Forest Fire Susceptibility Mapping Using Deep Neural Network

Ganesh Pandey[1], Bhoj Raj Ghimire[2]
ganeshpandey362@gmail.com[1], bghimire@nou.edu.np[2]
Survey Department[1], Nepal Open University[2]

KEYWORDS

Forest fire, Susceptibility mapping, Machine learning, Deep learning, Kailali, Dang

ABSTRACT

Forest fires are an increasing environmental problem in Nepal, threatening biodiversity, ecosystem stability, and the livelihoods of forest-dependent communities. In recent years, both the frequency and intensity of fires have increased, highlighting the need for accurate forest fire susceptibility mapping to support effective management and risk reduction. This study develops a forest fire susceptibility model for Kailali District using a deep learning approach, integrating twelve explanatory variables related to topography, climate, vegetation, and human influence. Historical fire data from NASA's VIIRS archive (2012–2024) were used for training and validation, with trend analysis indicating peak fire events in 2016 and the lowest in 2020. The dataset was split into 70% training and 30% testing, and model performance was evaluated using accuracy, precision, recall, and F1-score, while the trained model was also applied to Dang District. The susceptibility map generated using the DNN model was classified into five risk zones from very low to very high, achieving accuracy, precision, recall, and F1-score values of 0.93, 0.92, 0.93, and 0.93, respectively. Overlay analysis of forest fire susceptibility map and historical fire occurrence showed that about 91% of observed fire events in Kailali and 88% in Dang District occurred within susceptible zones. This study demonstrates that integrating geospatial data with deep learning can effectively improve forest fire risk assessment in Nepal. The resulting susceptibility maps provide useful information for early warning systems, disaster preparedness, and sustainable forest management.

1. INTRODUCTION

Forest ecosystems provide essential ecological, economic, and social services, including biodiversity conservation, carbon sequestration, soil stabilization, and livelihood support for millions of people (Shi & Zhang, 2023). Despite their importance, forests are increasingly threatened by frequent and severe forest fires driven by climate change, land-use transformation, and anthropogenic activities (B. Mishra et al., 2023; Sharma & Khanal, 2024). In Nepal, forest fires occur predominantly during the dry pre-monsoon season (March–May), causing extensive damage to forest resources, wildlife habitats, air quality, and human health(FRA, 2015) (Parajuli et al., 2023). Forest fires in Nepal are a newly explored area, and the importance of such studies is not fully acknowledged. There are not many detailed studies available on forest fires. With the acceleration of urbanization and increasingly inevitable human activities, the problems of forest ecological management are increasingly prominent (Mohajane et al., 2021, Vecín-Arias et al., 2016). Forest fire susceptibility maps are essential for understanding and predicting potential hazards in forest ecosystems. They support land-use planning, reduce vulnerability, and improve ecological risk management decisions(Banjade & Dhungana, 2025; Bouhissi et al., 2020). Developing these maps requires a forest fire inventory as the target variable, along with multiple explanatory factors. GIS and RS can be play crucial role in proper assessment, planning and management of forest fire hazard (Bouhissi et al., 2020; Eugenio et al., 2016; Mohajane et al., 2021) . These systems by utilizing the geospatial data can help in mapping the risk zone by identifying vulnerable areas and evaluating risks at various scales from global to community levels.

More recently, machine learning and deep learning approaches have been applied in environmental hazard mapping, offering higher predictive accuracy compared to conventional statistical methods (Tuyen et al., 2021; Aarich et al., 2024). Artificial intelligence (AI) and machine learning (ML) are frequently employed to map and track forest fire susceptibility in different parts of the globe (Ahmed et al., 2022) (Rihan et al., 2023) (Mohajane et al., 2021) (Tuyen et al., 2021). In Nepal, research on forest fires is still quite limited and most existing studies have used traditional approach (B. Mishra et al., 2023) (Parajuli et al., 2023). Traditional forest fire risk assessment methods in Nepal have largely relied on expert-based approaches and multi-criteria decision analysis techniques such as the Analytical Hierarchy Process (AHP). While these methods are useful, they often involve subjective weighting schemes and limited ability to capture complex nonlinear interactions among variables. Recent advancements in machine learning (ML) and deep learning (DL) offer powerful alternatives capable of learning complex patterns from large geospatial datasets. Deep Neural Networks (DNNs), in particular, have shown superior performance in hazard susceptibility mapping due to their ability to model high-dimensional, nonlinear relationships. Hence, this research aims to prepare wildfire susceptibility map of Kailali district by deep learning technique.

