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Mapping climate change induced forest fire susceptibility using tree-based machine learning algorithms in Bangladesh

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ABSTRACT

Forest fires in forested areas are an environmental disaster resulting from either natural phenomena or human activities. Forest fires pose a substantial risk in the forested and grassland areas of the Chittagong Hill Tracts. Therefore, mitigating the danger of forest fires is crucial for lessening their potential negative effects. This study employs tree-based machine learning (ML) algorithms to assess Forest Fire Susceptibility in the Chittagong Hill Tracts (CHT) of Bangladesh under current and anticipated climate change scenarios. Nineteen environmental and climatic variables were analyzed, with temperature, precipitation, wind speed, and height identified as the most relevant factors. This research analyses 267 historical instances of forest fires. Historical fire data and environmental attributes were utilized to train and validate eight ML models: Random Forest (RF), LightGBM, XGBoost, Decision Tree (DT), Gradient Boosting Machine (GBM), Adaptive Boosting (AdaBoost), Categorical Boosting (CatBoost), and Bagging. AdaBoost had the highest predictive accuracy (AUC: 0.82), classifying 4.31% of the study area as very susceptible, 66.74% as moderately susceptible, and 28.94% as having low Susceptibility. Future fire Susceptibility were projected under Representative Concentration Pathways (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) for respective years of 2040, 2060, 2080, and 2100, indicating an increase in fire-prone regions, with high-susceptible areas expected to grow by as much as 15.39% under RCP 8.5 by 2080. These findings underscore the growing vulnerability of forested regions due to climate change and highlight the necessity of implementing proactive fire management strategies. The results of this research give significant novel insights for authorities in forestry administration and legislators, facilitating the development of climate-adaptive fire mitigation policies to strengthen environmental resilience and safeguard natural resources, while also supporting local governments in implementing sustainable forest resource management practices that improve the welfare of residents in Bangladesh.

1. Introduction

Forest fires cause extensive harm to the environment, property, and existence of people. Forest fire disasters are regarded as a primary factor in the significant loss of global forest ecosystems (Venkatesh et al., 2020). In forested regions, forest fires symbolize among the most devastating natural disasters, ravaging millions of hectares annually and leading to the deterioration of biodiversity, soil quality, and carbon dioxide sequestration (Bo et al., 2020; Bowman et al., 2009; Jager & Coutant, 2020; Meng et al., 2015; Natole et al., 2021). Human activity must not be overlooked, even while climate change (i.e., rising temperatures and decreasing precipitation) contributes to an increase in fire incidents. Owing to current global warming and its impact on human well-being, ecosystem function processes, and resources, fire regimes have grown progressively more prominent in many locations. (Hong et al., 2016; Li et al., 2019; Zema et al., 2020a). Some of the consequences include land degradation, soil erosion, and the decline of soil ecology and water hydrology (Santana et al., 2014; Zema et al., 2020b). Consequently, the ecology becomes unbalanced as a result of this calamity. In spite of the significant damage it does, forest fires play an important part in a wide variety of forest processes. For instance, forest fires have an effect on the structure and successional phases of the forest, and they also serve as a selecting factor for the characteristic's plants possess (Agarwal & Chakraborty, 2024; Escudero et al., 2000; Fernández-García et al., 2019; Keeley et al., 2011; Pausas & Vallejo, 1999; Santana et al., 2014). In order to efficiently allocate firefighting resources and create fire management strategies, it is necessary to identify locations with high or extremely high fire susceptibility (Bollasina et al.,

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2014; Goleiji et al., 2017; Jaafari et al., 2019a; Oliveira et al., 2012a; Sakellariou et al., 2019). Authors as well as engineers need rigorous methods and tools to anticipate future fire time, location, and extent (Jaafari et al., 2019b; Satir et al., 2016; Sevinc et al., 2020; Tien Bui et al., 2018; G. Zhang et al., 2019). Bangladesh is currently experiencing various natural hazards including forest fire. Climate change has significantly affected Bangladesh's ecological system, particularly its forest areas and Chittagong Hill Tracts (CHT) are also highly vulnerable to environmental threats such soil erosion, carbon emissions forest fire and notably 88 % of the country's fire related hotspots have been recorded in the CHT (Farukh et al., 2023a; Markert & Sarker, 2017; Sadia et al., 2023). Currently, the CHT region is under immense strain due to factors like fire intensity and deforestation. It has been observed that this region experiences the highest number of forest fire in Bangladesh with fires spreading over vast areas of protected forests and nearby settlements. Enhancements in methods for predicting fire susceptibility and classifying forested areas into different susceptibility categories can aid forest administrators and policymakers in achieving a deeper understanding of fire dynamics, thereby aiding the formulation of preventive strategies for fire-prone forests (Mhawej et al., 2017; Natole et al., 2021). Forest in the CHT threaten both ecosystem and indigenous communities who rely on forest for livelihoods (Ahammad & Stacey, 2016). The 'dry season' from November through April corresponded to 98 % of total fire occurrences with the very active fire period from late March to early April coinciding with the slash-and-burn cycle of shifting cultivation, making fire a recurring environmental threat in CHT region (Farukh et al., 2023b). Deforestation shifting cultivation and human activities have increased fire susceptibility, leading to biodiversity loss, soil erosion and water scarcity (Markert & Sarker, 2017). Fire also disrupts farming and force relocations endangering food security and protected areas like Kaptai National Park (Ahammad & Stacey, 2016). In addition to climate factors, human activities such as deforestation, hilly-cutting and unplanned land use have been identified as key contributors to environmental degradation and increased fire susceptibility (Rimi et al., 2024). Addressing these risks is crucial for sustainable forest management and community resilience.

Making Forest Fire Susceptibility maps requires for certain explanatory factors as well as a target variable that is forest fire inventory. Numerous studies included land use data, meteorological data (temperature, humidity, wind, and rainfall), and topography data (slope, elevation and aspect) as forest fire governing factors (Bui et al., 2016; Krawchuk et al., 2006; Vecín-Arias et al., 2016; Verdú et al., 2012). When it comes to choosing the right ignition variables, there is no universally accepted standard. Due to the complex structures of the models and the variety of data sources, the most difficult part of creating forest fire maps for vast study regions is processing the conditioning factors (Bui et al., 2016). Numerous research utilized different factors such as wind speed, NDMI, DEM, TWI, distance from road, Curvature, location of villages, LULC, elevation, slope, aspects, distance from settlement, NDVI and temperature (Mambile et al., 2024; Moghim & Mehrabi, 2024; Pourtaghi et al., 2016). GIS are useful for handling and adding geospatial data. They can be used to work with these kinds of datasets and can assist in improvement of digital mapping of forest fire (Hafyani et al., 2020; Teodoro & Duarte, 2013). On top of that, the construction of Forest Fire Risks maps is significantly aided by the utilization of remote sensing techniques and satellite imagery, which are widely used as a standard method of data collecting. ML and deep learning (DL) are extensively utilized in Forest Fire Risks mapping (Mohajane et al., 2021a; Tuyen et al., 2021). However, challenges such as data availability, algorithm selection and field data validation persist. (Xie & Peng, 2019) developed an ensemble ML approach for forest fire prediction in Portugal while authors like (Kantarcioglu et al., 2023) assess Turkey's forest risk based on artificial neural networks (ANN) but didn't account for climatic factors. In India, ML based studies are limited often relying only three (RF, SVM, MARS) models with recommendations to expand comparisons (Bera et al., 2022). Additional studies primarily utilized traditional mathematical & statistical and Geographic information system based method (de Souza et al., 2015; Pragya et al., 2023). ML algorithms effectively handle date with complex dynamics and solve critical problems (Chen et al., 2019; Knudby et al., 2010; Maskooni et al., 2020). (Pourtaghi et al., 2016) found that boosted regression trees (BRT) in forest fire mapping. (Jaafari et al., 2018) compared five decision trees classifiers where Alternating Decision Tree (ADT) achieving the highest accuracy. In Bangladesh, a few research have been done on forest fire. (Farukh et al., 2023c) analyzed historical weather pattern and fire events but the research was not conducted to map forest fire zones or susceptibility. (Markert & Sarker, 2017) used remote sensing to assess fire hazards in CHT but overlooked key inputs factors for ML and DL models. In previous year, first research on forest fire was published to predict areas susceptible to forest fire using different ML and DL algorithms in CHT but they did not predict climate scenario on forest fire and tree-based machine learning algorithm (Haydar et al., 2024a). This study aims to enhance the model selection with climate scenario for mapping forest fire Susceptibility zones in CHT.

Bangladeshi forest fire research is still in its infancy, with little attention paid to the CHT. Previous research has mostly employed meteorological trends to pinpoint fire-prone regions or geographic data to evaluate fire concentration. To date, no study has incorporated a tree-based machine learning algorithm to forecast forest fire susceptibility in CHT under various climatic conditions. Research via data-driven tree-based ML techniques to evaluate the Forest Fire Susceptibility in CHT is, however, severely lacking. By employing tree-based machine learning algorithms to map Forest Fire Risks in the CHT, this study seeks to fill in current research gaps. The key objectives include: (i) to examine the impact of various environment environmental and climatic factors on fire susceptibility in CHT; (ii) to identify high, moderate and low susceptible zones using tree-based machine learning algorithms; (iii) to evaluate the performance of different tree-based models for mapping Forest Fire Susceptibility and (iv) to project future susceptibility scenarios based on Representative Concentration Pathways (RCP). The study will enhance predictive modelling accuracy, contribute to better fire management strategies and offer insights into climate driven fire risks. By integrating advanced tree-based machine learning algorithm with climate projections, this work will support data-driven decision making for forest conservation and disaster mitigation.

