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Research article

Forest fire vulnerability in Nepal's chure region: Investigating the influencing factors using generalized linear model

Khagendra Prasad Joshi [a], Gunjan Adhikari [b], Divya Bhattarai [c,e], Ayush Adhikari [d], Saurav Lamichanne [c,e,*]

[a] *Kathmandu Forestry College, Tribhuvan University, Kathmandu, 44600, Nepal*
[b] *Institute of Forestry, Pokhara Campus, Tribhuvan University, Pokhara, Nepal*
[c] *Faculty of Forestry, Agriculture and Forestry University, Hetauda, 44100, Nepal*
[d] *Enviromatics Nepal, Kathmandu, 44100, Nepal*
[e] *Nepal Conservation and Research Center, Ratnanagar-6, Sauraha, Chitwan, Nepal*

A R T I C L E I N F O

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A B S T R A C T

The Chure region, among the world's youngest mountains, stands out as highly susceptible to natural calamities, particularly forest fires. The region has consistently experienced forest fire incidents, resulting in the degradation of valuable natural and anthropogenic resources. Despite its vulnerability, there have been limited studies to understand the relationship of various causative factors for the recurring fire problem. Hence, to comprehend the influencing factors for the recurring forest fire problem and its extent, we utilized generalized linear modeling under binary logistic regression to combine the dependent variable of satellite detected fire points and various independent variables. We conducted a variance inflation factor (VIF) test and correlation matrix to identify the 14 suitable variables for the study. The analysis revealed that forest fires occurred mostly during the three pre-monsoon periods and had a significant positive relation with the area under forest, rangeland, bare-grounds, and Normalized Difference Vegetation Index (NDVI) ($P < 0.05$). Consequently, our model showed that the probability of fire incidents decreases with elevation, precipitation, and population density ($P < 0.05$). Among the significant variables, the forest areas emerges as the most influencing factor, followed by precipitation, elevation, area of rangeland, population density, NDVI, and the area of bare ground. The validation of the model was done through the area under the curve ($AUC = 0.92$) and accuracy ($ACC = 0.89$) assessments, which showed the model performed excellently in terms of predictive capabilities. The modeling result and the forest fire susceptible map provide valuable insights into the forest fire vulnerability in the region, offering baseline information about forest fires that will be helpful for line agencies to prepare management strategies to further prevent the deterioration of the region.

1. Introduction

Forests play a pivotal role in environmental, ecological and socio-economic aspects [1]. However amidst ongoing climate change, forest fires emerge as a critical environmental issue, jeopardizing both human lives and ecosystems [2]. Forest fires, as an

* Corresponding author. Faculty of Forestry, Agriculture and Forestry University, Hetauda, 44100, Nepal.
E-mail address: sauravlc8@gmail.com (S. Lamichanne).

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unpredictable calamity in nature have caused significant harm to people, animals, and ecosystems, resulting in extinction events and significant financial losses for inhabitants [3–6]. Additionally, these fires adversely impact the livelihoods of local communities by restricting access to crucial forest resources essential for their survival [7]. Globally from 2001 to 2019, around 1.1 million km^2 of forest has been lost due to fire at an alarmingly high rate of 60 thousand km^2 of forest lost per year [8]. In South Asia, forest fires are commonly utilized to clear land for shifting cultivation, stimulate the growth of new grass, and for controlled burning purposes [9–12]. In the Hindu Kush region, forest fire is one of the important factors negatively impacting the forest ecosystem [13]. Furthermore, various studies have reported increased fire incidents, burnt area, and fire severity across different region of the globe due to various factors, including changing temperature, precipitation patterns, drought conditions, and anthropogenic activities [14–18]. Specifically, in Nepal major part of the country's natural landscape suffers as each year 40,000 ha land is burnt by forest fires [19].

Annually, forest fires occur in all the physiographic/climatic regions of Nepal, but instances of fire are more severe in the lower elevated Terai and Churia range [20,21]. The Chure region that extends more than two thousand km stripe through India, Nepal and Pakistan [22], and is the most fragile and vulnerable zone due to various natural and anthropogenic factors [23–25].The inhabitants are heavily dependent on forest resources in the core region of Chure range [26], but calamities like forest fire is one of the serious issues for forest degradation [25]. In Nepal, fire occurs mostly in November to June which is the dry season and attains its peak between March to May [7,27]. The increasing trend of forest fire is degrading the natural ecosystem and also human settlements [27]. This problem is worsened in underdeveloped nations like Nepal since there are frequently inadequate management and informational

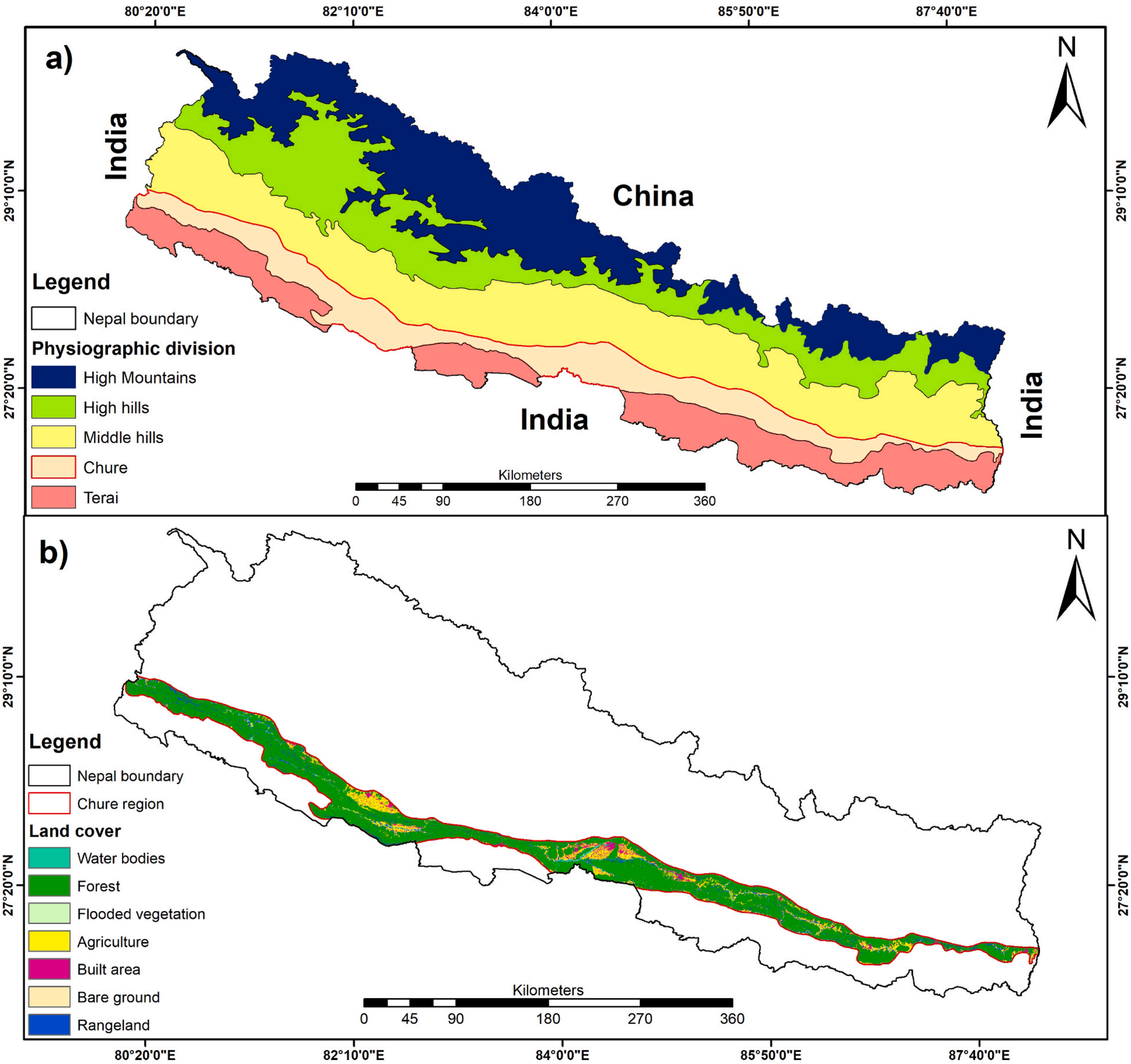

Fig. 1. Study area map: a) Different physiographic division of Nepal, b) location of Chure region in Nepal along with its land cover map.

systems [28,29]. In order to develop appropriate management strategies and land-use policies there is an utmost need to predict what influences fire hazards and how fire hazards may continue to develop in future [30,31].