2. STUDY AREA

Kailali District is located in the southwestern Terai region of Nepal within Sudurpashchim Province. The district covers an area of approximately 3,235 km² and exhibits diverse topographic conditions, ranging from flat lowland plains to the hilly terrain of the Chure range. Elevation varies from 109 m to 1,950 m above sea level. Approximately 63% of the district is covered by forest, making it highly vulnerable to forest fire incidents. The climate of Kailali ranges from tropical to subtropical, with an average annual rainfall of around 1,840 mm. Dang District, selected for model transferability assessment, shares similar biophysical and socio-economic characteristics, making it suitable for comparative analysis.

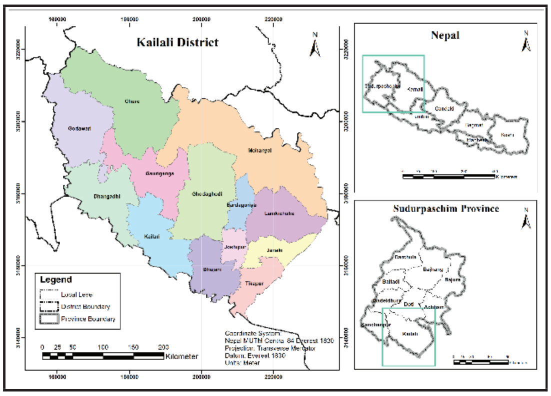

Figure 1: Kailali district

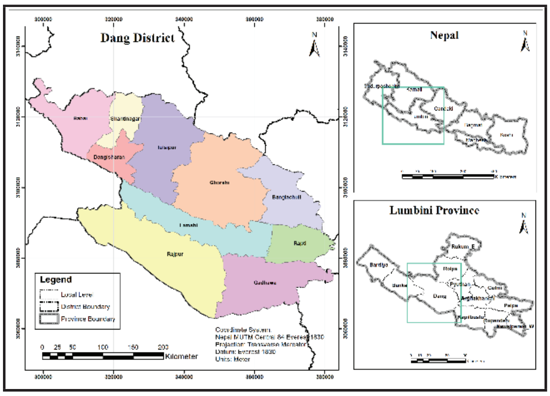

Figure 2: Dang district

3. MATERIAL AND METHODS

3.1 Datasets and software

This study integrated multiple geospatial datasets representing topographic, climatic, vegetation, and anthropogenic factors influencing forest fire occurrence. All these factors were selected based upon previous studies (Joshi et al., 2025; B. Mishra et al., 2023; Parajuli et al., 2020, 2023) . Elevation, slope, and aspect were derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model. Vegetation condition was represented using the Normalized Difference Vegetation Index (NDVI) derived from Landsat-8 imagery processed in Google Earth Engine (GEE). Land surface temperature (LST) and precipitation variables were obtained from satellite-based datasets, while anthropogenic factors such as distance to roads, settlements, rivers, and population density were derived from OpenStreetMap and national census data.

Table 1: Datasets

S. N.	Data	Resolution/ scale	Source
1	Administrative Boundary		Survey Department
2	Digital Elevation Model	30 meters	SRTM USGS Earth Explorer
3	Population Density	Excel ward level data	National Statistics Office
4	River Network	~1 cm at equator	OpenStreetMap (OSM)
5	Road Network	~1 cm at equator	OpenStreetMap (OSM)
6	Settlement	1:25000	Survey Department
6	Precipitation	30 sec	WorldClim
7	Landsat-8 Image	30 meter	USGS EarthExplorer via GEE
8	LST	30 meter	USGS EarthExplorer via GEE
9	NDVI	30 meter	USGS EarthExplorer via GEE
10	Land cover	30 meter	ICIMOD
11	WildFire Occurrence Data		FIRMS-VIIRS S-NPP 375m.

Historical forest fire occurrence data from 2012 to 2024 were collected from the NASA Fire Information for Resource Management System (FIRMS) VIIRS product. Equal numbers of fire and non-fire sample points were generated to construct a balanced dataset. All numerical variables were standardized using the StandardScaler technique, and categorical land cover data were encoded using one-hot encoding. A feedforward Deep Neural Network was developed using Python and TensorFlow. Following software's and tools were used in the analysis:

a) GIS and RStudio for spatial analysis and mapping.

b) Cloud computing platform to write

and execute Python for Landsat images processing, analysis, model training and testing.

c) Python packages (pandas, numpy, rasterio, sklearn, tensorflow).

d) R packages (dplyr, Kendall, lubridate)

3.2 Methodology

This study adopts a data-driven approach to model forest fire susceptibility using a deep neural network (DNN). The methodology comprises planning and literature review, data collection and pre-processing, trend analysis using the Mann-Kendall (MK) test, dataset preparation, susceptibility modelling, model evaluation, and spatial mapping. The overall methodology used for susceptibility mapping followed shown Figure 3 below.