2. Methods and materials

2.1. Description of the study area

The Chittagong Hill Tracts (CHT) (Fig. 1) is the sole mountainous area in Bangladesh, situated in the southeastern corner of the country, spanning latitudes 21°25′ N to 23°45′ N and longitudes 91°54′ E to 92°50′ E (Hasan et al., 2020). It is bordered to the north by Tripura (India), to the southeast by Mizoram, to the west by the Chittagong district, and to the southwest by the Cox's Bazar district. The CHT encompasses an area of 13,294 square kilometers, predominantly characterized by hilly terrain, with steep slopes comprising approximately two-thirds of the landscape (Hasan et al., 2020; Haydar, Rafi, et al., 2024). The area has three districts: Rangamati, Khagrachhari, and Bandarban (BBS, 2016). The 2022 census reveals that CHT has a total population of 1,842,815, with around 49.94 % (920,248 individuals) consisting of various ethnic tribes. The population density is roughly 140 persons per square kilometer (Asiva Noor Rachmayani, 2015). The climate is subtropical, defined by mean maximum monthly temperatures of 25 °C to 34 °C, with annual precipitation between 2,032 mm and 3,910 mm, with 80 % occurring from May to September (Chakma et al., 2023a). More than 70 % of the region consists of natural and cultivated forests, primarily tropical wet evergreen, semi-evergreen, and deciduous species classified as hill forests (Chakma et al., 2023b; Rasul, 2007). The primary sources of sustenance include agriculture, cattle, and forest resource extraction. The Chittagong Hill Tracts (CHT) was chosen as the

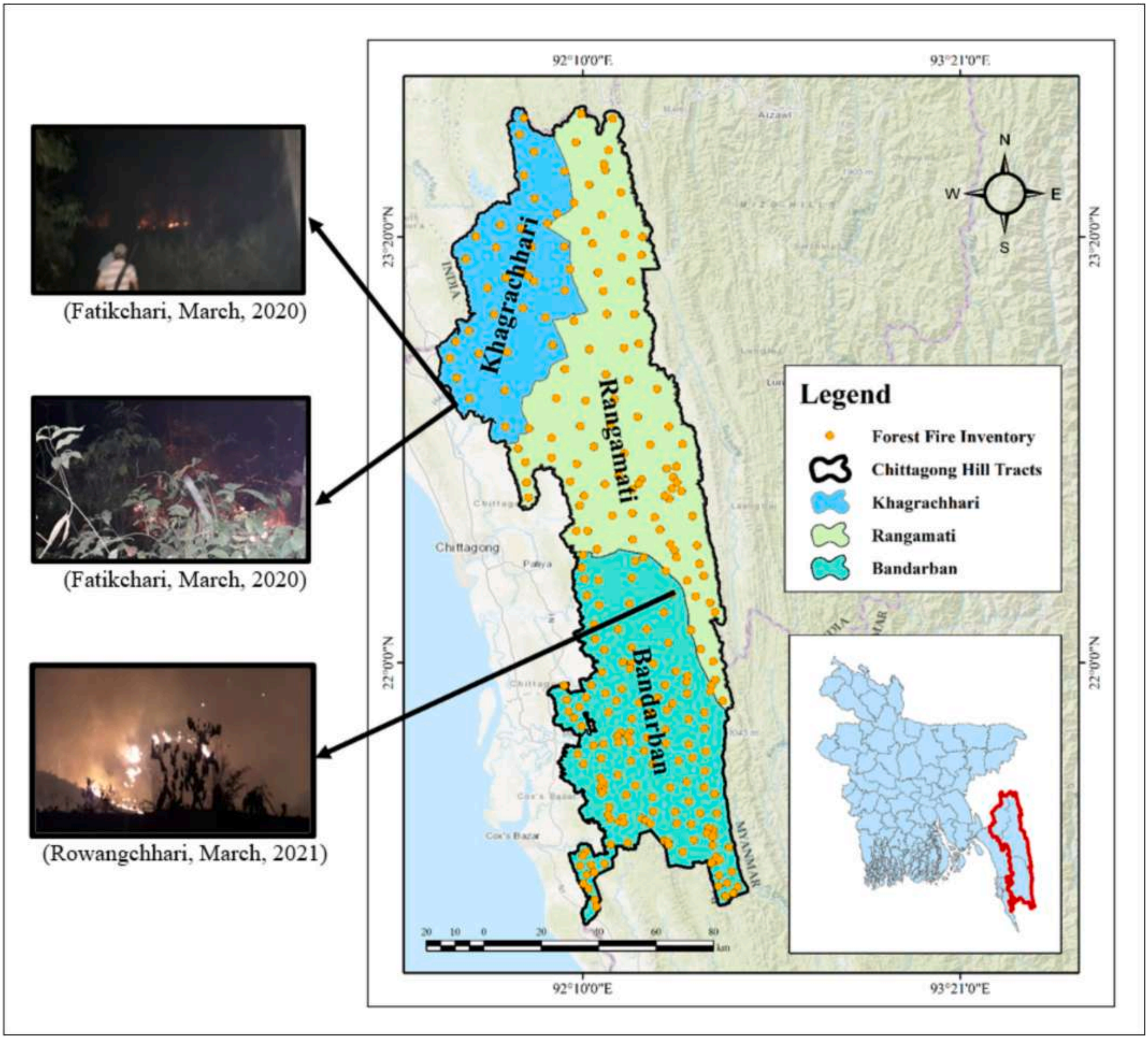


Fig. 1. Geographical setting of the study area and Inventory of Forest Fire Events.

study site due to its unique steep topography, significant forest density, and heightened risks to forest fires. The intricate relationship between human and environmental components in the region is essential for evaluating fire hazards and formulating models of projection for sustainable management. Fires occurred twice in Fatikchari (March 2020) and once in Rowangchhari (March 2021) (Haydar, Rafi, et al., 2024). The Department of Forests indicated that these incidents destroyed over 5 ha in 2020 and 4 ha in 2021. Given the region's sensitivity, fire incidence models predicated on risks and future projections are essential for risk mitigation and sustainable management (Pragya et al., 2023).

2.2. Description of data

This study examines the correlation between the spatial coordinates of historical forest fires and the corresponding governing parameters at those locations. This relationship constitutes the foundation of the inquiry. Maintaining an accurate record of forest fires is crucial. This study employed data from the Fire Information for Resource Management System's historical forest fire density map to create an inventory (Markert & Sarker, 2017). The fire events were cross-verified using official records from the Department of Forest under the Ministry of Environment and Forests ensuring the data reliability. The events in the forest were documented in a comprehensive general diary kept by Nazirhat Highway Police Fari, Fatikchari, in conjunction with an extensive review of relevant literature, records from the Department of Forest, and newspaper articles related to incidents in Sajek and Lama (Haydar, Rafi, et al., 2024; Markert & Sarker, 2017). Any potential missing data was mitigated by triangulating multiple sources including governments records and media reports to construct a more complete historical fire dataset. 118 forest fire locations were chosen for model calibration and validation. Locations devoid of forest fires were chosen from regions with no recorded history of such incidents as an additional dataset. This was performed to enhance the existing dataset. A random sampling strategy was utilized to select 149 fire areas not associated with forests. The proposed approach was assessed and refined utilizing data from one hundred eighteen (118) fire locations and one hundred forty-nine (149) non-fire areas. Nineteen parameters were incorporated into this endeavors including elevation, slope, curvature, aspect, roughness, precipitation, evapotranspiration, land surface temperature, temperature, relative humidity, wind velocity, aridity index, climatic water deficit (CWD), land use land cover (LULC), normalized difference water index (NDWI), normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), normalized difference built-up index (NDBI), and leaf area index (LAI). The initial data compilation utilized a GIS and RS framework, where thematic layers for governing factors were produced by remote sensing techniques in Google earth engine (GEE) and ArcGIS (Fig. 2).

Six factors as elevation, slope, curvature, aspect, and roughness were acquired from SRTM-DEM via GEE platform. The gradient of fire-prone terrain substantially affects wildfire spread, as flames propagate more swiftly uphill than downhill, intensified by the fire's inclination to rise along steeper slopes due to their closeness to the ground (Lentile et al., 2006). The slope significantly influences wildfire spread, since flames and heat rise more efficiently, preheating the vegetation above and accelerating combustion. Elevation directly impacts temperature, precipitation, humidity, and wind, while indirectly influencing vegetation and fuel moisture. Thus, it is incorporated into the study, as elevated regions are often colder and have increased precipitation, which reduces fire danger, whereas lower elevations are warmer and drier, heightening risks (Gao et al., 2011). The factor element was incorporated into the research because it correlated with the solar energy share of the area encountered (Adab et al., 2013). It profoundly affects wildfire activity by determining the amount of solar energy an area receives. The curvature indicates the morphology of topography and has been recognized in studies for its impact on fire propagation (Pourghasemi, 2016). Roughness emphasizes areas with significant elevation variations to analyze statistical trends and the causes of forest fires. Elevated roughness can amplify wind turbulence and alter fire dynamics, whereas

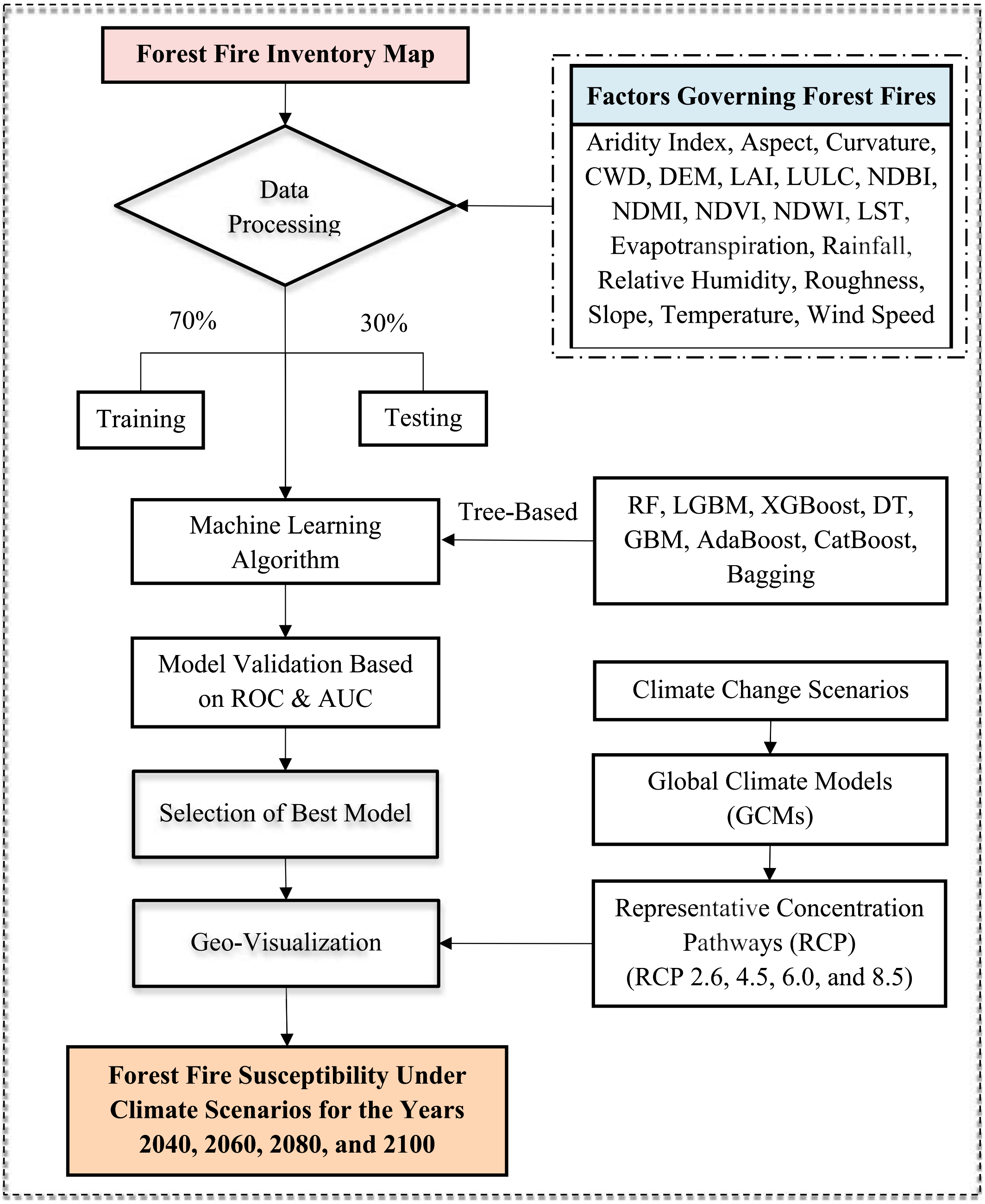


Fig. 2. Research methodological framework.

smoother areas may facilitate a more uniform fire distribution (Nunes et al., 2016).