Recently, the rapid advancement and widespread implementation of remote sensing and GIS tools in predicting forest fire risk across a spectrum of scales, from global to local Recently, the rapid advancement and widespread implementation of remote sensing and GIS tools in predicting forest fire risk across a spectrum of scales, from global to local [29,32,33]. It is necessary to understand the dynamics and various factors and environment variables that effect the forest fire in order to grasp the idea of their behaviour [34]. Analysing such influencing variables various studies have utilized various statistical, physical and machine learning approaches to study fire behaviours, extents, patterns and susceptibility modelling. These approaches include logistic regression (LR) [35], multiple linear regression [36], frequency ratio method [37], analytical hierarchical process [38,39], fuzzy AHP [29], Generalized Linear Model (GLM) [40–43] and machine learning approaches [44,45]. While methods like WLC (Weighted Linear Composition Method) offer convenience to solve complex multi-criteria decision-making problems [46] and the Analytical Hierarchical Process (AHP) has been used in the GIS-MCDA process, but they are based on hypothesis making them inaccurate [47]. In recent years, generalized linear models have has proven superior in while handling non-normally distributed response variables, offering a more effective approach than log-linear models [48]. GLM, composed of a response variable, predictor variables, and a link function linking linear predictors to the mean of the response variable, facilitates clear interpretation by preserving predictor and response variables on the same scale [48, 49], in contrast to the challenges posed by complex analysis and large data volume in various machine learning approaches [50–52], and the reduced interpretability associated with stacking fusion models [53]. Additionally, GLM provides great flexibility for modelling according to data type with various exponential family such as normal, binomial, poisson, gaussian, gamma etc. [49].

Understanding the spatiotemporal patterns and causative factors of forest fires is essential for formulating an efficient fire management plan [19]. However, Nepal lacks sufficient statistical data relating to forest fires to prepare reliable fire management strategy [29]. Specifically, the Chure range is highly vulnerable to disturbances such as fire [21] yet so far limited studies have focused on geo-spatial analysis of fires here. Previous studies on fire analysis in the Chure range have been limited in scope, with some covering only specific areas partially [29,54], and while others have addressed the entire country but have been limited to extent of fire risk not analysis of causative factors [7,29,55,56]. This research aims to address the gaps in previous research by employing spatial technologies to identify multiple variables influencing forest fires in the entire Chure region. The satellite data relating to forest incidents are modelled under GLM along with various predictor variables, thus producing a final susceptibility map. This research is pivotal for analysing the risk factors that increase forest fire risk in the Chure region, enabling the development of a proactive fire management strategy. Furthermore, the risk map will provide valuable insights to policy makers, line agencies and other related stakeholders to develop robust policy and efficacy while allocating resources to the fire prone areas with utmost need.

2. Methodology

2.1. Study area

The Chure region which is often referred as one of the youngest mountains of the world is situated between the mid-hills and plain Terai as shown in Fig. 1a. It is also known as Siwalik locally and is located between 80°9′25″ and 88°11′16″ longitudes and 26°37′47″ to 29°10′27″ latitudes [25]. The range's typical maximum and lowest temperatures are 31.8 °C to 15.8 and receives on average 1400–2000 mm of precipitation each year [57]. As illustrated in Fig. 1b, Chure region predominantly comprises forests accounting for 23.04% of Nepal's total forest area including 14 forest ecosystems [58]. Despite of the rich forest biodiversity, the forests of Chure region are highly disturbed by grazing, forest fire, landslide and bush cutting [25]. In the case of forest fires most of Nepal's burnt area has been found to be in the Chure region and mainly in the pre-monsoon season making it one of the most vulnerable area [20]. Consequently, to preserve the vulnerable range, Chure conservation program was started by the Nepal government through the President Chure-Terai Madhesh Conservation Development Committee (also known as the Chure conservation board) [57]. The major land cover type of chure region are shown in Fig. 1b.

2.2. Datasets and preparation

To analyse the forest fire occurrence and the various influence of variable we utilized the Moderate Resolution Imaging Spectroradiometer (MODIS) fire frequency data as dependent variable [59]. MODIS satellites namely ACQUA and TERRA with the resolution of 1 Km have been a popular instrument to understand and predict forest fire risk areas [7,11,54]. We used MODIS fire frequency data downloaded through the FIRMS website (http://earthdata.nasa.gov/data/nrt-data/firms) from 2014 to Sept. 30, 2023 providing us ample data for the analysis at Spatial-temporal level [11]. Furthermore, we filtered MODIS fire occurrence data and used only the points with confidence level exceeding 50% to ensure detected fires were accurate, had minimal false incidents but did not exclude small fires, aligning with prior research recommendations [60,61].

The potential explanatory variables used in this study were selected through literature search of various other forest fire research, as detailed in supplementary file (**Appendix 1**). The commonly used and freely available data was selected for the analysis of the variables from the literatures. Hence, a total of 16 commonly used landscape predictors were compiled for the final analysis categorized into four categories (Table 1). The biophysical data set comprised of the Land cover data and NDVI. Land cover data is one of the consistently used forest fire predictors across various studies [7,29,54]. Land cover provides information about different vegetation types in the region which influence the spread of fire [34]. Similar to land cover, NDVI is one of the commonly used remote sensing indices the values of which can be used to separate different vegetation types as well as available soil moisture content [62]. We utilized the readily available land cover data obtained from ESRI for the year 2022 through which each of the land cover classes that were relevant for forest fire were made as single variable by calculating their area. Also, the NDVI data was extracted using the cloud based Google Earth Engine (GEE) platform using Sentinel-2 website for the pre-monsoon months of the year 2014–2022 and averaged in the study area. The NDVI was calculated using Sentinel-2 imagery's near-infrared (NIR) and red spectral bands using Equation (1).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{1}$$

Along with vegetation, terrain features have significant influence on the survivability of the forest in case of fire [63]. In our study slope and elevation were used as an indicator of the topographical feature of the study region which were extracted from Digital Elevation Model (DEM). The Digital Elevation Model (DEM) file was obtained through the USGS website [64]. Using the spatial analyst tool in ArcGIS 10.8, a slope layer was derived from the DEM.

According to Ganteaum et al. [65], the majority of forest fires are caused by anthropogenic factors and the key indicators used to model forest fires include distance to road networks, urban areas, and recreational areas. Hence, to analyse the human influence on fire we used three specific datasets. The road and settlement location of the Department of Survey was downloaded (https://opendatanepal.com/dataset) which were later rasterized using ArcGIS for calculating Euclidean distance to create distance from roads and proximity to settlement variables. The population density was acquired from the Socioeconomic Data and Application Center (SEDAC) web portal [66].

While forest fire ignitions are primarily caused by anthropogenic factors, climatic variables such as temperature, precipitation, and wind velocity exhibit statistically significant relationships with fire occurrence [41].Hence four climatic variables were utilized: precipitation, land surface temperature, wind speed, and solar radiation. We utilized global precipitation data for the pre-monsoon months from 2014 to 2018, compiled from both global weather stations and the MODIS satellite platform, which was downloaded from WorldClim [67]. Similarly for wind speed variable, we utilized the freely and readily available high resolution global wind dataset obtained from Global Wind Atlas web portal [68]. Solar radiation, influenced by topographic orientation, affects the rate of decrease of fuel moisture content, thereby creating suitable conditions for fire occurrence [69]. Solar radiation was calculated by using the "Area solar radiation" tool in ArcGIS from the DEM file. As for land surface temperature (LST), the MODIS satellite based product (MOD11C3) which provides monthly temperature data was downloaded. The data was then filtered and compiled for the mean monthly data of pre-monsoon period for each year using ArcGIS 10.8. The collection of various variables for the pre-monsoon period (March–May) was done because the period is known to cause majority of forest fire cases in Nepal [7,54]. Furthermore, variables like temperature and precipitation exhibit fluctuating patterns over time. To capture their overall trends, they were combined over time to generate a raster layer representing their mean values as shown in Table 1. Whereas, less fluctuating variables like elevation and land cover were treated as static, one-time variables. All the variable layers used in this study are presented in the supplementary file (Appendix 2).