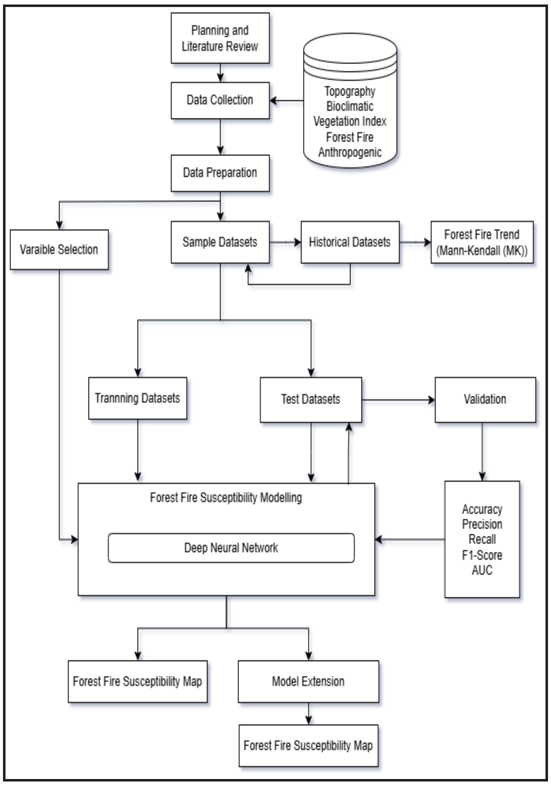

Figure 3: Forest fire susceptibility mapping

3.2.1 Data preparation

Collected data were projected to a common coordinate system UTM Zone 44N, WGS 84 datum and clipped to the administrative boundary of Kailali and dang district. The raster datasets were resampled to a consistent resolution having cell size 30m, and vector datasets (roads, rivers, settlements, population density) were converted to proximity raster's using Euclidean distance. NDVI and LST were derived from Landsat-8 imagery using Google Earth Engine (GEE). Historical forest fire occurrence data from 2012 to 2024 were collected from the NASA Fire Information for Resource Management System (FIRMS) VIIRS product. Equal numbers of fire and non-fire sample points were generated to construct a balanced dataset. For each sampled point Predictor and Target Variables were used. NDVI, LST, precipitation, elevation, slope, aspect, population density, distances to roads/rivers/settlements, and land cover class were used as input variables whereas Fire occurrence data were used as Target Variable. Each parameter that were used in susceptibility mapping were normalized by using standerscaler. All numerical variables were normalized by transforming the original data linearly. By using StandardScaler, each numeric feature was transformed to have zero mean and unit variance, ensuring that all features contribute equally to the model training process. Each value was then changed using following formula. The resulting data will have value ranging from 0 to 1.

$$Xscaled = \frac{x-\mu}{\sigma} \quad \ldots\ldots\ldots\ldots\ldots(1)$$

Where, X represents the original data value, μ represents the mean of the feature and σ is the standard deviation. Xscaled represents normalized data value. The OneHotEncoder from the scikit-learn library was used to convert categorical values into binary vectors, allowing algorithms to interpret them numerically without implying any ordinal relationship. The encoder was fitted to the land cover data and transformed it into a binary matrix. The datasets were divided into training and testing sets. 70% of all the data points were used to train the deep learning model, while 30% were used to assess how well the model performed. A 70%–30% data split is used because it has been widely adopted in previous studies and consistently provides a good balance between model training and reliable validation performance (Chen et al., 2015; B. Mishra et al., 2023; Mohajane et al., 2021; Pham et al., 2020). To do this, the train_test_split() function was used to randomly split the datasets into training and testing parts.

3.2.2 Trend analysis

Trend analysis of historical fire data is essential in forest fire susceptibility mapping because it reveals spatiotemporal patterns of past fires, which are directly used to model and predict fire-prone areas in susceptibility assessments (Kumar & Kumar, 2022; M. Mishra et al., 2024; Tariq et al., 2021; Zhang et al., 2024). Mann-Kendall (MK) trend test method was used for the trend analysis for 2012–2023 time duration. This non-parametric test identifies the presence and direction of significant trends in fire frequency over time. The test results help contextualize whether wildfire frequency is increasing, decreasing, or stable. This approach is especially useful when working with time series data that isn't normally distributed, meaning the data might have outliers or follow a nonlinear pattern. A MK test with a 90% confidence level was used to check for a monotonic trend. During the test, the null hypothesis (H0) states that there is no trend in the population that the dataset comes from. The alternative hypothesis (H1) suggests there is a trend present. The null hypothesis is rejected if the p-value is less than or equal to 0.1 (Partal & Kahya, 2006) (Karpouzos et al., 2010) (Poudel & Shaw, 2016).