The climatic characteristics substantially affect an area's vulnerability to wildfires; so, this study includes temperature, precipitation, land surface temperature (LST), wind speed, aridity index, relative humidity, cumulative water deficit (CWD), and evapotranspiration (Sachdeva et al., 2018). Wind velocity markedly affects precipitation rate and soil hydration, as intense winds can carry embers across extensive distances, igniting new fires and intensifying fire severity (Mohajane et al., 2021b). Furthermore, wind velocity influences soil moisture and evaporation rates, hence affecting fire risk. Climate change intensifies the degradation of these ecosystems, as reduced precipitation and elevated temperatures result in prolonged droughts, lowering vegetation moisture and increasing fire vulnerability (Simioni et al., 2020). Evapotranspiration regulates forest moisture and meteorological factors, alleviating aridity and fire risk, thereby serving a crucial function in fire risk management. Increased evapotranspiration rates indicate heightened water loss from soil and vegetation, leading to drier conditions that elevate wildfire vulnerability (Wu et al., 2023). Land surface temperature is crucial for assessing aridity and fire risk, significantly contributing to forest fire forecasting, as prolonged elevated LST values signify increased fire vulnerability (Kalantar et al., 2020). The aridity index functions as a measure of a region's dryness or humidity, where a high index signifies arid conditions favorable for wildfires, and a lower index indicates more humid conditions that may inhibit fire spread (Xu et al., 2024). Relative humidity influences wildfire risk by controlling fuel moisture; reduced humidity swiftly desiccates fine fuels, which is critical for fire prediction and management, since lower relative humidity accelerates the drying of vegetation, heightening its risks to ignition (Tariq et al., 2021). The Climate Water Deficit influences forest fires. Elevated CWD can increase fire frequency and reduce vegetation productivity in water-scarce locations, where high CWD levels indicate significant water deficiency, hence decreasing plant resilience and increasing the likelihood of fire incidents in arid environments (Mueller et al., 2020). These parameters were extracted using GEE from its respective data source mentioned in Table 1. Then standardized and visualized in ArcGIS.

The land use and its surrounding characteristics, such as LAI, LULC, NDVI, NDBI, NDMI, and NDWI, influence the likelihood of a potential forest fire (Bui et al., 2016; Eugenio et al., 2016; Sachdeva et al., 2018). The land use and land cover (LULC) of an area affects fire occurrence to different degrees, depending on the types of cover and human interactions, which are critical in analyzing forest fires, moisture levels, and human influences that impact fire start and spread (Kalantar et al., 2020b). The occurrence of forest fires is significantly affected by the structure of vegetation, which is typically evaluated through the measurement of vegetation canopy via NDVI, the most commonly employed index for vegetation analysis. This index is essential in forest fire research as it assists in evaluating vegetation health and density, which are critical elements affecting fuel availability and fire behavior (Navarro et al., 2017), those with high NDVI values typically have increased biomass that can fuel fires, whereas NDVI value tends to zero may indicate parched or degraded vegetation prone to ignition. To address the inherent limitations of each index (Gibson et al., 2020), we integrated the well-established NDMI with the NDVI to better explain the vegetation dynamics in the study area, where lower NDMI values indicate arid vegetation, thereby increasing fire risk, while higher values represent healthy, hydrated vegetation that is less prone to ignition (Kalantar et al., 2020b; Rahman et al., 2024). It is essential to recognize the significant correlation between the variables, which may lead to multicollinearity issues in the modeling process, where low NDWI values denote arid conditions, increasing fire risk, while high NDWI values represent water-saturated environments that may hinder fire spread (Pham et al., 2024). The leaf area index (LAI) quantifies vegetation density, productivity, and solar radiation absorption for photosynthesis. Elevated LAI values signify thick vegetation, potentially heightening fire intensity, whilst diminished values denote sparse canopies with reduced fire risk (Haydar, Rafi, et al., 2024). The Normalized Difference Built-up Index (NDBI) enables the evaluation of urban sprawl and land changes, aiding in the understanding of the effects of prescribed burns on vegetation and fuel load, which is essential for forest fire management and relevant to fire research, as urban expansion alters land cover and affects fire regimes (Tariq et al., 2021). The radiometric indices (LAI, NDVI, NDWI, NDMI and NDBI) were generated using respective bands of sentinel-2 in GEE and visualized in ArcGIS. The study utilized satellite imagery, ground truth data, corrected distortions, extracted features, applied a classification algorithm, assessed accuracy using validation data, and extracted LULC using Google Earth Engine.

Table 1
Comprehensive clarification of the sources and datasets applied to determine forest fire risks.

Indicators	Data Sources	Data Type	Resolution
Elevation	SRTM	Raster	30 *m*
Slope	Developed from SRTM-DEM	Raster	30 *m*
Curvature	Developed from SRTM-DEM	Raster	30 *m*
Aspect	Developed from SRTM-DEM	Raster	30 *m*
Roughness	Developed from SRTM-DEM	Raster	30 *m*
Rainfall	CHIRPS	Raster	0.05°
Evapotranspiration	MODIS	Raster	500 *m*
LST	MODIS	Raster	1000 *m*
Temperature	ERA5	Raster	0.25°
Relative Humidity	GLDAS	Raster	0.25°
Wind Speed	ERA5	Raster	10 *m*
Aridity Index	Global-Aridity_ET0	Raster	1000 *m*
Cumulative Water Deficit	TerraClimate	Raster	1/24°
LAI	Copernicus/S2_SR	Raster	10 *m*
Land Use Land Cover	Sentinel-2	Raster	10 *m*
Normalized difference vegetation index	Sentinel-2	Raster	10 *m*
Normalized Difference Built-up Index	Sentinel-2	Raster	10 *m*
Normalized Difference Moisture Index	Sentinel-2	Raster	10 *m*
Normalized Difference Water Index	Sentinel-2	Raster	10 *m*
Forest Fire Inventory	Department of Forest, LiteratureReview (Haydar, Hossain Rafi, et al., 2024; Markert & Sarker, 2017), Newspaper	Vector	–
Projected Temperature Data (RCP)	UCAR	Vector	–

2.3. Analytical methods—Tree-based machine learning

Random Forest (RF) is a renowned and precise ensemble learning technique that employs many decision trees (Jin et al., 2020). It manages multidimensional datasets, mitigates overfitting, and addresses complex interactions in the modeling process by employing a bootstrap method to construct multiple decision trees from unique subsets of the training data (Al-Fugara et al., 2020). The original dataset is divided into two segments: 30 % of the samples are designated for validation, while 70 % are allocated for training.

LightGBM, an open-source GBDT algorithm created by Microsoft, utilizes a histogram-based methodology to improve the training process, decrease complexity, and incorporate sophisticated network communication for optimizing parallel learning, known as the parallel voting decision tree algorithm (Sivanandam et al., 2024). LightGBM employs a leaf-wise methodology to identify and cultivate trees by maximizing variance gain. The training examples are ranked based on their absolute gradient values in decreasing order (Machado et al., 2019). LightGBM offers superior prediction or classification capabilities compared to conventional GBDT frameworks. Two datasets are created, with seventy percent allocated for training and thirty percent allocated for testing.

XGBoost, a supervised learning technique, is categorized within the Gradient Boosting Decision Trees framework (Xiong et al., 2023). In contrast to conventional boosting strategies that employ regularization to mitigate overfitting and improve a model's generalization capabilities, this approach significantly enhances computational efficiency by integrating many weak learners concurrently to construct a robust learner (Xiong et al., 2023). XGBoost is a scalable and efficient ensemble learning framework utilizing tree topologies that employs gradient boosting for user-defined predictive tasks, encompassing regression, classification, ranking, and supervised learning (Haydar, Rafi, et al., 2024). The study deployed the XGBoost algorithm, designating 70 % of the dataset for training purposes and 30 % for testing purposes.

GBM, or gradient-boosted regression tree, is a boosting ensemble technique (Park and Kim, 2021). The boosting technique offers several predictive models, such as bagging. Boosting incrementally builds decision trees by using knowledge from previously created trees, in contrast to bagging (Park and Kim, 2021). This method employs gradient boosting to adjust each tree to the residuals of the prior model using a gradient descent technique that minimizes ensemble loss (Zanotti et al., 2019). Gradient Boosting Decision Trees (GBDT) are a method for technological integration that enhances classification accuracy via the iterative development of a new regression decision tree (Haidong et al., 2020). The GBDT model effectively addresses this problem by using an ensemble of weak decision trees to formulate a robust algorithm that produces accurate predictions. The initial set of data is partitioned into two sections: 30 % of the samples are assigned for validation, and 70 % are designated for training.

AdaBoost employs adaptive boosting for classification trees. (Mosavi et al., 2021) presented it to improve the accuracy of classification-based machine learning. This non-parametric method efficiently identifies outliers without necessitating the identification of poor learners. To train AdaBoost, an initial decision tree (DT) is constructed by allocating uniform weights to the dataset (Mosavi et al., 2021). AdaBoost exhibits sensitivity to noisy or distorted datasets (Kégl & Busa-Fekete, 2009). In some classification situations, it may exhibit excessive sensitivity to alternative learning techniques (Hu et al., 2008). This study used the AdaBoost algorithm, designating 70:30 training testing split.

Catboost effectively captures multiple variables affecting water potential while adeptly handling noisy and heterogeneous data. Catboost, grounded in the Gradient Boosting Decision Trees framework, is a robust machine-learning technique adept at addressing challenges involving noisy data, complex relationships, and diverse features (Y. Zhang et al., 2020). This study employs a target-based statistics technique that entails randomly sorting 70 % of the training dataset, subsequently calculating the average label value for each category, and positioning it before the provided label in the permutation (Huang et al., 2019).

Bagging is an ensemble method that entails repeatedly training the identical algorithm on various subsets of the training data (Breiman, 2020). The ultimate output prediction is thereafter averaged across all sub-model projections. In summary, bagging enhances classification accuracy by diminishing classification uncertainty (Chan & Paelinckx, 2008). Bagging can enhance accuracy if a substantial alteration in the learning set notably affects the derived predictor. The ensemble's majority vote is employed to forecast the result of a test sample (Korecki et al., 2008). Two data sets are generated: the initial 70 % is allocated for training, while the remaining 30 % is designated for testing.

