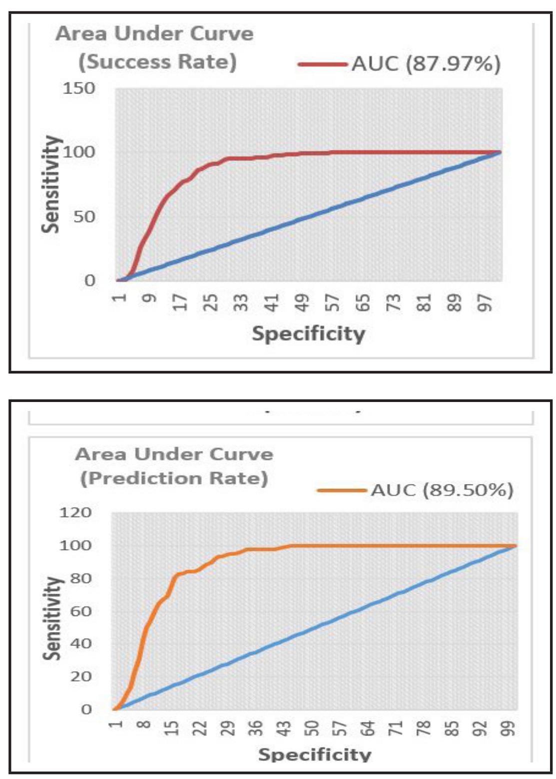

Figure 7: Model Validation

4.6 Impact of potential risk

The impact of potential fire risk assessment is carried out by the process of spatial overlay operation using zonal statistics of fire risk susceptibility layer with land use layer 2017. The potential fire risk in the land use categories is shown in Table 4.

Table 4: Impact of Fire Risk on Land Use

S.N.	Land Use Type	Fire Risk Susceptibility (in ha)				
		High	Medium	Low	Total	%
1	Agriculture	0.00	0.17	0.32	0.49	0.02
2	Forest	0.00	32.62	2037.12	2069.74	90.13
3	Water body	0.00	0.15	17.95	18.10	0.79
4	Residential	1.13	12.10	130.47	143.70	6.26
5	Other	0.00	0.77	14.15	14.92	0.65
6	Public Use	0.22	3.83	24.04	28.08	1.22
7	Industrial	0.00	2.29	12.93	15.22	0.66
8	Commercial	0.00	0.99	4.14	5.13	0.22
9	Cultural & Archeology	0.00	0.00	0.94	0.94	0.04
	Total	1.34	52.92	2242.06	2296.33	100.00

Among the municipality extent, about 21.14 percent of area is the fire risk prone zone. 47 percent of forest land use area is found to be risky by fire burn zone. 58 percent of total residential area is fire risk in which 13 ha residential area for high and moderate risk. Likewise, 38 percent of industrial land occurred under medium and low fire risk in which 12 ha industrial area along the surrounding of high voltage transmission line. Similarly, 27 percent of commercial area is occurred under the medium and low fire risk. 34 percent of total public use area is fire risk in which 4 ha residential area for high and moderate risk.15 ha other land use mainly open area and 1 ha cultural & archeological area are found under low fire risk threat. 33 ha forest land in medium risk and 2037 ha forest land in low risk are major affected area; these forest area need to be protected for environment sustainability. The risk of fire is reduced in the forest region to enhance the potential for protection of the environment and forest management sustainability. The incidents of forest fire are minimized through taking preventive measures in high and medium fire risk area.

5. CONCLUSION

In the context of Sambhunath municipality, the factor for forest risk assessment are established identified in the local situation. These factors might be used in fire risk susceptibility assessments of potential fire zone in different part of Nepal as well. The high risk of potential fire zone were identified along the east west highway surrounding to the high voltage transmission route and petrol pump location. Likewise, potential high risk of forest fire also found in the dense forest area in elevation greater than 400m. Also, in GIS environment, spatial modeling with integration of MCE, fuzzy and AHP is effectively and widely applicable in the fire risk susceptibility assessment. The developed susceptibility model provides an appropriate and acceptable framework for risk zonation.

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