3.2.3 Forest fire susceptibility modelling

3.2.3.1 Deep neural network model

A feedforward DNN model was developed to predict the occurrence of forest fires based on the input variables. First of all, selection of input variables was performed for the collected dependent and independent data. The Variance Inflation Factor (VIF) was calculated by removing variables with the largest VIF value one at a time until all remaining variables have a VIF less than defined limit, typically less than 10 (Campo-Bescós et al., 2013) (B. Mishra et al., 2023). VIF was applied to remove correlated metrics. The correlation among the different variables selected after VIF applied is shown in Figure 4 below.

TensorFlow and Keras libraries were used for developing the model. This model was designed to perform binary classification, where the target variables indicate the presence and absence of fire. TensorFlow is an open-source machine learning framework widely used for deep learning applications. Keras, which is integrated within TensorFlow, offers a high-level API for constructing and training neural networks (Truong et al., 2023; A et al., 2024).

The model was designed using a sequential architecture with 3 hidden and 1 output layer.

- Input layer: In this layer number of input features were defined.
- Hidden layer: Three layers were used as hidden layers. The first hidden layer contains 64 neurons and ReLU activation function. The second hidden layer contains 32 neurons and ReLU as activation function. The third hidden layer contains 16 neurons and ReLU as activation function.
- Output layer: The output layer contains a single neuron with a sigmoid activation function. The output of this function is between 0 and 1.

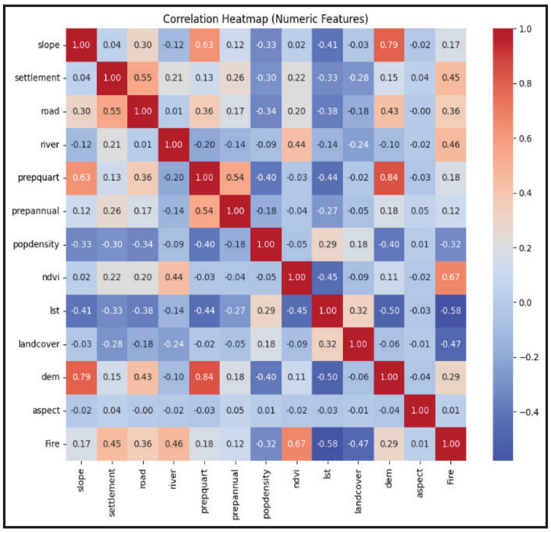

Figure 4: Correlation heatmap of variables

After defining the layers model was compiled by specifying the optimiation strategy, loss function, and evaluation matrix. Adam (Adaptive Moments Estimation) optimizer was selected for training the model. This algorithm was defined by Kingma and Ba (2014) for DNN model optimization. Adam is widely used because it works well and is efficient. It uses information from past gradients and changes the learning rate for each parameter on its own. This makes the model learn quicker and prevents issues like getting stuck in parts where learning slows down. Adam takes the best parts of two other optimization techniques, AdaGrad and RMSProp. It is also good at handling noisy data and can be applied with various types of networks structures and tasks (Wang et al., 2019). The binary_ crossentropy was used as loss function. This function is commonly used as loss function for binary classification problems. It measures the difference between the predicted probabilities and the actual binary labels.

3.2.3.1 Model validation

To evaluate the performance of the DNN model, popular matrixes precision, recall, accuracy, and F1-score were employed. The forest fire susceptibility map generated through modeling was validated using the historical fire occurrence data. Overlay analysis of forest fire susceptibility map and historical fire occurrence was done in ArcGIS. This spatial overlay process provided both visual and quantitative insights into the model's predictive performance and served as a foundational step for subsequent validation and analysis.

3.2.4 Forest fire susceptibility mapping

Using the trained DNN, a pixel-wise prediction was applied across the entire study area using the geospatial input layers. For this first all 12 variables were converted to raster. Raster file of all variables aspect, slope, elevation, distance from road, river, settlement, annual precipitation, precipitation of direst quarter, land surface temperature, landcover, population density, NDVI were imported in google colab environment and their CRS, resolution and extent were checked and ensured they have same coordinate reference system, resolution and extent. Then all the individual raster layers were stacked into a single multi-band raster file. Then the stacked raster was reshaped, StandardScaler and OneHotEncoder were applied as fitted on the training data, and DataFrame was created for prediction. This process is essential for integrating various spectral bands or thematic layers into a unified dataset, which can then be used for further modeling.

Stacking raster facilitate multi-band analysis and enhance the interpretability of geospatial data. After stacking raster, prediction was made. The data was the feed into the model to obtain the predicted outcomes for each pixel in the raster. After generating predictions for each pixel using the trained machine learning model, the results were reshaped and saved as a raster file in GeoTIFF format. Subsequently, the spatial distribution of predicted outcomes was visualized and analyzed using GIS software. The binary classification map was further classed into five zones as Very low, low, moderate, high and very high.