The decision tree (DT) method systematically divides independent variables into uniform areas (Cho & Kurup, 2011; Myles et al., 2004). DT model seeks to provide rules that can forecast outcomes based on input variables. The decision tree (DT) has demonstrated efficacy in various practical applications for categorization and prediction (Murthy, 1998). This research employs the DT method to partition the data into training and testing sets. Thirty percent of the data is allocated for testing, and the remaining seventy percent is designated for training.

2.4. Validation of The models (ROC curve and AUC)

This study assessed each model utilizing the widely employed receiver operating characteristics (ROC) curve. The integration of ROC curve characteristics produces the AUC. The data is allocated to training: testing split as 70:30 to enable data exploration. The evaluation of the classifier's performance is conducted using the ROC curve and AUC score. A higher AUC indicates enhanced performance, and an ideal classifier demonstrates a ROC curve located in the upper-left quadrant. (Tests, 1978) states that AUC values range from 0 to 1, with elevated values signifying superior model efficacy in differentiating across various classes. A model with an AUC value ranging from 0.91 to 1.00 is deemed "Excellent," indicating exceptional classification accuracy; scores between 0.81 and 0.90 are designated as "Very Good," indicating robust model performance with negligible misclassification; an AUC value ranging from 0.71 to 0.80 signifies "Good" performance, reflecting a fairly competent classifier; models with scores between 0.61 and 0.70 are classified as "Satisfactory," indicating moderate predictive efficacy; an AUC score ranging from 0.51 to 0.60 is classified as "Unsatisfactory," indicating that the model's performance is marginally superior to random chance and may necessitate additional optimization to improve its predicted accuracy (Haydar et al., 2024b; Tests, 1978). The ultimate tree-based ML model was selected based on its efficacy as assessed by the Receiver Operating Characteristic (ROC) curve, which measures the model's ability to differentiate between classes.

2.5. Future climate change models

The Climate Model Intercomparison Project Phase 5 (CMIP5) frameworks are employed to produce predictions from global climate models. The frameworks establish a solid basis for evaluating climate variability and its effects on environmental resources (Sarkar et al., 2024a). Representative Concentration Pathways (RCPs) depict various trajectories of greenhouse gas concentration, serving as the basis for the CMIP5 framework. The analysis utilized four RCP scenarios: RCP 2.5, RCP 4.5, RCP 6.0, and RCP 8.5. These trajectories offer various predictions on future climate conditions and their implications (Ghazi et al., 2021). The research examines variations in temperature scenarios based on the selected RCP utilizing prediction data for the years 2040, 2060, 2080, and 2100. The data employed in this study is obtained from the NCAR GIS Initiative Climate Change Scenario website (https://gisclimatechange.ucar.edu), which provides accessible climate projections at no cost.

2.6. Future forest fire projection

A global climate model generated 12 potential Forest Fire Risks maps for the years 2040, 2060, 2080, and 2100, based on various climate change scenarios. The scenarios were based on Representative Concentration Pathways (RCPs). A raster calculator was employed to integrate RCP scenario-related factors with the AdaBoost outputs to incorporate climate change with forest fire dynamics. To forecast future forest fire, the resultant maps were categorized into classifications ranging from very high to low forest fire risks.

3. Results

3.1. Description of parameters

Fig. 3 illustrates the regional distribution of various environmental variables in the Chittagong Hill Tracts (CHT). Higher values for the Aridity Index (Fig. 3.a), relative humidity (Fig. 3.o), slope (Fig. 3.q), and Normalized Difference Moisture Index (NDMI) (Fig. 3.k) are noted in the southern region of CHT. Fig. 3.c presents the curvature map, which accurately depicts the topographical contours of the region. The central region, characterized by significant water bodies, demonstrates high

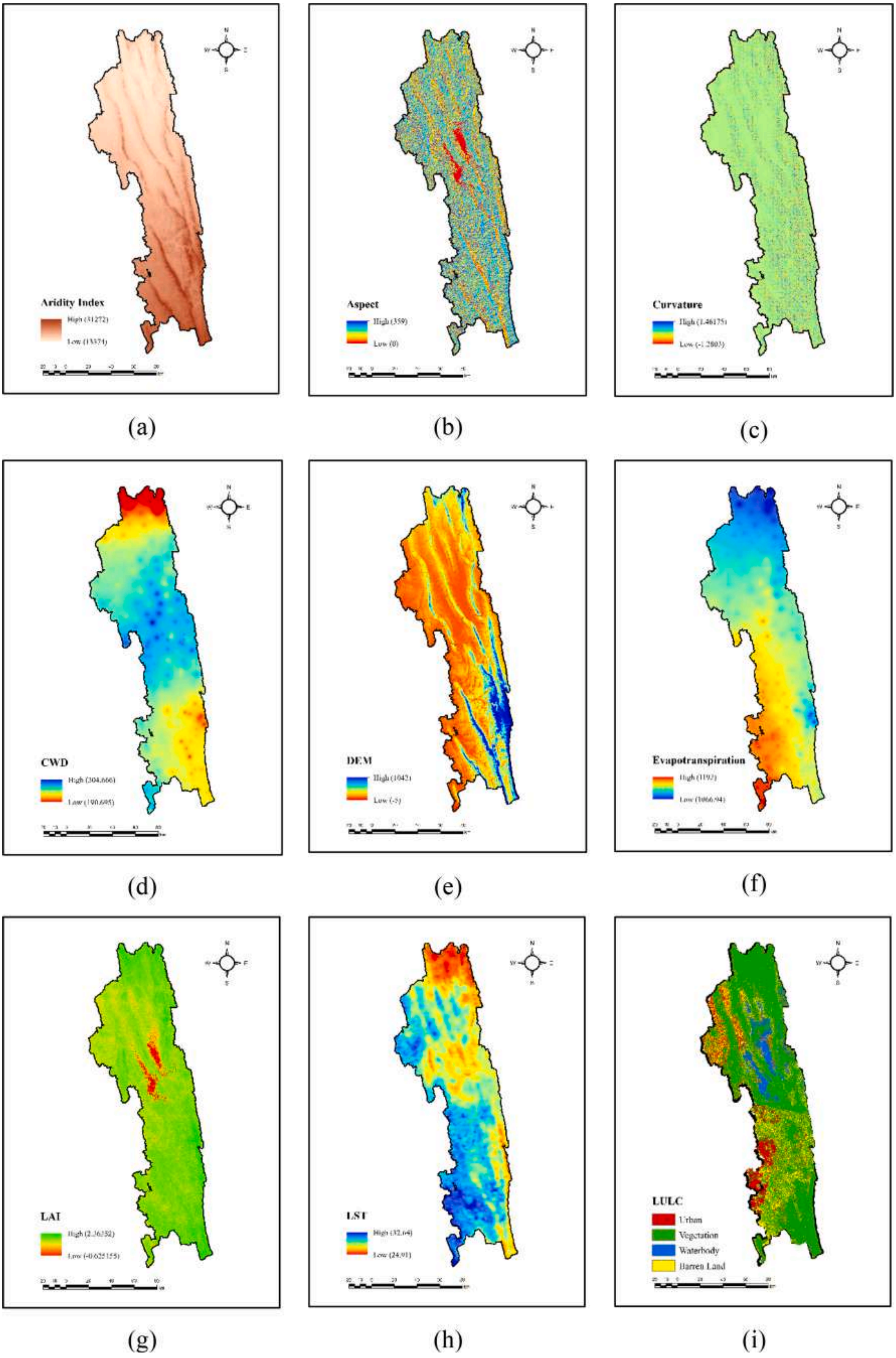
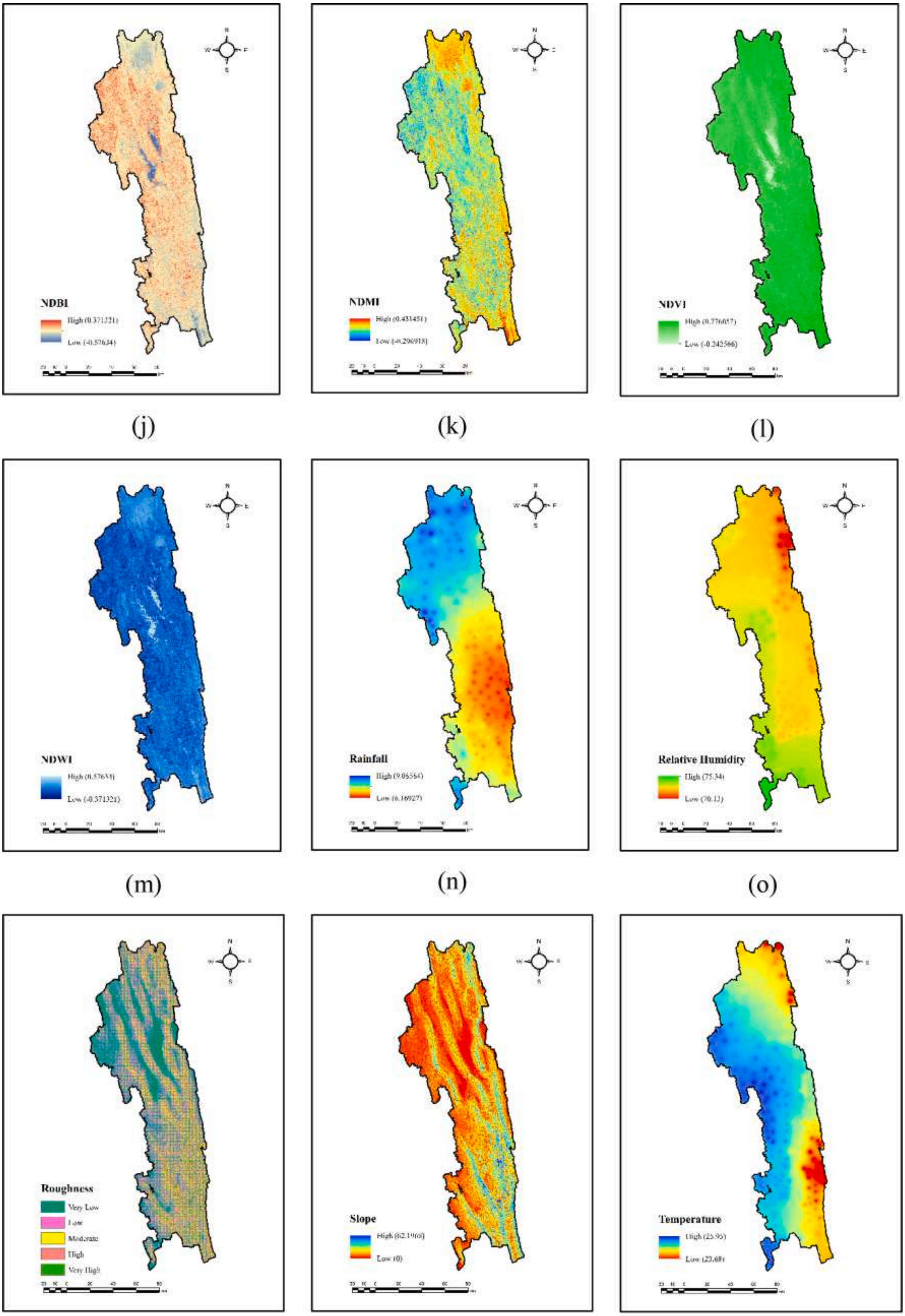


Fig. 3. Factors (a) Aridity Index, (b) Aspect, (c) Curvature, (d) CWD, (e) DEM, (f) Evapotranspiration, (g)LAI, (h) LST, (i) LULC, (j) NDBI, (k) NDMI, (l) NDVI, (m) NDWI, (n) Rainfall, (o) RH, (p) Roughness, (q) Slope, (r) Temperature, (s) Wind Speed.