After acquisition of all the variables, all of the variables were resampled to same resolution (30*30 m) and same geographic extent using the boundary file of Chure region. Finally, to ascertain spatial factor at coarser level and to reduce chances of autocorrelation [11], the study area was stratified in to 5*5 km^2 (i.e., 25 km^2) grids (n = 1010) using ARC GIS 10.8.

2.3. Data analysis

2.3.1. Multicollinearity and correlation test

Data analysis in this study was done in the R Statistical package v 4.0.4 [72]. Prior to building the model, we conducted a multicollinearity test for all variables using the Variance Inflation Factor (VIF). The VIF test was performed using the package 'Faraway' [73]. Variables exhibiting multicollinearity, with VIF values exceeding 5, were systematically excluded during the model construction process, aligning with the approach outlined by Ref. [74] (Table 2).

Additionally, a correlation test was performed for the rest of the variables using Pearson's algorithm using 'Metan' package [75]. The Pearson's correlation values range from −1 to +1, with +1 indicating a perfect positive linear association, −1 representing a perfect negative linear association, and 0 indicating no association between the variables. In general, the correlation coefficient values

Table 1
Datasets used in the study and their information.

Variable type	Variable name	Resolution/Scale	Data type	Data Period	Source/Reference
Biophysical	Land cover	10 m	Raster	2022	ESRI [70]
	Normalized difference vegetation index	10 m	Raster	2014–2022	Sentinel 2
Topographical	Digital Elevation Model	30 m	Raster	2019	ASTER [64]
	Slope	30 m	Raster	2019	Delineated from DEM
Anthropogenic	Road	1:25000	Polyline	2015	Department of Survey
	Settlement	1:25000	Point	2015	Department of Survey
	Population density	1 km	Raster	2020	SEDAC [66]
Climatic	Land surface temperature	1 km	Raster	2014–2023	MODIS [71]
	Precipitation	4.5 km	Raster	2014–2018	Worldclim [67]
	Wind speed	250 m	Raster		Global wind atlas [68]
	Solar radiation	30 m	Raster	2019	Delineated from DEM
Dependent variable	Past fire points	1 km	Point	2014–2023	MODIS

higher than 0.7 shows strong and above 0.9 shows very strong between the variables [76]. The result showed the proximity to settlement (PS) and distance to road (DR) had strong correlation with coefficient value of 0.72 (Fig. 2). Therefore, proximity to settlement variable was removed, leaving the final 14 variables.

2.3.2. Generalized linear model (GLM)

GLM is one of the most highly utilized regression analysis across a multitude of fields. GLMs in comparison to other linear regressions offer a reliable prediction and estimation when data are not normally distributed [49]. The decision to employ GLM was based on its suitability for modeling based on our data [77] and its ability to make a balance between simplicity and interpretability, which aligns well with our research objectives. GLMs are tailored to different dataset types, with binary (presence-absence) and Poisson (count) being commonly utilized variants. In our study, we utilized GLM of the binary family utilizing the suggestions from previous research [52,78]. The GLM framework involves specifying the probability distribution of the response variable (binomial distribution in the case of binary regression), the link function, and the linear predictor that models the relationship between the predictors and the expected value of the response variable [79]. The probability distribution function and the link function in our binomial GLM were computed using equations (2) and (3), respectively.

$$P(y;\theta,\varphi) = \exp\left(\frac{Y\theta - b(\theta)}{a(\varphi)} + c(y,\varphi)\right) \tag{2}$$

$$g(\mu) = \ln\left(\frac{\mu}{1-\mu}\right) \tag{3}$$

Where, y is the response variable, θ is the linear predictor (i.e., $\theta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots \ldots \beta_n x_n$), φ is the dispersion parameter, P is the probability function, a is the dispersion function, b is the cumulant generating function and c is the normalizing constant, μ is the mean of the response variable and finally g is the canonical link function which in our case is the logit function.

We used the GLM in R, specifically choosing a binomial distribution to predict binary outcomes. The GLM algorithm in R provides estimates of each selected variables, standard error as well as a p value estimated computed from Wald test based on maximum likelihood estimation (see Table 4). We incorporated 14 continuous variables as predictors (explanatory variables) using the packages 'Desctools' [80] and 'Manipulate' [81]. Before modeling, the total fire points were randomly separated for modeling and validation. The 80% subset ($n = 808$) was used for building the model, while the remaining 20% ($n = 202$) was used for validation. In the modeling of the extent of fire counts, we utilized the presence or absence of fire incidents as the response variable. We followed a binary coding system for recording of the fire incidents (response variable) by coding 1 and 0 where 1 represents the presence of a fire incident in a grid, while 0 indicates the absence of a fire incident in a grid. The absence of fire incidents was taken as the reference variable when running the models.

2.3.3. Model selection

To choose the best-fitted model, we employed Akaike's Information Criterion (AIC) as introduced by Akaike [82]. The methodology selects the best model by considering how well the model fits the data while remaining parsimonious, i.e., preferring simpler models over complex ones to avoid overfitting. The selection process for the best model involved calculating AIC, then adjusting for small sample sizes with AICc, followed by computing delta AIC (ΔAIC) and Akaike weights (Wt.) using equations (4)–(7), respectively. The model with the lowest AIC, AICc, or ΔAIC, or the highest Akaike weight (Wt.) is considered the best model [83].

$$AIC = 2K - 2\log(L) \tag{4}$$

Table 2
VIF values of the variable before and after removing variables. The bold and italicized value is of the removed variable due to multicollinearity.

Variables	Abbreviation	Before	After
Forest area	AF	1.316	1.299
Flooded vegetation area	AFV	1.049	1.047
Rangeland area	AR	1.625	1.603
Agriculture area	AAG	1.906	1.681
Built-up area	ABU	1.730	1.696
Bare-grounds	AB	1.424	1.417
Normalized difference vegetation index	NDVI	2.183	2.112
Digital elevation model	DEM	3.274	1.977
Slope		***5.136***	
Distance from road	DR	1.871	1.872
Proximity to settlement	PS	2.390	2.370
Population density	PD	1.475	1.470
Land surface temperature	LST	1.313	1.210
Precipitation	PPT	1.539	1.494
Wind speed	WS	1.265	1.215
Solar radiation	SR	1.881	1.270

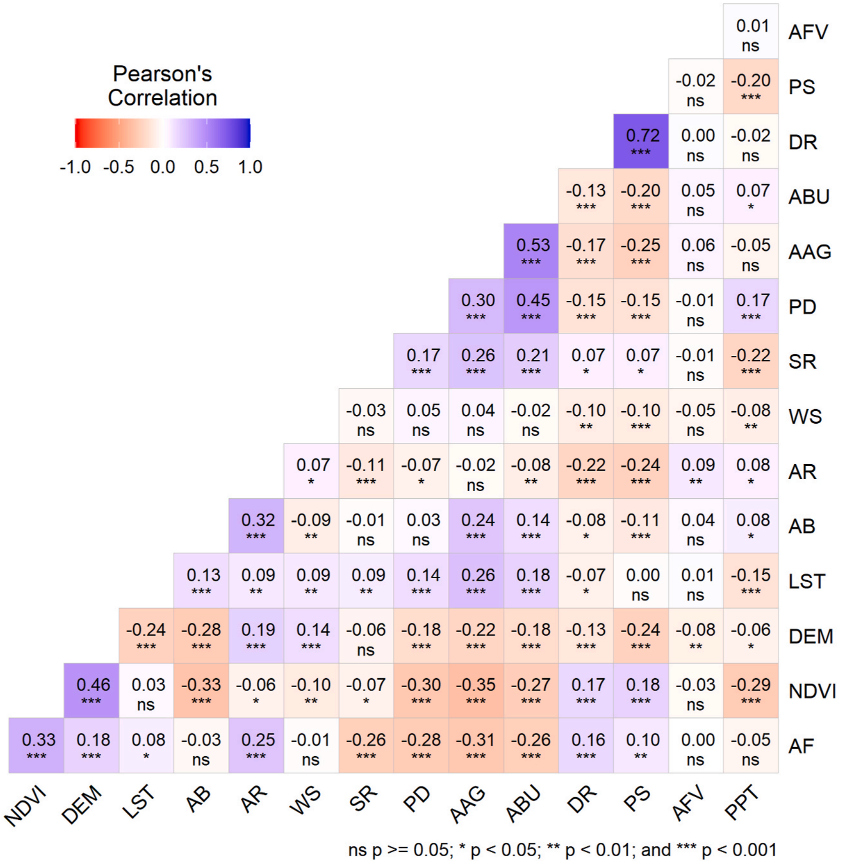

Fig. 2. Pearson correlation matrix for the variables. Refer to Table 2 for Abbreviation.