3.2.5 Extension of DNN model

The trained DNN model was applied to the prepared predictor layers from Dang District. Kailali and Dang districts share similar Climatic zones (Tropical/Subtropical), vegetation types (Sal Forest, grasslands), Socioeconomic influences (agriculture, settlement encroachment), Fire ignition sources (human-induced) (ICIMOD,2023; Rokaya et al., 2024; Shakya et al., 2007) . Thus, using a model trained on Kailali for Dang is a valid application of spatial generalization in machine learning, enhancing scalability and operational use in data-scarce regions.

Similar data were collected for dang district as well. Topographical data, land cover and vegetation data, temperature and precipitation data, Euclidean distance from settlement, roads and rivers networks were projected to a common coordinate system (UTM Zone 44N, WGS 84 datum) and clipped to the administrative boundary of Dang district. The raster datasets were resampled to a consistent resolution (30m), and vector datasets (roads, rivers, settlements, population density) were converted to proximity raster's using Euclidean distance. NDVI and LST were derived from Landsat-8 imagery using Google Earth Engine (GEE).

4. RESULTS AND DISCUSSION

4.1. Result

The Mann-Kendall analysis for the period 2012–2016 yielded a Kendall's tau value of 0.20 with a p-value of 0.8065. This indicates a slight upward movement in annual fire counts during these years. However, the high p-value shows that the observed change is not statistically significant, meaning it may simply reflect normal year-to-year variability rather than a genuine increasing pattern. For the period 2016–2024, the Kendall's tau value was –0.0556 with a p-value of 0.91697. The negative tau suggests a very small decline in fire counts, but again the extremely high p-value indicates that this variation is not meaningful from a statistical standpoint. The historical data illustrate that the number of fire incident are maximum in the month of April and May.

The trained DNN model demonstrated strong predictive performance on the test dataset, achieving high accuracy and balanced precision-recall values. Besides the DNN, Random Forest (RF) and Support Vector Machine (SVM) were also applied to assess forest fire susceptibility in the Kailali District. The Random Forest model was efficient in managing nonlinear data relationships and identifying the significance of various environmental factors through its ensemble-based structure. Similarly, the Support Vector Machine showed strong performance in classifying complex datasets and handling multidimensional feature spaces. Nevertheless, the DNN was chosen as the main modeling technique since it provided relatively higher prediction accuracy and effectively captured complex spatial patterns and nonlinear dependencies among influencing factors. With its layered structure capable of learning detailed features from input data, the DNN proved more suitable for predicting forest fire susceptibility across the varied terrain of the Kailali District.

The predicted probability outputs were spatially mapped and classified into five forest fire susceptibility zones: very low, low, moderate, high, and very high. The spatial distribution of fire points within demonstrated that the northern, central, and southeastern regions of Kailali District show a very dense clustering of fire points, indicating these are the most fire-prone areas historically. Some southern and western areas have fewer fire points. In Kailali District, high and very high susceptibility zones were primarily concentrated in low-elevation forested areas close to roads and settlements, reflecting the influence of anthropogenic activities on fire ignition. Validation using historical fire data revealed that approximately 91% of fire events occurred within high and very high susceptibility zones. When applied to Dang District, the model maintained robust performance, with 88% of historical fire events falling within high-risk zones.

Table 2: Evaluation Matrix of DNN, RF and SVM model

Model / Evaluation Matrix	DNN	RF	SVM
Accuracy	0.93	0.91	0.9
Precision	0.92	0.91	0.9
Recall	0.93	0.91	0.9
F1-score	0.93	0.91	0.9

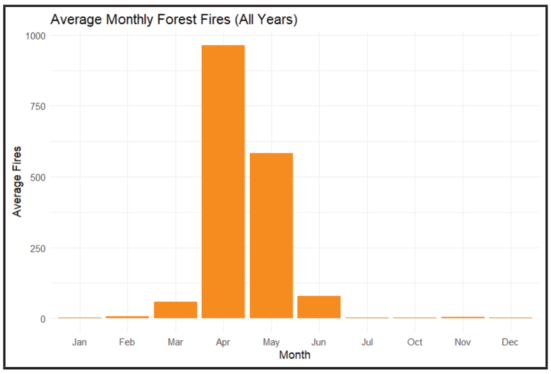

Figure 5: Average monthly forest fire in all years from 2012 to 2024

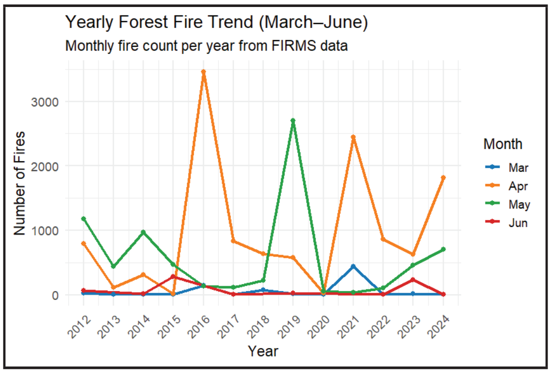

Figure 6: Monthly Forest fires count in March, April, May and June from 2012 to 2024