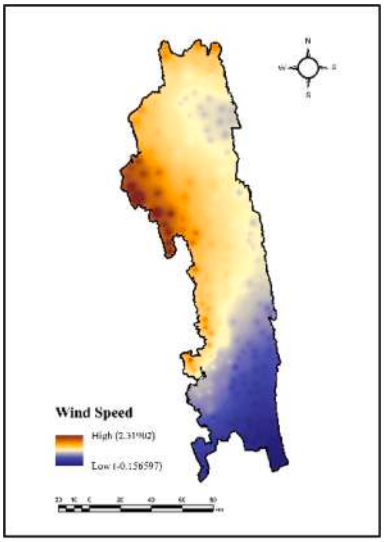


(j) (k) (l)

(m) (n) (o)

(p) (q) (r)

Fig. 3. (*continued*).



(s)

Fig. 3. (*continued*).

values for both the Normalized Difference Water Index (NDWI) (Fig. 3.m) and the Climatic Water Deficit (CWD) (Fig. 3.d). The Normalized Difference Vegetation Index (NDVI) (Fig. 3.L) and the Leaf Area Index (LAI) (Fig. 3.g) remain relatively low. Rainfall (Fig. 3.n) patterns across the CHT exhibit significant variance, with the northern regions receiving heavier rainfall and the eastern regions receiving lesser quantities, as illustrated in the rainfall map. Correspondingly, the Land Surface Temperature (LST) (Fig. 3.h) and evapotranspiration (Fig. 3.f) maps indicate that the northern regions exhibit lower values, implying reduced temperatures and diminished atmospheric moisture loss. The examination of the Digital Elevation Model (DEM) (Fig. 3.e) underscores the increased terrain in the southern part of CHT. Fig. 3. i illustrates the Land Use and Land Cover (LULC) classification, which encompasses several types of land cover, including urban areas, vegetation, and water bodies where most of the areas are vegetation in CHT. The southeastern region has elevated values for the Normalized Difference Built-up Index (NDBI) (Fig. 3.j), signifying a substantial rise in urban areas. This region experiences elevated temperatures (Fig. 3.r), which exacerbates the urban heat island impact. Conversely, reduced temperatures in the western region suggest a more temperate environment, either influenced by dense vegetation or diminished anthropogenic activity. Finally, elevated wind speeds (Fig. 3.s) in the midwestern region of CHT may significantly increase the risk of forest fires, potentially exacerbating environmental vulnerabilities in this ecologically sensitive area.

3.2. *Mapping areas susceptible to forest fire based on tree-based models*

This endeavor evolved eight tree-based machine learning models as Random Forest (RF), LightGBM (LGBM), XGBoost, Decision Tree, Gradient Boosting Machine (GBM), AdaBoost, CatBoost, and Bagging to analyze forest fire susceptibility utilizing 19 governing parameters. Among these models, temperature proved to be the most significant component, demonstrating the highest significance scores across all models, as depicted in Fig. 4. The RF, LGBM, XGBoost, Decision Tree, GBM, AdaBoost, CatBoost, and Bagging scores are 11, 13, 19, 22, 27, 14, 13, and 21, respectively. This underscores the critical role of temperature in affecting forest fire incidents. Besides temperature, rainfall, digital elevation model (DEM), and wind speed exhibited moderate significance scores throughout the other models. These elements influence fire danger by impacting moisture availability, topographical factors, and fire propagation dynamics. In contrast, factors including Climatic Water Deficit (CWD), Leaf Area Index (LAI), Land Use and Land Cover (LULC), Normalized Difference Water Index (NDWI), and Normalized Difference Moisture Index (NDMI) had much lower relevance scores. In the XGBoost, Decision Tree, GBM, and Bagging models, the significance scores for CWD, LAI, LULC, NDWI, and NDMI were 5, 2, 1, 1, and 2, respectively. This indicates that although these elements may exert some influence on forest fire dynamics, their impact is comparatively negligible relative to temperature, rainfall, wind speed, and elevatio.

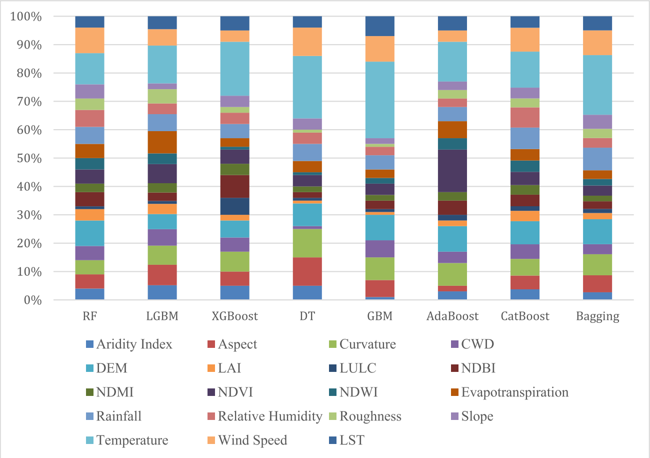
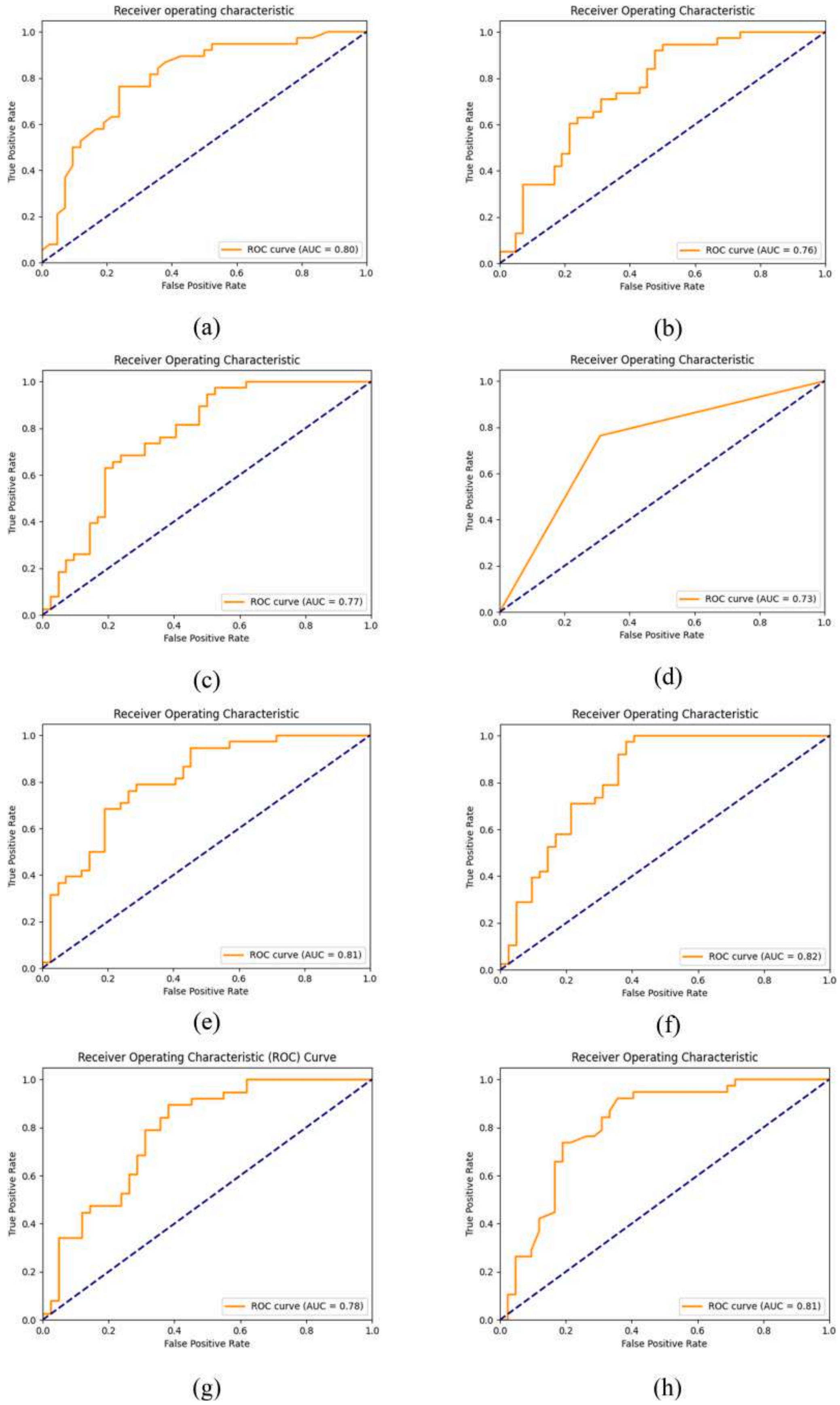


Fig. 4. Importance score of the governing factors of Forest Fire.

3.3. *Model validation by ROC and AUC*

The Receiver Operating Characteristic – Area Under the Curve (ROC-AUC) metric was utilized to evaluate the efficacy of the machine learning models in determining forest fire hazards, as illustrated in Fig. 5. AdaBoost exhibited the best ROC-AUC score of 0.82 among all models, establishing it as the most effective model for identifying regions at elevated risk of forest fires. The Gradient Boosting Machine (GBM) and Bagging models attained an AUC value of 0.81. The Random Forest model demonstrated dependable performance, with a slightly lower but competitive AUC score of 0.80. The CatBoost, XGBoost, and



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 5. ROC-AUC for Tree-based ML Techniques (a)RF, (b) LGBM, (c) XGboost, (d) Decision Tree, (e) GBM, (f) AdaBoost, (g) Catboost, (h) Bagging.

LightGBM (LGBM) models produced AUC values of 0.79, 0.77, and 0.76, respectively. Although these models exhibited commendable performance, their lower scores indicate a minor decrease in efficacy for identifying fire-prone regions. The Decision Tree model exhibited the lowest ROC-AUC value of 0.73.