$$\text{AICc} = \text{AIC} + \frac{2K(K+1)}{n-K-1} \tag{5}$$

$$\Delta\text{AIC} = \text{AICc(i)} - \text{AICc(m)} \tag{6}$$

$$\text{Wt.} = \frac{\exp^{(-0.5\times\Delta\text{AICi})}}{\sum_{j=1}^{N}\exp^{(-0.5\times\Delta\text{AICj})}} \tag{7}$$

Where, K is the number of independent variable used, L is the maximized values of the likelihood function, n is the sample size, AICc(i) is the individual AICc score of each model, AICc(m) is the minimum AICc score of the model being tested, N is the number of model and j is the model being tested.

The assessment of the model's performance was done using the 'MuMIn' package [84], conducting a global model comparison through the dredge function and identifying the best model based on selection criteria. Then Model averaging was performed to account for the uncertainty associated with multiple candidate models using the Package 'AICcmodavg' [85]. All possible models were constructed and ranked based on small-sampled AICc [84]. The final model was obtained by averaging the top candidate models (delta AIC $\leq$2) [83].

Finally, to understand the impact of key variables on the model predictions, we predicted probabilities for significant variables such as " Forest area(AF)," " Rangeland area (AR)," " Baregrounds(AB)," "Normalized difference vegetation index (NDVI)," "Digital elevation model (DEM)," "Population density (PD)," and "Precipitation (PPT)." We employed the 'glm.predict' package [86] to execute the prediction function with the optimal-fit model. The ggplot2 package [87] facilitated the creation of informative and visually appealing plots to illustrate the relationships between these variables and the predicted probabilities as well as the variable importance plot. Subsequently, the resulting prediction values of the best fit model were exported and then subjected to reclassification utilizing the natural jenks classification method within ArcGIS 10.8 to create the forest fire susceptibility map of the Chure region. Fig. 3 outlines the concise methodological framework used in the study.

2.3.4. Validation

In testing the predictive performance of the primary model, we utilized three statistical measure namely, Receiver Operating Characteristic (ROC), Area under the Curve (AUC) and Accuracy (ACC). The validation was done independently by using the presence absence data for one fifth of the grids (n = 202). We used the 'ROCR' package [88] to generate a Receiver Operating Characteristic (ROC) curve and calculate AUC/ACC values. The ROC function lies in its ability to test the precision of a test, assigning values within the range of 0–1. The ROC was plotted for true positive rate (sensitivity) and false positive rate (1-specificity) for different threshold (Equations (8) and (9)). The AUC assesses how well a binary classification model distinguishes between positive and negative classes across all possible thresholds with a single scalar value in the range of 0–1. AUC score of 0 characterizes a test as imprecise, while a score of 1 denotes precision [89]. Generally, an AUC value of 0.5 suggests a lack of discrimination in the test, with values between 0.7 and 0.8 deemed acceptable, 0.8–0.9 considered excellent, and scores surpassing 0.9 considered as superior benchmarks [90,91]. Similar to AUC, ACC is also one of the commonly used index for any model validation which gives the valuation of correctly identified object by the model with higher values indicating better model [92,93]. The accuracy (ACC) of the model in our study was calculated as the proportion of correctly predicted classes using the same allocated validation grid based dataset as outlined in equation (10). The predicted probabilities were converted to binary classes with threshold of 0.5. If the predicted probability is greater than 0.5 class was set to 1 otherwise 0. The accuracy gives out the measure of overall correctness of the predictions made by the model. Among these metrics the AUC method is regarded as superior due to its ability to deal with imbalanced data and assessing model performance across different threshold [94]. We used both so as to compare models discriminatory ability as well as the correctness providing insights into its performance.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{8}$$

$$\text{Specificity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{9}$$

$$\text{Accuracy (ACC)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{10}$$

Where, TP is the True Positive, TN is the True Negative, FP is the False Negative and FN is the False Negative.

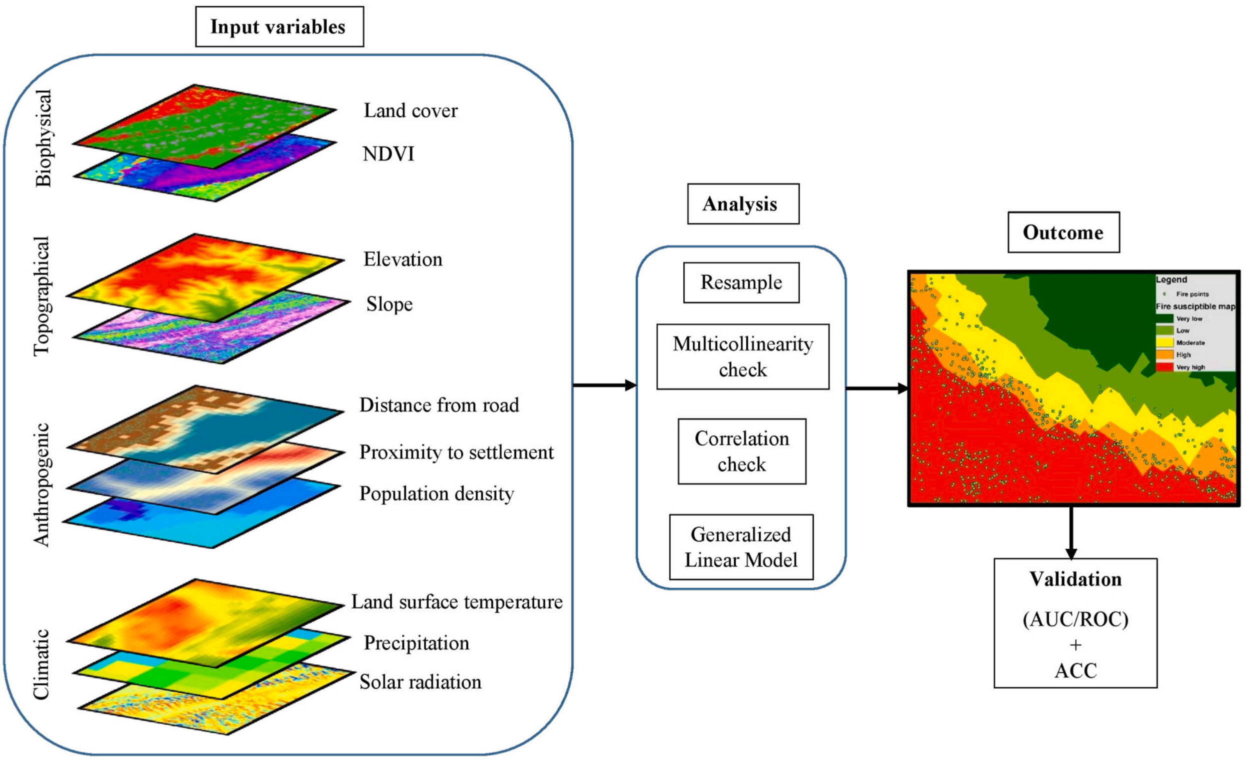

Fig. 3. Methodological framework for the modeling.

3. Results

3.1. Fire incidence in chure region

Altogether a total of 8544 fire points was recorded by the MODIS satellite with confidence level above 50% during the period of 2014–2023. The highest fire point was recorded in the year 2016 followed by 2021 and 2019 (Fig. 4). These three years accounted for approximately 57.40 % of total recorded forest fires. Month wise April recorded the highest forest fire (n = 4869, 56.98%) followed by March (23.44%, n = 2003) and May (14.91%, n = 1274).