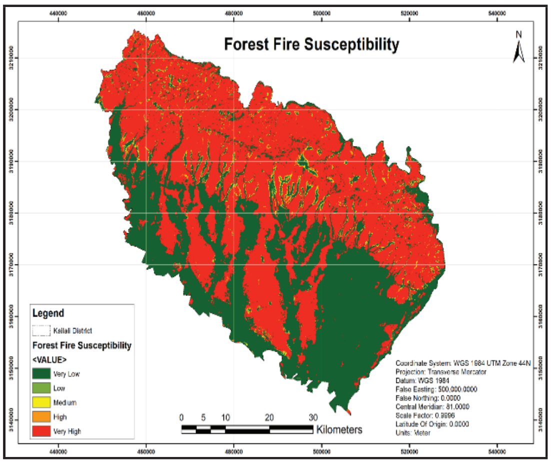

Figure 7: Forest fire susceptibility map of Kailali

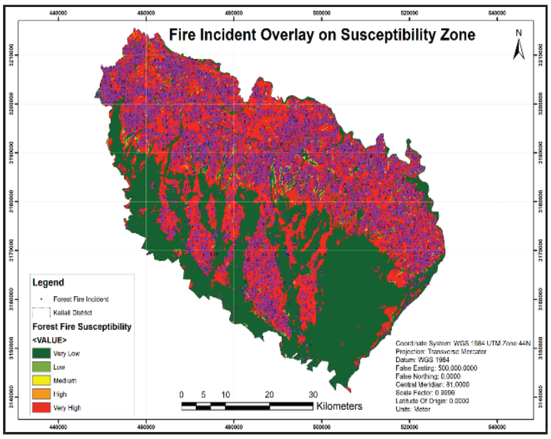

Figure 8: Fire incident overlay on susceptibility map in Kailali

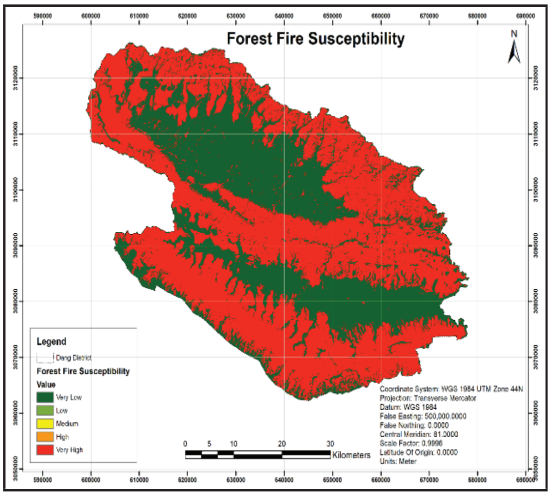

Figure 9: Forest fire susceptibility map of Dang

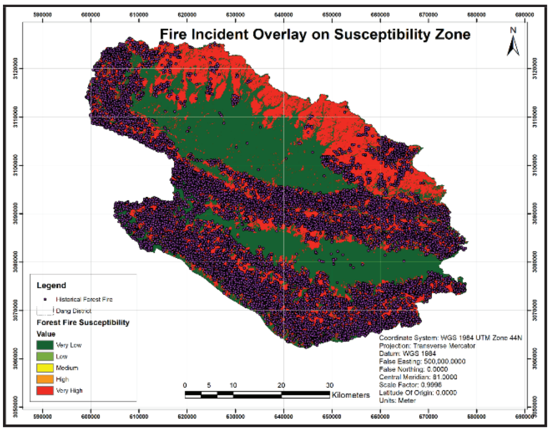

Figure 10: Fire incident overlay on susceptibility map in Dang

4.2 Discussion

The historical forest fire patterns are essential for accurate susceptibility modeling. In Kailali district, past fire events cluster seasonally and spatially, mostly during dry months from March to May. The yearly forest fire trend in Kailali shows an increase in the number of fire incidents in 2016, 2019, and 2021, with the highest number recorded in 2016. Also, number of fire incident are maximum in the month of April and May.

The selection and analysis of input variables are crucial for the performance of deep learning models in fire susceptibility mapping. Elevation, slope, aspect, population density, euclidean distance from river network, road network and settlement, annual precipitation, mean precipitation of driest quarter, land surface temperature, NDVI, land cover and historical fire data are used as input variables. Many other past research have also used these parameters for forest fire susceptibility mapping (Joshi et al., 2025; B. Mishra et al., 2023; Parajuli et al., 2020, 2023). The results provide high accuracy, with a score above 0.93, and the susceptibility maps generated aligned well with known fire hotspot.