3.4. Distribution of areas susceptible to forest fire based on tree-based models

Table 2 and Fig. 6 demonstrate that the Random Forest (RF) model displayed the minimal percentage of low-risk zones at 9.81 %, closely succeeded by CatBoost at 10.61 %. Conversely, LightGBM (LGBM) recognized the lowest proportion of low-risk areas, including at 6.35 %. Alternative models, including Bagging, XGBoost, GBM, and Decision Tree, identified a moderate percentage of low-risk areas: 25.77 %, 23.17 %, 22.92 %, and 22.16 %, respectively. AdaBoost demonstrated the greatest percentage of low-risk classification, allocating 28.94 % of the region to low risk, 66.74 % to moderate risk, and 4.31 % to high danger. In the moderate-risk category, LGBM exhibited the greatest percentage at 92.43 %, followed closely by RF at 89.32 % and CatBoost at 88.34 %. AdaBoost detected the lowest proportion of moderate-risk areas, at 66.74 %. The XGBoost model demonstrated a moderate-risk percentage of 75.83 %, somewhat above the Decision Tree's 74.97 % and the GBM's 73.14 %. Additionally, bagging classified 70.85 % of the area as moderate risk, placing it in the intermediate range compared to other models. The Decision Tree model identified 2.88 % of the region as high-risk, which is marginally lower than Bagging at 3.38 % and GBM at 3.94 %. AdaBoost exhibited the highest percentage of high-risk sites at 4.31 %, trailed by GBM at 3.94 % and Bagging at 3.38 %. Conversely, RF detected the lowest percentages of high-risk locations, approximately 0.87 %. XGBoost, LGBM, and CatBoost identified 1.01 %, 1.21 %, and 1.05 % of the area as high risk, respectively.

3.5. Distribution of areas susceptible to forest fire based on best tree-based model- AdaBoost

Fig. 7 and Table 3 illustrate the categorization of forest fire vulnerability across several districts utilizing the AdaBoost model. Analysis indicates that Bandarban possesses the lowest proportion of low-risk forest fire zones among all districts, encompassing 6.23 % of its territory. Moreover, Bandarban displays the greatest percentage of moderate-risk areas, comprising 86.47 % of the district, signifying that the majority of its territory is moderately vulnerable to forest fires. Furthermore, 7.30 % of Bandarban is classified as high-risk, underscoring its susceptibility to significant fire events. Conversely, Khagrachhari is categorized into merely two danger zones low and moderate as illustrated. The lack of high-risk areas in Khagrachhari is due to the region's elevated concentration of water bodies, which reduces fire hazards. The district's land area comprises 36.34 % low-risk zones and 63.66 % moderate-risk zones, indicating a balanced distribution of fire susceptibility. The Rangamati district noted for its elevated density of water bodies, exhibits a unique fire risk pattern. A substantial 66.30 % of the district is categorized as high-risk, demonstrating a pronounced vulnerability to forest fires, notwithstanding a considerable part of moderate-risk areas. Simultaneously, 29.53 % of Rangamati is classified as low-risk, further highlighting the region's varied fire risk levels.

3.6. Distribution of areas susceptible to forest fire based on different future climate change scenarios

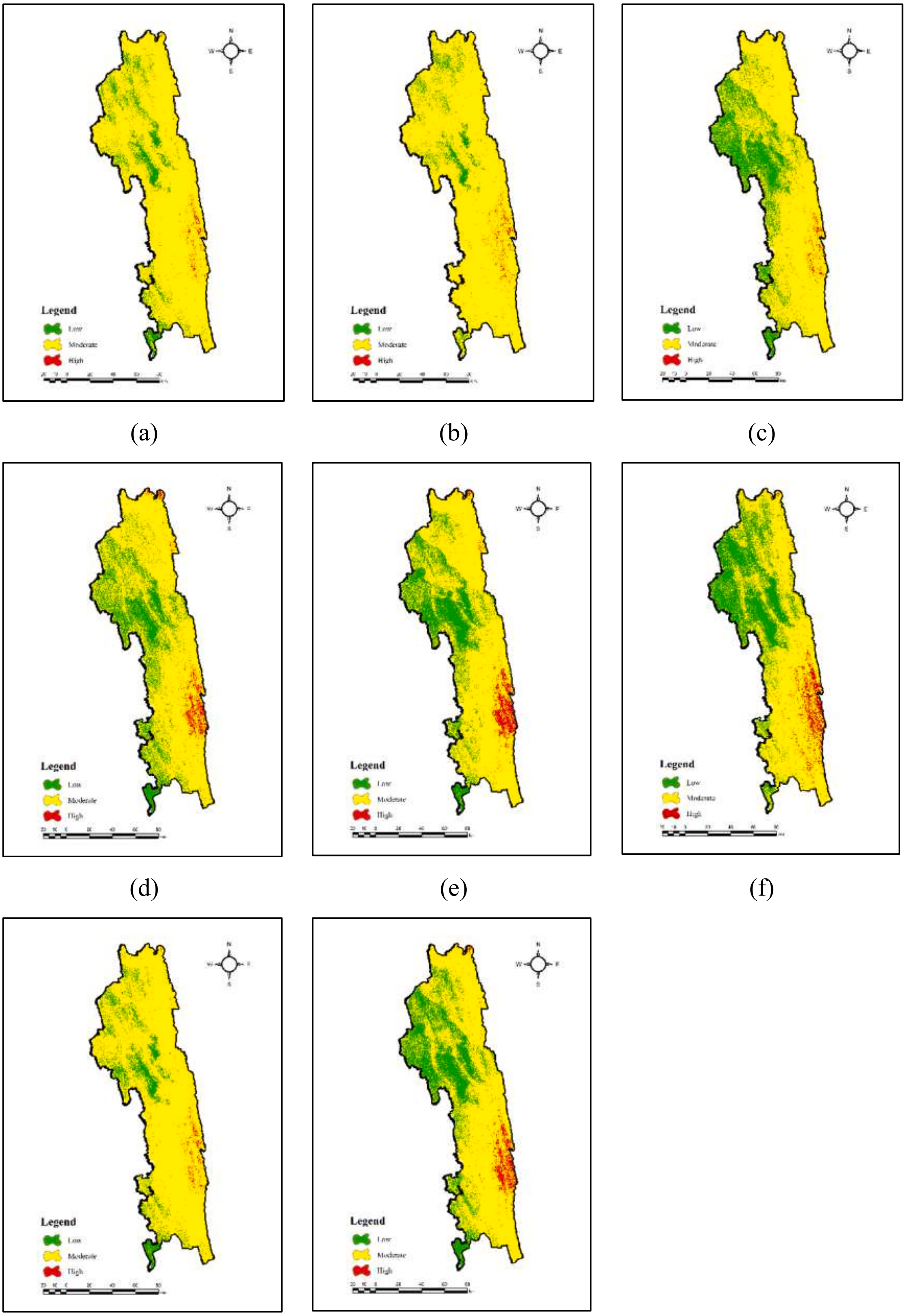
Fig. 8 displays temperature maps across various RCP scenarios, indicating the highest temperatures in the southern region and the lowest temperatures in the northeastern section of CHT. Temperature variations are anticipated for the years 2040, 2060, 2080, and 2100, according to RCP temperature projections. By 2040, all four scenarios forecast a temperature increase, with RCP 2.6 demonstrating minimal warming and RCP 8.5 indicating the maximum temperature rise. By 2060, the divergence among the scenarios becomes increasingly evident, with RCP 8.5 undergoing a substantial temperature increase, whereas RCP 4.5 and RCP 6.0 exhibit moderate warming increases. By 2080, RCP 2.6 stabilizes, signifying negligible more warming. Nonetheless, RCP 8.5 attains important warming thresholds, indicating significant climatic repercussions. Simultaneously, RCP 4.5 and RCP 6.0 persist in demonstrating a consistent increase in temperature. By 2100, RCP 2.6 predicts a predominantly stable climate, but RCP 4.5 and RCP 6.0 forecast substantial temperature escalations. RCP 8.5 predicts excessive temperatures, signifying significant climate consequences and possible prolonged environmental strain in the area.

The AdaBoost model was utilized to evaluate forest fire hazards across different Representative Concentration Pathway (RCP) scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) spanning the timeframe of 2040 to 2100, with analyses performed at 20-year intervals. The results, illustrated in Table 4 and Fig. 9, demonstrate that all RCP models uniformly forecast diminished forest fire risks in the southern region, whereas the northern and center regions display increased vulnerability to forest fires. By 2040, most of the region will be classified as moderate-risk, with percentages varying from 71.99 % (RCP 2.6) to 73.40 % (RCP 8.5). The low-risk group spans from 11.54 % (RCP 8.5) to 14.73 % (RCP 2.6), whilst the high-risk category is anticipated to range from 13.28 % (RCP 2.6) to 15.07 % (RCP 8.5). By 2060, the moderate-risk group will expand, signifying a heightened susceptibility to forest fires. The greatest percentage of moderate-risk places is anticipated under RCP 2.6 (76.22 %), whilst RCP 6.0 forecasts the lowest percentage (73.29 %). Furthermore, the low-risk category demonstrates its peak value at RCP 6.0 (13.39 %), which subsequently declines to 10.94 % by 2080. Notably, under RCP 6.0, the low-risk category will rise to 13.82 % by 2100, indicating variability in risk patterns. In 2080, the forecasts for moderate and high-risk areas across the RCP models exhibit negligible variation, underscoring the reliability of the predictions. The maximum proportion of moderate risk is shown in RCP 2.6 (75.36 %), whereas RCP 8.5 exhibits the lowest proportion (73.13 %). In high-risk zones, the maximum value is 15.39 %, while the minimum is 13.49 %, indicating a limited range of variation. By 2100, the moderate-risk group regularly exhibits high values, ranging from 71.46 % (RCP 4.5) to 75.32 % (RCP 8.5). The greatest susceptibility to forest fires in high-risk areas is anticipated under RCP 4.5 (15.39 %), whereas RCP 6.0 exhibits the

Table 2

Share of areas susceptible to forest fire based on tree-based models among districts.

Classes	Low		Moderate		High	
Classifier	%	Area in km^2	%	Area in km^2	%	Area in km^2
RF	9.81 %	1293.39	89.32 %	11775.61	0.87 %	115.00
LGBM	**6.35 %**	**837.40**	**92.43 %**	**12186.60**	**1.21 %**	**159.98**
XGBoost	23.17 %	3054.14	75.83 %	9997.01	1.01 %	132.86
DT	22.16 %	2921.10	74.97 %	9883.58	2.88 %	379.32
GBM	22.92 %	3021.23	73.14 %	9643.42	3.94 %	519.35
AdaBoost	28.94 %	3815.57	66.74 %	8799.54	4.31 %	568.89
CatBoost	10.61 %	1398.41	88.34 %	11647.13	1.05 %	138.46
Bagging	25.77 %	3397.57	70.85 %	9340.25	3.38 %	446.18



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 6. Forest fire susceptibility using tree-based models (a)RF, (b) LGBM, (c) XGBoost, (d) Decision Tree, (e) GBM, (f) AdaBoost, (g) CatBoost, (h) Bagging.