3.2. Variable influence and probability of fire occurrence

As described in the data analysis section (subsection 2.3.3), best fit model was calculated best on the modified Akaike information criterion (AICc), delta AIC (ΔAIC) and Akaike weight (Wt.) The model identified as the best fit, with a weight (Wt.) of 0.12, comprises the predictors AB (Bare-grounds area), AF (Forest area), AR (Rangeland area), DEM (Digital elevation model), NDVI (Normalized Difference Vegetation Index), PD (Population Density), and PPT (Precipitation). The weight reflects the model's relative likelihood of being the best among the considered set. This chosen model achieved an AICc of 576.79, indicating its superior performance in balancing goodness of fit and model complexity (Table 3).

In our study, we examined the significance of various variables regarding the presence or absence of forest fire incidents (Table 4). The Forest area (AF) shows a significant and positive impact ($\beta = 2.09E\text{-}07$, $P < 0.001$), indicating a strong co-relation with forest fire incidents. This implies that larger forested areas can play a major role in contributing to the forest fire. Normalized Difference Vegetation Index (NDVI) has also positive and significant impact ($\beta = 5.75E+00$, $P = 0.000829$). This demonstrated that higher NDVI values are indicative of healthier vegetation and also correlated with an increased in forest fire incidents. Bare grounds (AB) also demonstrated significant positive correlation with forest fire incidents ($\beta = 8.62E\text{-}07$, $P = 0.003$) suggesting that larger bare ground can increased the chances of forest fire occurrence. Similarly, Rangeland area (AR) also demonstrated a significant positive correlation with forest fire incidents ($\beta = 3.63E\text{-}07$, $P = 0.002$).

On the other hand, Precipitation (PPT) shows a significant and negative association ($ß = -1.98E\text{-}02$, $P < 0.001$), suggesting that an increase in precipitation is associated with a decrease in the forest fire incidents. Population density (PD) were also found to be statistically significant ($ß = -1.17E\text{-}03$, $p < 0.01$) suggesting that an increase in population density is associated with a lower probability of forest fire incidents. The Digital Elevation Model (DEM) is also significant, revealing a negative impact ($ß = -1.98E\text{-}03$,

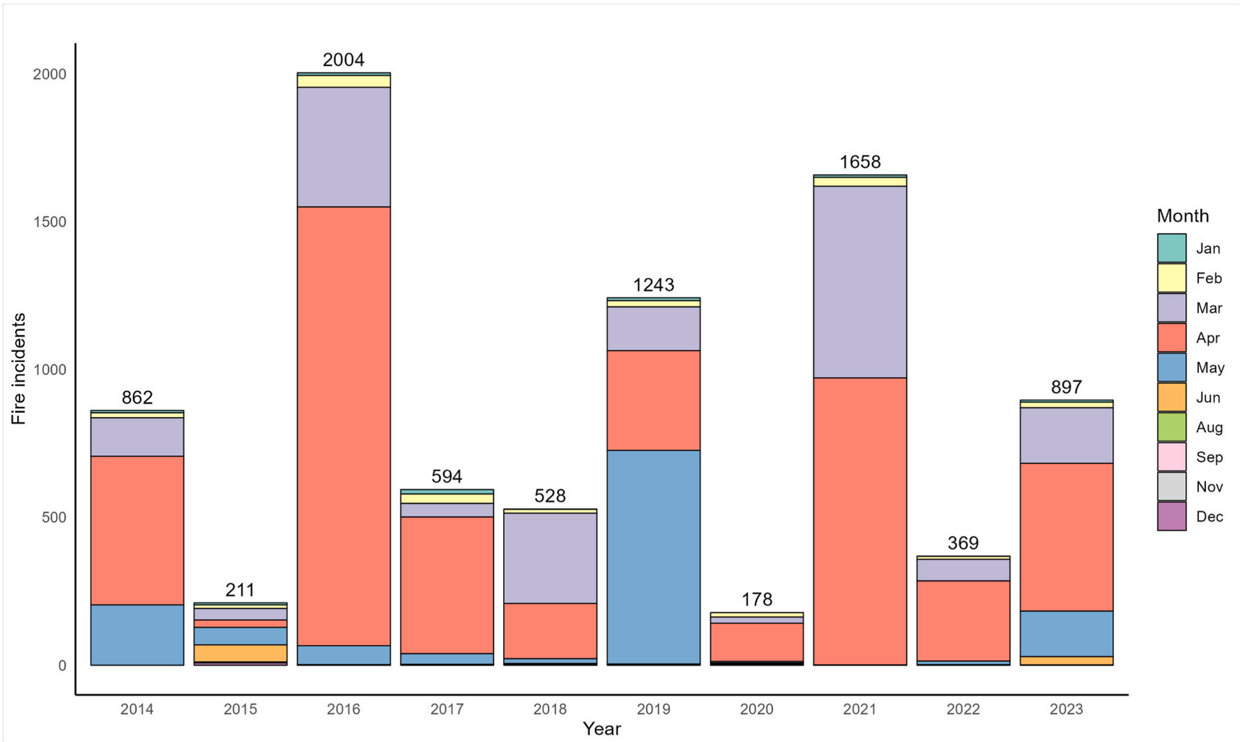

Fig. 4. Fire points recorded in Chure region by MODIS for the study period (2014–2023). The data labels indicate annual fire counts, while month-wise fire occurrences are visually represented using distinct colour combinations as per the index. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Akaike Information criterion scores of models with ΔAIC <2 and best fitting model for predicting probability of fire occurrence.

Component models:	df	logLik	AICc	ΔAIC	Wt.
fire ~ AB + AF + AR + DEM + NDVI + PD + PPT	8	−280.32	576.79	0	0.12
fire ~ AB + AF + AR + DEM + LST + NDVI + PD + PPT	9	−279.35	576.89	0.1	0.12
fire ~ AB + ABU + AF + AR + DEM + NDVI + PD + PPT	9	−279.52	577.22	0.43	0.1
fire ~ AB + ABU + AF + AR + DEM + LST + NDVI + PD + PPT	10	−278.75	577.72	0.93	0.08
fire ~ AB + ABU + AF + AR + DEM + NDVI + PD + PPT + SR	9	−280	578.19	1.4	0.06
fire ~ AB + AF + AFV + AR + DEM + NDVI + PD + PPT	9	−280.08	578.34	1.55	0.06
fire ~ AB + AF + AR + DEM + LST + NDVI + PD + PPT + SR	10	−279.07	578.36	1.57	0.06
fire ~ AAG + AB + ABU + AF + AR + DEM + NDVI + PD + PPT	10	−279.07	578.37	1.58	0.06
fire ~ AAG + AB + AF + AR + DEM + LST + NDVI + PD + PPT	10	−279.08	578.37	1.58	0.06
fire ~ AAG + AB + ABU + AF + AR + DEM + LST + NDVI + PD + PPT	11	−278.06	578.38	1.59	0.06
fire ~ AB + AF + AFV + AR + DEM + LST + NDVI + PD + PPT	10	−279.12	578.46	1.67	0.05
fire ~ AB + ABU + AF + AFV + AR + DEM + NDVI + PD + PPT	10	−279.16	578.53	1.74	0.05
fire ~ AAG + AB + AF + AR + DEM + NDVI + PD + PPT	9	−280.23	578.64	1.85	0.05
fire ~ AB + AF + AR + DEM + DR + NDVI + PD + PPT	9	−280.27	578.72	1.93	0.05
fire ~ AB + AF + AR + DEM + NDVI + PD + PPT + WS	9	−280.3	578.78	1.99	0.05

Abbreviation: Forest area (AF), Flooded vegetation area (AFG), Rangeland area (AR), Agricultural area (AAG), Bare-grounds (AB), Built-up area (ABU), Normalized difference vegetation index (NDVI), Digital elevation model (DEM), Distance from road (DR), Population density (PD), Land surface temperature (LST), Precipitation (PPT), Wind speed (WS) and Solar radiation (SR).

P = 0.000132), indicating a relationship between lower elevation and higher forest fire incidents. Conversely, variables such as Flooded vegetation (AFV), Agricultural area (AAG), Built-up area (ABU), and Distance from Road (DR), Land Surface Temperature (LST), Wind Speed (WS), and Solar Radiation (SR) did not show any statistical significance in predicting forest fires probability.