To check if the model could perform well beyond the initial area, we tested it in the Dang district. Although the terrain and land use there are different, the model still did a good job pinpointing high-risk zones that aligned with historical fire records. The successful transfer of the model to Dang District highlights its generalizability and potential applicability to other fire-prone regions of Nepal.

5. CONCLUSION

This study explores the application of geospatial technology and machine learning approach to map forest fire susceptibility in Kailali and Dang district. In this study, elevation, slope, aspect, population density, Euclidean distance from river network, road network and settlement, annual precipitation, mean precipitation of driest quarter, land surface temperature, NDVI, land cover and historical fire data were used for forest fire susceptibility modeling. The deep learning approach was used to develop the forest fire susceptibility model of Kailali district. DNN was implemented for forest fire prediction in Kailali district. Then the developed model was extended for forest fire prediction in dang district. The successful application of this approach in Kailali and Dang districts demonstrates its potential for expansion to other fire-prone areas of Nepal, contributing to a national-level framework. Incorporating advanced techniques such as hybrid models that integrate deep learning, GIS, and ensemble methods can further enhance predictive performance. These types of research can be explored at local levels as well. A hybrid model combining deep learning with GIS analysis, ensemble learning utilizing different machine learning algorithms can be used for improved interpretability and robustness, especially in complex terrains or data-scarce regions.

REFERENCES

Banjade, R., & Dhungana, J. (2025). *The Consequences of Forest Fires in Nepal: A Comprehensive Review* [Dataset]. Zenodo. https://doi.org/10.5281/ZENODO.15617231

Bouhissi, M. E., Bouidjra, S. E. B., & Benabdeli, K. (2020). GIS, Forest Fire Prevention and Risk Matrix in the National Forest of Khoudida, Sidi Bel Abbes, Algeria. *Open Journal of Ecology*, *10*(6), Article 6. https://doi.org/10.4236/oje.2020.106022

Campo-Bescós, M., Muñoz-Carpena, R., Southworth, J., Zhu, L., Waylen, P., & Bunting, E. (2013). Combined Spatial and Temporal Effects of Environmental Controls on Long-Term Monthly NDVI in the Southern Africa Savanna. *Remote Sensing*, *5*(12), 6513–6538. https://doi.org/10.3390/rs5126513

Chen, F., Du, Y., Niu, S., & Zhao, J. (2015). Modeling Forest Lightning Fire Occurrence in the Daxinganling Mountains of Northeastern China with MAXENT. *Forests*, *6*(5), 1422–1438. https://doi.org/10.3390/f6051422

Eugenio, F. C., Dos Santos, A. R., Fiedler, N. C., Ribeiro, G. A., Da Silva, A. G., Dos Santos, Á. B., Paneto, G. G., & Schettino, V. R. (2016). Applying GIS to develop a model for forest fire risk: A case study in Espírito Santo, Brazil. *Journal of Environmental Management*, *173*, 65–71. https://doi.org/10.1016/j.jenvman.2016.02.021

DFRS. (2015). *State of Nepal's forests*. Department of Forest Research and Survey, Forest Resource Assessment (FRA) Nepal.

ICIMOD. (2023). *SERVIR-HKH*. Retrieved August 20, 2025, from https://servir.icimod.org/press_releases/new-fire-risk-system-for-nepal/

Joshi, K. P., Giri, S., Kuinkel, D., Kuikel, S., Devkota, R., Pradhananga, D., Marahatta, S., & Pokharel, B. (2025). Forest fire dynamics in Nepal: Regional trends and socio-ecological drivers. *Trees, Forests and People*, *21*, 100942. https://doi.org/10.1016/j.tfp.2025.100942

Kingma, D. P., & Ba, J. (2014). *Adam: A Method for Stochastic Optimization* (Version 9). arXiv. https://doi.org/10.48550/ARXIV.1412.6980

Kumar, S., & Kumar, A. (2022). Hotspot and trend analysis of forest fires and its relation to climatic factors in the western Himalayas. *Natural Hazards*, *114*(3), 3529–3544. https://doi.org/10.1007/s11069-022-05530-5

Mishra, B., Panthi, S., Poudel, S., & Ghimire, B. R. (2023). Forest fire pattern and vulnerability mapping using deep learning in Nepal. *Fire Ecology*, *19*(1), 3. https://doi.org/10.1186/s42408-022-00162-3

Mishra, M., Guria, R., Baraj, B., Nanda, A. P., Santos, C. A. G., Silva, R. M. D., & Laksono, F. A. T. (2024). Spatial analysis and machine learning prediction of forest fire susceptibility: A comprehensive approach for effective management and mitigation. *Science of The Total Environment*, *926*, 171713. https://doi.org/10.1016/j.scitotenv.2024.171713