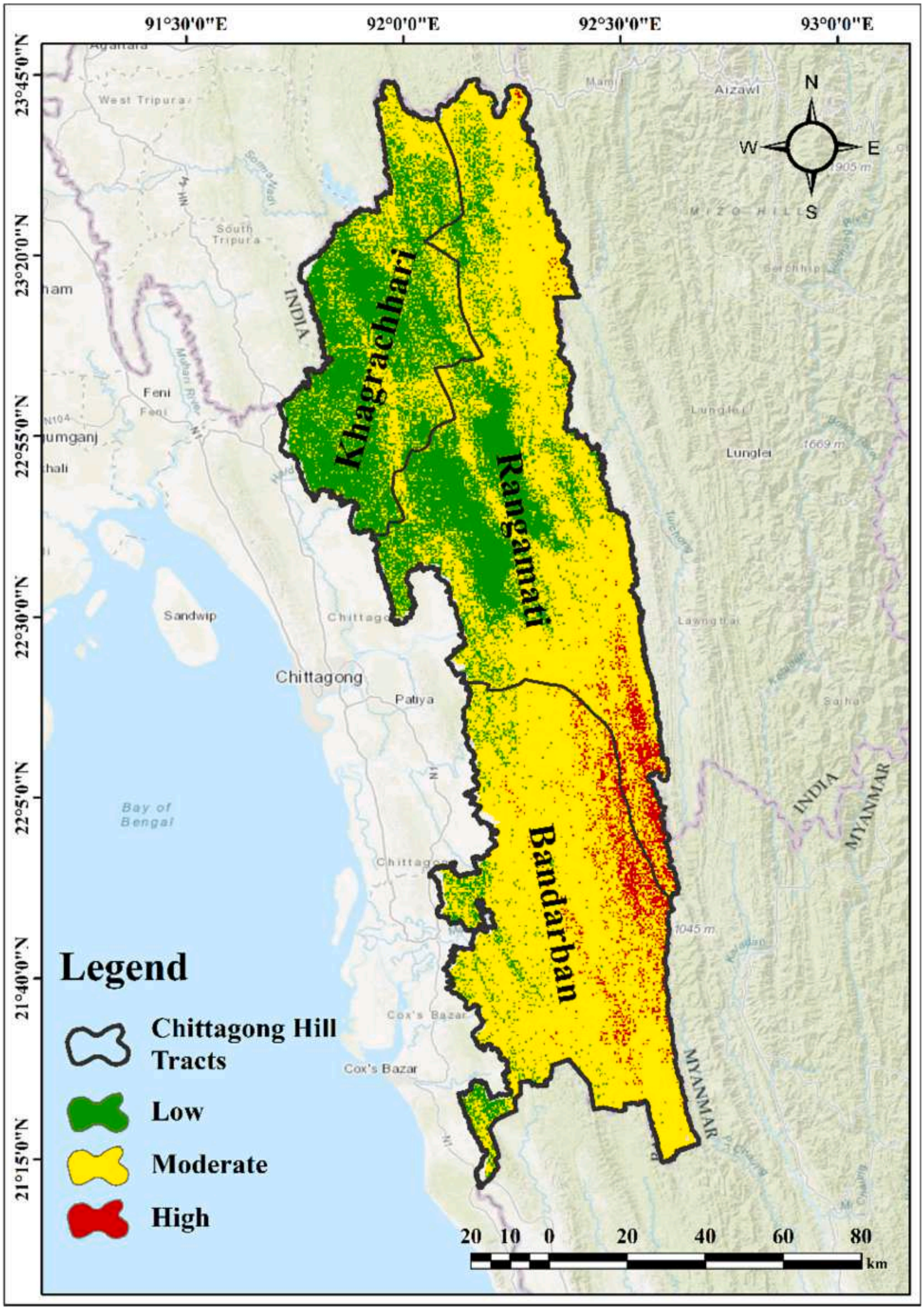


Fig. 7. District-wise Forest Fire Susceptibility by the best model (AdaBoost).

Table 3
Share of areas susceptible to forest fire in different districts by the best model (AdaBoost).

Classes	Low		Moderate		High	
District	%	Area in km^2	%	Area in km^2	%	Area in km^2
Bandarban	6.23 %	278.95	86.47 %	3873.07	7.30 %	326.97
Khagrachhari	63.66 %	2851.25	36.34 %	1627.75	0.00 %	0.00
Rangamati	29.53 %	1322.54	66.30 %	2969.52	4.17 %	186.93

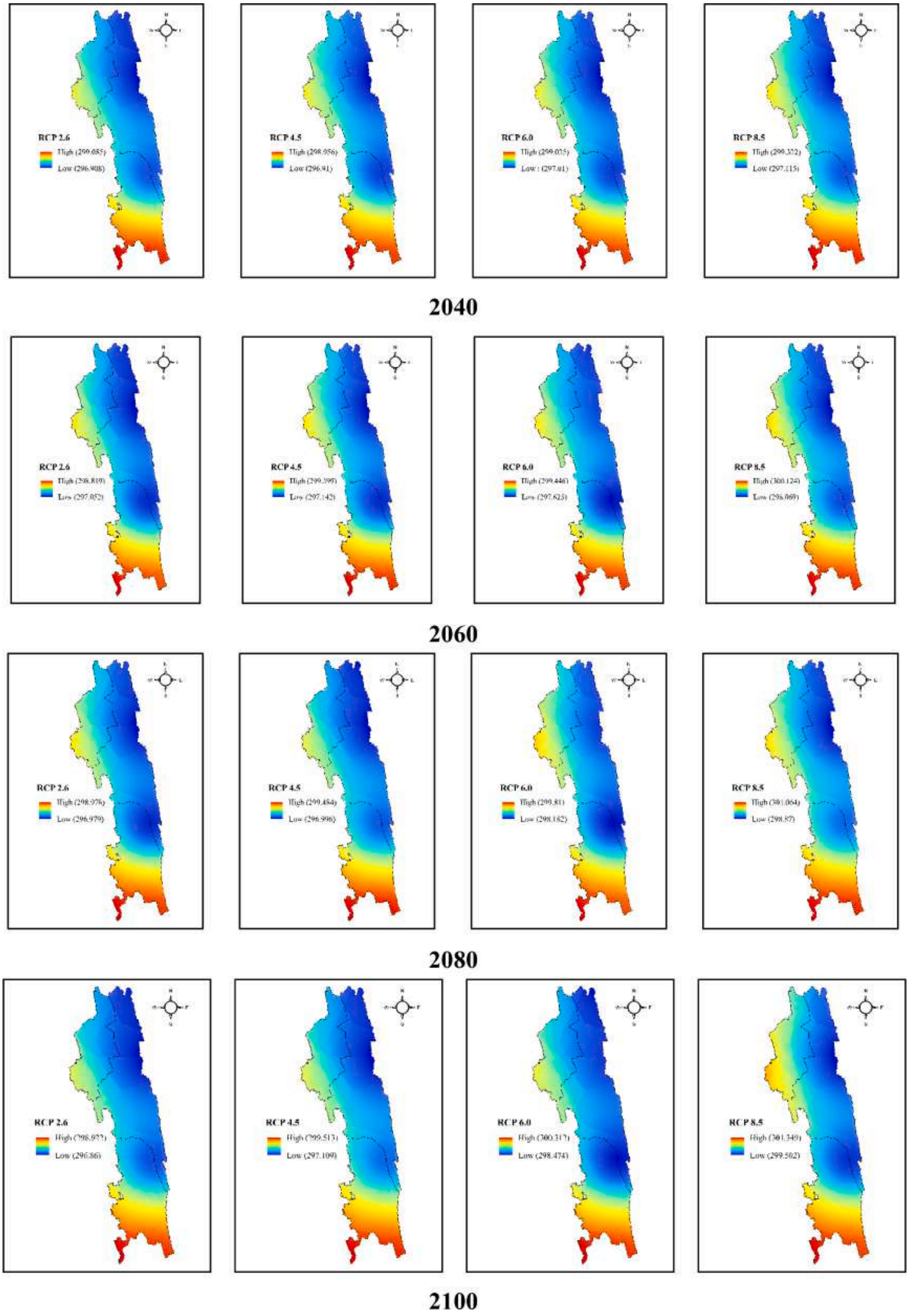


Fig. 8. Temperature for Various RCP Scenarios – Temperature (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) from 2040 to 2100.

lowest high-risk percentage (13.42 %).

4. Discussion

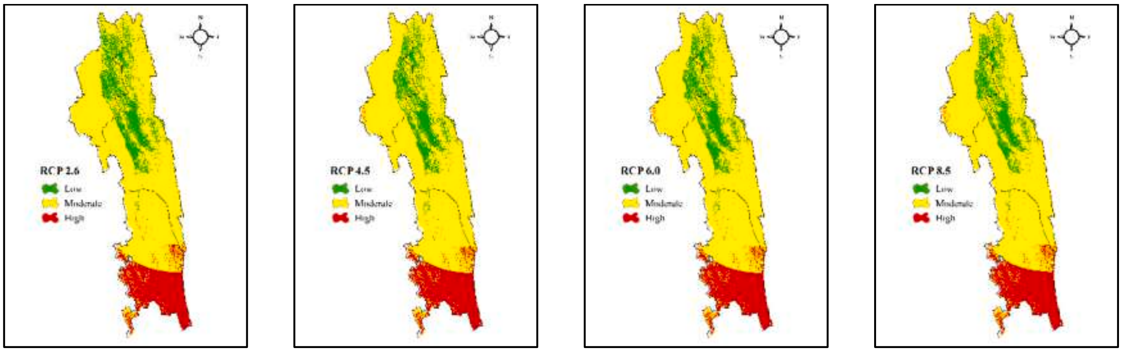
The study presents an innovative methodology for mapping forest fire the risks in CHT through the use of tree-based machine learning algorithms, effectively addressing previous research deficiencies by integrating climate change scenarios. The findings emphasize significant contributing elements, regional risks classifications, and predicts under future climatic scenarios, providing critical insights for fire management

Table 4

Distribution of areas susceptible to forest fire according to Different RCP Scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) from 2030 to 2050 with Best Model (AdaBoost).