3.2.1. Importance of significant variables and model validation

The area of forest emerges as the most influencing factor, followed by precipitation, elevation, area of rangeland, population density, NDVI, and area of bare ground (Fig. 5). The predicted probabilities of fire occurrence with the significant variables are also visualized in Fig. 6. The figures clearly demonstrate that the probability of forest fire occurrence increases with larger forest area (Fig. 6a), rangeland area (Fig. 6b), and bare grounds (Fig. 6c), as well as with higher NDVI values (Fig. 6d). Conversely, the probability decreases with higher elevation (Fig. 6e), population density (Fig. 6f), and precipitation (Fig. 6g).Finally, for validation of the dominant model (GLM with binomial structure) AUC/ROC method and accuracy (ACC) was calculated. The result of the all three validation techniques showed excellent result with Area under curve (AUC) value of 0.92 and accuracy (ACC) of 0.89 (Fig. 7).

3.3. Forest fire susceptibility

The majority of the area falls into categories of "High" and "Very High," constituting approximately 65.50% of the total landscape. Specifically, the "High" category covers 32.16% of the area, while the "Very High" category extends over 33.34%. In contrast, lower-risk categories such as "Very low," "Low," and "Moderate" collectively account for the remaining 34.50% of the study area. The predictive map based on the model averaged coefficients indicated that pockets, especially lower and middle elevation range within

Table 4
Model-averaged coefficients of the variables predicting forest fire occurrence probability of forest fire.

Variables	Estimate	Std. Error	Z value	Pr(>|z|)	
(Intercept)	−2.24E+00	1.84E+00	1.216	0.223989	
AF	2.09E-07	1.82E-08	11.485	<2e-16	***
AFV	−1.50E-05	1.93E-05	0.776	0.43782	
AR	3.63E-07	1.19E-07	3.043	0.002344	**
AAG	−2.31E-08	2.87E-08	0.806	0.420042	
ABU	7.09E-08	5.40E-08	1.312	0.189463	
AB	8.62E-07	4.09E-07	2.106	0.035203	*
NDVI	5.75E+00	1.72E+00	3.343	0.000829	***
DEM	−1.98E-03	5.18E-04	3.823	0.000132	***
DR	−2.79E-05	8.63E-05	0.323	0.74676	
PD	−1.17E-03	4.36E-04	2.683	0.007303	**
LST	3.21E-02	2.55E-02	1.26	0.207517	
PPT	−1.98E-02	4.42E-03	4.486	7.30E-06	***
WS	5.31E-02	2.61E-01	0.204	0.838635	
SR	4.03E-06	5.23E-06	0.769	0.441673	

Significance codes: '***' P < 0.001, '**' P < 0.01, '*' P < 0.05.
Abbreviation: Forest area(AF), Flooded vegetation area (AFG), Rangeland area (AR), Agricultural area (AAG), Bare-grounds (AB), Built-up area (ABU), Normalized difference vegetation index (NDVI), Digital elevation model (DEM), Distance from road (DR), Population density (PD), land surface temperature (LST), Precipitation (PPT), Wind speed (WS) and Solar radiation (SR).

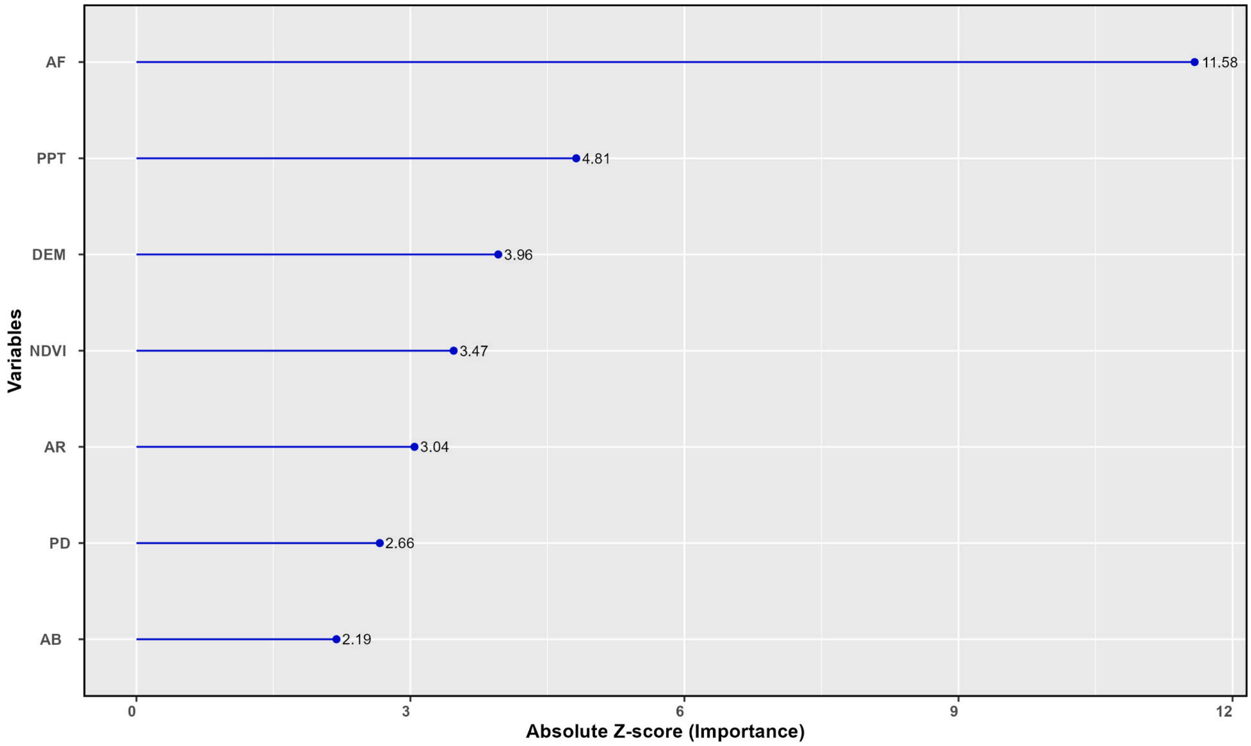

Fig. 5. Variable importance plot based on absolute Z-scores of best fit model indicating the magnitude of the impact of each significant variable on forest fire incidents.

central and western parts of Chure region were hot spots of forest fire risk (Fig. 8).

4. Discussion

4.1. Temporal analysis of forest fire in chure region

In this research we utilized the MODIS fire data for the analysis of forest fire in one of the most fragile and vulnerable region of Chure. Through the temporal analysis of fire data over a period of 10 years we found that most of the fires were detected in the month of March, April and May. Similarly, several prior studies on the spatial and temporal analysis of forest fires in Nepal have consistently identified the three pre-monsoon months as the peak of the active fire season [7,11,27,54]. This is attributed to the heavy leaf fall in broadleaved woodlands during the pre-monsoon period, which increases the fuel load in the forest, raising the likelihood of forest fires [29]. Furthermore, we observed that 2016 and 2021 recorded the highest number of fire incidents, this observation aligns with findings of Parajuli et al. [29] in Terai arc landscape of Nepal. According to Pokharel et al. [95], extreme drought conditions and precipitation deficit were the likely reason for triggering the record breaking 2021 wildfire season. Additionally, we analysed the forest fire data to identify factors influencing fires in the Chure region using the GLM approach and created a forest fire susceptibility map. The research findings are detailed in the following subtopics.

4.2. Vegetation provides fuel to fire

The vegetation layers used in our study were area under forest, rangeland, flooded vegetation, and normalized difference vegetation index (NDVI). Our analysis revealed that all of these variable were significant influencer of forest fire except for the flooded vegetation area. Furthermore, we found that probability of forest fire increases with increased area of forest, rangeland and higher values of NDVI which is in line with the findings of Chuvieco & Congalton [34] indicating that greater vegetation coverage contributes to higher fuel content, leading to more severe and frequent fires. Our result showcases that both forest area and rangeland of Chure range are highly susceptible to frequent fire session which is in alignment with the national forest survey [25]. Due to lack of accurate dataset regarding different forest type in the region we were limited to solely employing land cover classification. Further research should be conducted to analyse the relation of various vegetation type and tree species in the region with fire incidence and burnt area.