Mohajane, M., Costache, R., Karimi, F., Bao Pham, Q., Essahlaoui, A., Nguyen, H., Laneve, G., & Oudija, F. (2021). Application of remote sensing and machine learning algorithms for forest fire mapping in a Mediterranean area. *Ecological Indicators*, *129*, 107869. https://doi.org/10.1016/j.ecolind.2021.107869

Parajuli, A., Gautam, A. P., Sharma, S. P., Bhujel, K. B., Sharma, G., Thapa, P. B., Bist, B. S., & Poudel, S. (2020). Forest fire risk mapping using GIS and remote sensing in two major landscapes of Nepal. *Geomatics, Natural Hazards and Risk*, *11*(1), Article 1. https://doi.org/10.1080/19475705.2020.1853251

Parajuli, A., Manzoor, S. A., & Lukac, M. (2023). Areas of the Terai Arc landscape in Nepal at risk of forest fire identified by fuzzy analytic hierarchy process. *Environmental Development*, *45*, 100810. https://doi.org/10.1016/j.envdev.2023.100810

Pham, B. T., Jaafari, A., Avand, M., Al-Ansari, N., Dinh Du, T., Yen, H. P. H., Phong, T. V., Nguyen, D. H., Le, H. V., Mafi-Gholami, D., Prakash, I., Thi Thuy, H., & Tuyen, T. T. (2020). Performance Evaluation of Machine Learning Methods for Forest Fire Modeling and Prediction. *Symmetry*, *12*(6), 1022. https://doi.org/10.3390/sym12061022

Rokaya, M. B., Parajuli, B., & Timsina, B. (2024). Vegetation and Forest in Nepal. In M. B. Rokaya & S. R. Sigdel (Eds.), *Flora and Vegetation of Nepal* (Vol. 19, pp. 37–88). Springer International Publishing. https://doi.org/10.1007/978-3-031-50702-1_3

Shakya, P. R., Shrestha, S., Basnet, T. B., & Bhuju, U. R. (2007). *Nepal Biodiversity Resource Book* (0 ed.). International Centre for Integrated Mountain Development (ICIMOD). https://doi.org/10.53055/ICIMOD.475

Sharma, S., & Khanal, P. (2024). Forest Fire Prediction: A Spatial Machine Learning and Neural Network Approach. *Fire*, *7*(6), 205. https://doi.org/10.3390/fire7060205

Shi, C., & Zhang, F. (2023). A Forest Fire Susceptibility Modeling Approach Based on Integration Machine Learning Algorithm. *Forests*, *14*(7), 1506. https://doi.org/10.3390/f14071506

Tariq, A., Shu, H., Siddiqui, S., Mousa, B. G., Munir, I., Nasri, A., Waqas, H., Lu, L., & Baqa, M. F. (2021). Forest fire monitoring using spatial-statistical and Geo-spatial analysis of factors determining forest fire in Margalla Hills, Islamabad, Pakistan. *Geomatics, Natural Hazards and Risk*, *12*(1), 1212–1233. https://doi.org/10.1080/19475705.2021.1920477

Truong, T. X., Nhu, V.-H., Phuong, D. T. N., Nghi, L. T., Hung, N. N., Hoa, P. V., & Bui, D. T. (2023). A New Approach Based on TensorFlow Deep Neural Networks with ADAM Optimizer and GIS for Spatial Prediction of Forest Fire Danger in Tropical Areas. *Remote Sensing*, *15*(14), 3458. https://doi.org/10.3390/rs15143458

Vecín-Arias, D., Castedo-Dorado, F., Ordóñez, C., & Rodríguez-Pérez, J. R. (2016). Biophysical and lightning characteristics drive lightning-induced fire occurrence in the central plateau of the Iberian Peninsula. *Agricultural and Forest Meteorology*, *225*, 36–47. https://doi.org/10.1016/j.agrformet.2016.05.003

Wang, Y., Liu, J., Misic, J., Misic, V. B., Lv, S., & Chang, X. (2019). Assessing Optimizer Impact on DNN Model Sensitivity to Adversarial Examples. *IEEE Access*, *7*, 152766–152776. https://doi.org/10.1109/ACCESS.2019.2948658

Zhang, Y., Lim, H. S., Hu, C., & Zhang, R. (2024). Spatiotemporal dynamics of forest fires in the context of climate change: A review. *Environmental Science and Pollution Research*. https://doi.org/10.1007/s11356-024-33305-x

Author's Information

Name	:	Ganesh Pandey
Academic Qualification	:	MSc Geoinformatics
Organization	:	Survey Department
Current Designation	:	Survey Officer