In our study, on an imperative note NDVI values ranged from -0.28 to 0.68. Since the extracted variable was only of three fire susceptible months of March, April and May. As our study was conducted during the period of (March–May) which is the leaf shedding season in Nepal, the NDVI score seems to be justifiable. A similar kind of NDVI score was also obtained from the research of Baniya [96]

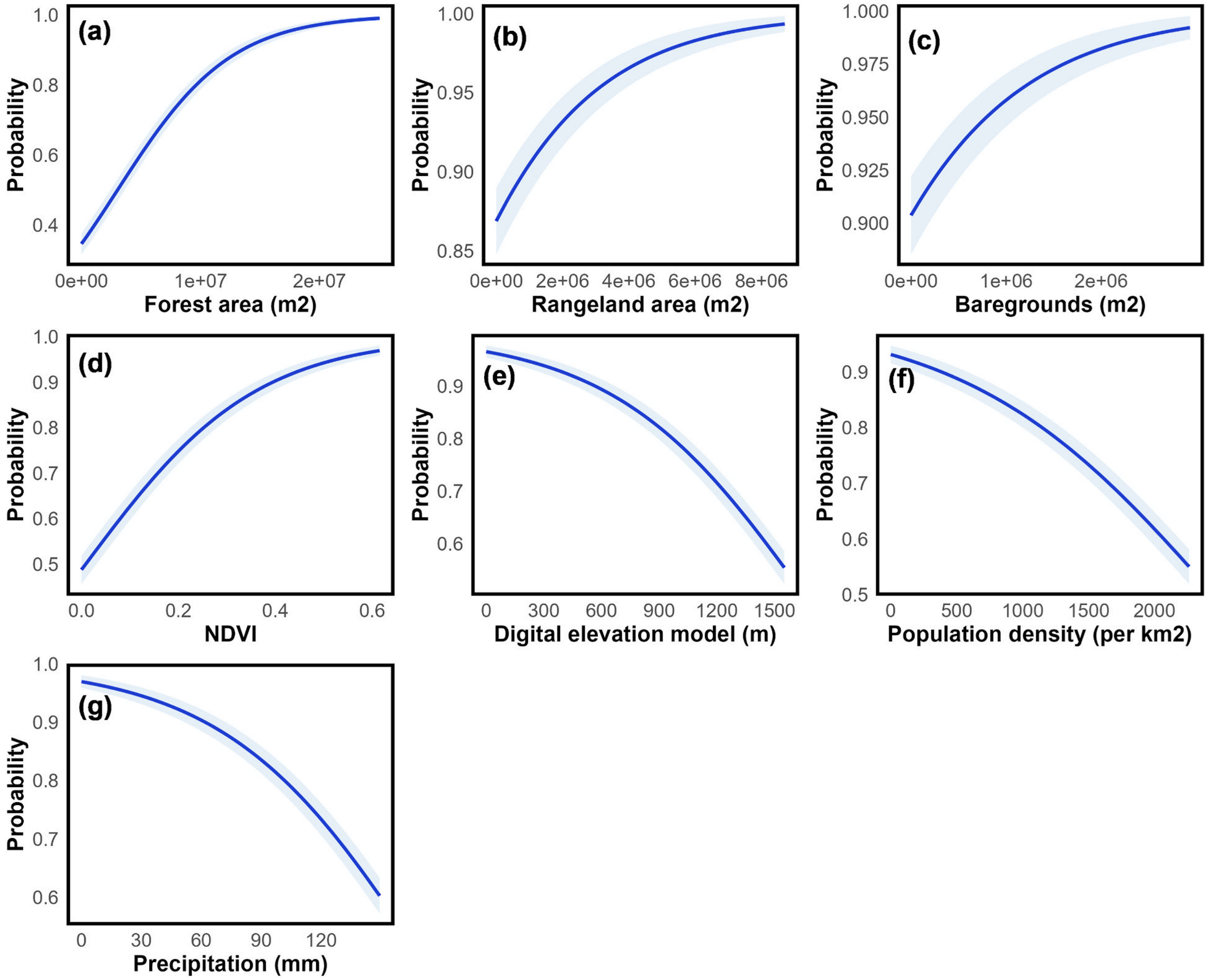

Fig. 6. Visual representation of the influence of various factors on the predicted probability of forest fire occurrence, as determined by the GLM. The y-axis reflects the predicted probability of forest fires, providing insight into the likelihood of their occurrence. The x-axis depicted the range of each individual factor, enabling an exploration of how alterations in these variables correspond to shifts in the predicted probability of forest fires. The shaded region is the uncertainty associated with each variable prediction.

and Parajuli et al. [29]. In addition to this, NDVI was significant and had positive correlation with the forest fire indicating the high NDVI values associated with the forest fire. NDVI values specifically in the range of 0.5–0.6 showcased very high probability of forest fire which is consistent to the findings of Quan et al. [97]. A similar kind of finding was established by Parajuli et al. [29] where the forest fire was recorded maximum in the forest whose NDVI value was greater than 0.5 in the pre-monsoon period. In our study, the area under flooded vegetation, representing forests area or swamp lands seasonally submerged under water [98], was considered an insignificant factor. This shows that humidity along with vegetation type plays a large role in influencing forest fire incidents in line to the findings of Shmuel & Heifetz [99] which reported areas with low relative humidity along with high NDVI values poses high risk of forest fire.

4.3. Anthropogenic factors influencing forest fire

The anthropogenic variables used in our study were area under agriculture, built-up area, bare ground, population density and distance from road. Among these five variables only area under bare ground and population density found to be a significant variable. We found that higher area of bare ground results in higher probability of forest fires. This can be due to the fact that people tend to use bare ground as playfield, picnic spots increasing human interference and carelessness which can result in uncontrolled fires. Our findings echoes to the result of Kunwar & Khaling [10] which reports that most of the fire in Terai region of Nepal is deliberately or accidently caused by people. Our research depicts that population density has a significant negative relationship with forest fire as shown in the result. Higher population density reduces the probability of forest fire to a large extent, in accord with several studies [99,

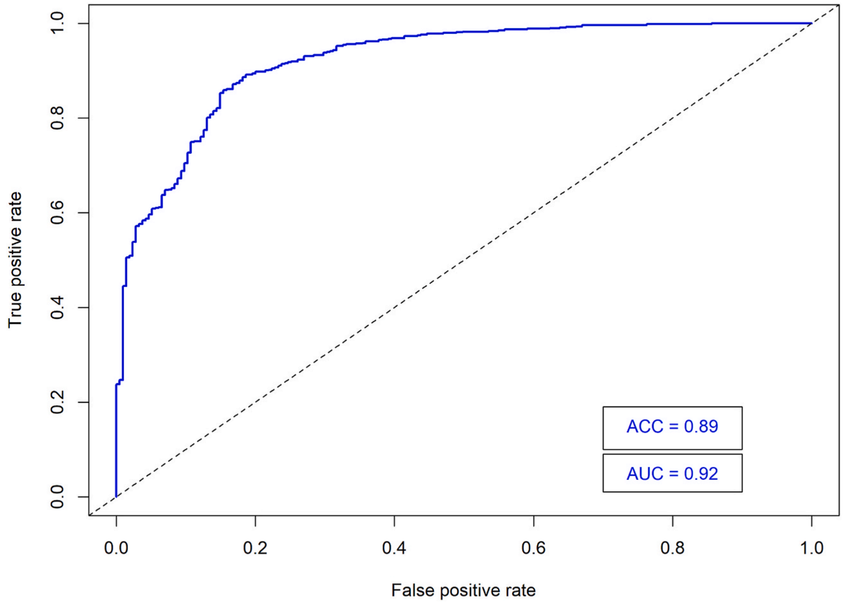

Fig. 7. ROC curve for the employed binary model with area under curve (AUC) and accuracy (ACC) values.

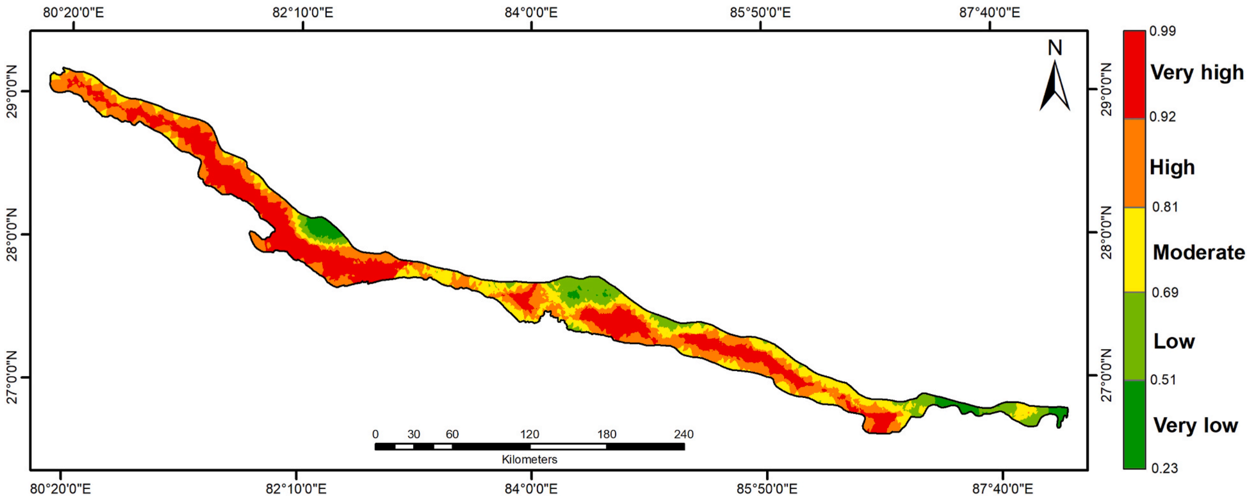

Fig. 8. Forest fire susceptible map of Chure region using GLM probability of fire occurrence prediction (0.23–0.99).

100]. Generally, there is a non-chromatic relationship between the population density and the forest fire. The risk of the fire initially increases up to a certain population threshold, but the intensity of the fire gradually decreases as the population density starts to increase [40]. The negative relation with forest fires can be due to places with higher population density are mostly agricultural or infrastructural zones and have very low vegetation to burn than natural landscapes [100–102]. Our research finding was also backed up by the research from Knorr et al. [101] who also found that the increase in the population density in the world has reduced the global fire frequency by 14% since 1800. Hence, our findings indicate that areas with lower population density, characterized by bare grounds surrounding forested land, are at a greater risk of fire compared to dense settlement areas.

4.4. Influence of topographic factors

The results from GLM model discloses that DEM plays a significant role in influencing forest fire in the Chure region of Nepal. Elevation is known to influence climatic conditions as well as vegetation. As the elevation increases the temperature decreases, resulting in low vegetation whereas the elevation decreases with the increasing temperature and leads to more vegetation and expands the chances of forest fire [103,104]. A similar kind of negative correlation is also demonstrated by our results which is also backed up by various previous studies [54,104,105]. Most of the studies consider lower elevations and modest slopes (∼15%) as high-risk areas for the forest fire [7,54]. The study area for this research is also located within a similar range.

4.5. Influence of climatic factors

Among the climatic variables only precipitation was found to have significant relation with forest fire. The findings of our study are consistent with the findings from Bhujel et al. [106] which concludes that the occasional precipitation can decrease the forest fire in the tropical lowland of Nepal. Similar findings were also lined up by Chen et al. [107] who established a significant relationship between occasional precipitation and forest fire in the five ecoregions of Yunnan in China. In the case of climatic variables like precipitation, the occurrence of forest fires is high in area with either very low or very high precipitation. Low precipitation in areas is often associated with drought conditions increasing the risk of dry fuels and causing the rapid spread of fire [108]. While the high precipitation areas are associated with high vegetation covers, and high fuel loads thus increasing the possibility of forest fire in the long term [109]. In our study area, the western part of the Chure region has a high area for fire susceptibility compared to the central and eastern parts of the region. The reason for this is the low level of precipitation in this region. This finding of the study is also validated by the research of Mishra et al. [20] stating the western part of Nepal receives very little rainfall compared to the east increasing the possibility of fire in the western region of Nepal.

The two insignificant climatic variables in our study were land surface temperature and solar radiance. Contrasting to our results various other studies have reported temperature as a crucial factor for the forest fire analysis in Nepal [11,20,29,54]. The presence of high forest cover in the region may be the likely reason for this insignificant relation, as areas with high forest cover and NDVI tend to exhibit lower land surface temperatures [110]. In the case of solar radiation, it has a comparable impact as aspect, with southern aspect receiving higher solar radiation and at higher fire risk [7]. However, these areas exhibit lower tree species, density as well as carbon stock compared to those receiving less solar radiation (north) [111,112] which could have resulted in the insignificant relation.

4.6. Variable importance, model validation and forest fire susceptible map

Among the various variables, the best fit model showed Area under forest was the highest influencer of forest fire followed by precipitation and elevation. Our results align with various previous study of Parajuli et al. [29] which reports that land cover classes specifically forest types are the main factors describing forest fires. Similarly, Qadir et al. [11] reported strong association of forest fires with precipitation in Nepal. Finally, our result echoes the findings of Janizadeh et al. [108] which reports elevation as a major influencer of forest fire of forest fire in Iran. According to Mishra et al. [20] bioclimatic and topographic factors have higher influence on fire than anthropogenic factors in Nepal which supports our results as population density and area under bare grounds were least ranked variables.

Validation of the primary model was done through AUC/ROC method and accuracy (ACC) assessment. The overall AUC value received by our model was 0.92 and the accuracy was 0.89 signifying our model as accurate. The AUC value received by our model is higher than Parajuli et al. [29] by fuzzy AHP (AUC = 0.83) and similar to that of Goleiji et al. [113] using AHP and analytical network process (AUC = 0.92). Furthermore, our models outscored the AUC and ACC values by various machine learning methods by previous research [114,115]. The final susceptible map produced through the best fit GLM model shows that the western and central parts of Nepal as the high-risk areas for fire occurrence, suggesting the concerned authorities to take proper management measures to avoid the potential loss. The findings of our study was also backed up by the findings of Mishra et al. [20] which concludes that the western part of Nepal, especially in the Chure and low regions are very high risk areas for the forest fire. Furthermore, almost 62% of the area were categorized into very high and highly susceptible area for forest fire in our model. Thus, based on our result and previous findings [20,106], it can be augmented that forest fire would have an enormous negative impact on the Chure ecosystem until and unless there are any changes in the policy and management regimes. Unlike the other natural hazards in the world, forest fire can be prevented and mitigated to the great extent if proper management plans are made and executed in an efficient and timely manner [116]. Hence, our research finding will be helpful to the various line agencies like The President Chure terai madhesh conservation development board to mitigate future fire risk through preparation of region specific fire management strategy.

5. Limitations

Although our model demonstrated an accuracy of 89% (ACC = 0.89) and an AUC value of 0.92, indicating that the GLM model can be used for modelling forest fires in similar regions, we did not consider other auxiliary variables such as socio-economic variables and real field-based data in this study. Additionally, our research was constrained by the absence of a dataset encompassing various forest types, restricting our analysis solely to land cover types. Therefore, future research should be guided towards incorporating these additional variables to further enhance the predictive performance of the model.

6. Conclusion

The research provides valuable insights into the various factors influencing forest fire incidents in the highly fragile Chure region. Pre-monsoon months (March, April, and May) should be considered a period of high alert by involved authorities for the minimization of large fire outbreaks. The results of the best-fit model indicate that the likelihood of forest fires in the Chure region increases with increasing forest area, rangeland area, bare ground area, and NDVI. Conversely, elevation, precipitation, and population density were found to have a significant negative relationship with forest fire incidents. The model demonstrated strong predictive performance with an accuracy of 89 (0.89) percent and AUC value of 0.92. The forest fire susceptibility map shows high vulnerability in the Chure region, with 33.34% areas classified as very high risk and 32.15% as high risk, emphasizing the urgent need for prioritized control measures to prevent future forest degradation. As a line of future research, we recommend the integration of field-based data and new auxiliary variables, such as socio-economic variables, to further enhance the predictive performance of the model.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Khagendra Prasad Joshi: Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Gunjan Adhikari:** Writing – original draft, Visualization, Validation, Software, Resources, Formal analysis, Data curation, Conceptualization. **Divya Bhattarai:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Investigation, Conceptualization. **Ayush Adhikari:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Conceptualization. **Saurav Lamichanne:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e28525.

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