Classes		Low		Moderate		High	
Year		%	Area in km^2	%	Area in km^2	%	Area in km^2
2040	RCP 2.6	14.73 %	1941.91	71.99 %	9490.68	13.28 %	1751.41
	RCP 4.5	11.78 %	1552.51	73.57 %	9699.91	14.65 %	1931.58
	RCP 6.0	12.02 %	1584.20	73.31 %	9665.42	14.67 %	1934.38
——	RCP 8.5	11.54 %	1521.17	73.40 %	9676.62	15.07 %	1986.21
2060	RCP 2.6	11.47 %	1512.42	76.22 %	10049.39	12.30 %	1622.20
	RCP 4.5	11.46 %	1510.49	74.17 %	9778.70	14.37 %	1894.81
	RCP 6.0	13.39 %	1765.07	73.29 %	9662.27	13.32 %	1756.66
	RCP 8.5	11.28 %	1486.68	73.74 %	9721.80	14.98 %	1975.53
2080	RCP 2.6	11.15 %	1469.87	75.36 %	9936.11	13.49 %	1778.03
	RCP 4.5	13.31 %	1755.26	71.76 %	9460.92	14.93 %	1967.82
	RCP 6.0	10.94 %	1442.21	75.04 %	9893.21	14.02 %	1848.59
	RCP 8.5	11.48 %	1514.17	73.13 %	9640.91	15.39 %	2028.93
2100	RCP 2.6	13.33 %	1756.84	71.69 %	9451.29	14.99 %	1975.88
	RCP 4.5	13.15 %	1733.38	71.46 %	9421.70	15.39 %	2028.93
	RCP 6.0	13.82 %	1821.80	72.76 %	9592.93	13.42 %	1769.27
	RCP 8.5	10.02 %	1321.39	75.32 %	9930.33	14.66 %	1932.28

and policy formulation. The study identified temperature, rainfall, wind speed and DEM show the most influential parameters in Forest Fire Susceptibility in CHT. The study's authors (Hong et al., 2018; Tuyen et al., 2021) found that temperature, aspect, height, and closeness to a road were the most critical elements affecting the occurrence and spread of forest fires, which is similar to our results. Besides, temperature was the dominant factor consistent with global finding that higher temperatures to increase fire probability (Flannigan et al., 2009; Oliveira et al., 2012b). Rainfall deficit and high wind speed also showed significant impact on forest fire which aligns with previous research that associates lower precipitation and higher wind velocity with greater fire risk (Syphard et al., 2021). DEM was found to influence fire risks by affecting fuel moisture and wind patterns reinforcing conclusions drawn in topographical fire studies (Amatulli et al., 2007). Furthermore, vegetation indices like NDVI and NDWI which indicate fuel availability and moisture content, were found to have moderate importance supporting prior findings by (Chuvieco & Congalton, 1989; Koutsias et al., 2004). Other comparable research indicated that the most influential characteristics are temperature, rainfall, and wind speed, which are the primary factors for forest fires (Abrha & Adhana, 2019; Bui et al., 2016; Markert & Sarker, 2017; Shu et al., 2022). This research developed Forest Fire Risks maps utilizing tree-based machine learning algorithms (MLAs). Specifically, models including RF, LGBM, XGBoost, DT, GBM, AdaBoost, CatBoost, and Bagging, as well as ensemble machine learning approaches, were utilized to predict and map Forest Fire Risks in CHT. AdaBoost had the greatest prediction accuracy, attaining an AUC value of 0.82. Thus, the findings underscore the robust effectiveness of the chosen models in accurately evaluating forest fire risk. The best performing mode AdaBoost (AOC: 0.82) classified 4.31 % of the region as highly susceptible, 66.74 % as moderately and 28.94 % as low risk. These findings are consistent with previous ML based fire risks studies in Mediterranean landscapes (Vilar et al., 2010) and mountainous regions of India (Sarkar et al., 2024b). Comparing to prior research in Bangladesh which primarily relied on geographic or meteorological analyses (Farukh et al., 2023c; Markert & Sarker, 2017), this study presents a data driven approach that significantly enhances fire risk assessment. Projection under RCPs indicate an increasing trend in fire risks particularly under RCP 8.5 where 15.39 % of the area is expected to be highly vulnerable by 2100. This aligns with studies that suggest climate change will intensify fire hazards by increasing temperature and reducing humidity (Batllori et al., 2013; Liu et al., 2010). The spatial distribution of risks suggests that future fires will be concentrated in the north central region of CH, necessitating proactive mitigation strategies. Comparable findings have been observed in research conducted in Australia (Bradstock, 2010), California (Abatzoglou and Williams, 2016a) and Amazon basin where climate projections indicate a rise in frequency and intensity of forest fire in the coming decades (Aragão et al., 2018). In the USA, (Abatzoglou and Williams, 2016b) demonstrated how climate change driven temperature increases and precipitation deficits have escalated forest fire frequency in the western states. The CHT experiences a subtropical monsoon climate characterized by high humidity, seasonal rainfall and distinct dry and wet periods (Chakma et al., 2023b). Similar to Mediterranean and tropical fire-prone regions that fire incidents in the CHT peak during the dry season when temperature rises and precipitation declines. This trend is comparable to Mediterranean ecosystems where prolonged dry periods lead to frequent and intense forest fire (Batllori et al., 2013). However, unlike temperate region where lighting is a dominant ignition sources, fires in the CHT mainly human-induced often associated with shifting cultivation practices (Farukh et al., 2023b). The CHT is covered with a mix of tropical evergreen, semi-green and deciduous forests (Chakma et al., 2023b). These forests differ from boreal ecosystems which are dominated by coniferous trees with highly flammable resin-rich leading to more severe crown fire (Flannigan et al., 2009). In contrast, fire-adapted ecosystems such as Australian eucalyptus forests have evolved with frequent fires where some species depend on fire for regeneration (Bradstock, 2010). Unlike such as fire-dependent ecosystems, the CHT forests are not naturally fire-adapted making them more vulnerable to long-term ecological degradation after repeated fire events. A significant factor differentiating the CHT from many fire-prone regions is the role of human activities. "Jhum cultivation" is a major contributor to fire frequency in the region (Ahammad & Stacey, 2016). This is similar to regions like the Amazon where deforestation-driven fire occurrences have been increasing due to land clearing for agriculture (Aragão et al., 2018). However, unlike in the Amazon where industrial-scale deforestation plays a key role, fires in the CHT are mainly small-scale but frequent leading to cumulative environmental degradation. Additionally, population pressure in the CHT contributes to forest encroachment and increased fire susceptibility which trends also observed in parts of India and Indonesia (Bera et al., 2022). In regions characterized by high to moderate sensitivity to forest fires, it is imperative for the appropriate authorities to incorporate proactive mitigation strategies into their forest management policies. This includes the establishment of firebreaks, burned areas, real-time fire monitoring systems, and the formation of fire patrol soldiers during peak fire seasons. This study emphasizes the necessity for the Chattogram South Forest Division to formulate comprehensive rules and directives that ensure forest-dependent communities are adequately informed and actively engaged in fire prevention and response initiatives. From a policy standpoint, the findings can aid forest management agencies in refining fire prevention strategies.



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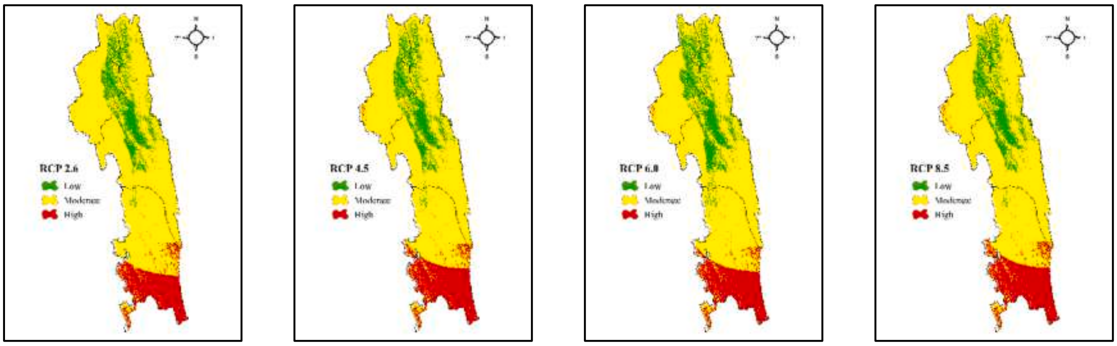

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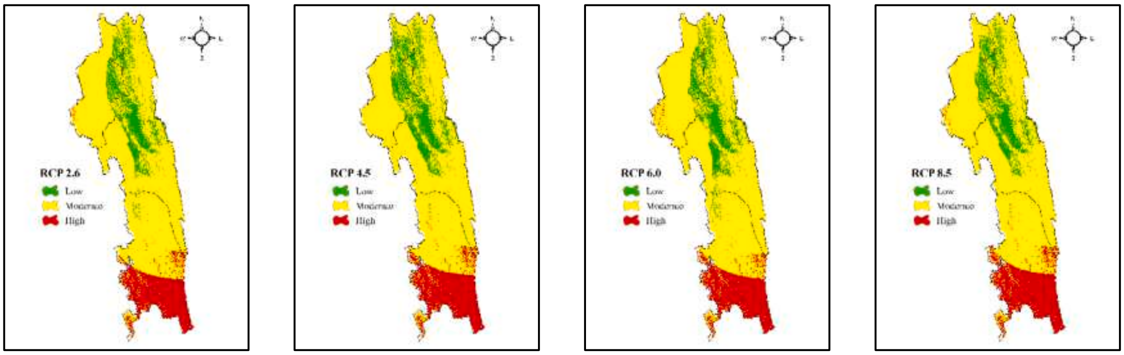

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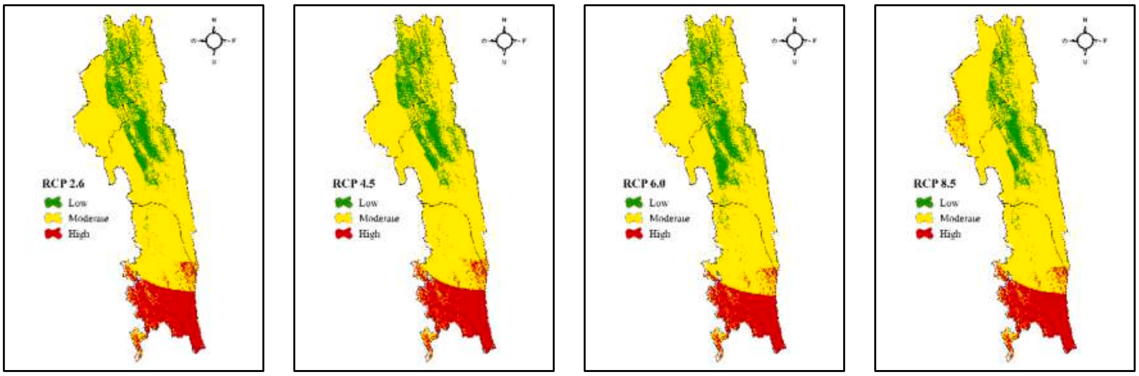

2100

Fig. 9. Forest Fire Risks for Different RCP Scenarios (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5) from 2040 to 2100 with Best Model (AdaBoost).

Given the projected increase in fire prone areas, proactive policies incorporating early warning systems, controlled burns and reforestation programs should be prioritized to mitigate fire risks in the CHT.

5. Conclusion

The historical fire regimes and fire suppression in the Chittagong Hill Tracts' forests have been contentious issues. Climate change, land use modifications, and anthropogenic activities have made several wooded areas in the region very vulnerable to Forest fires. Forest fires in these woods threaten biodiversity, ecological balance, and community livelihoods, requiring immediate fire management and restoration initiatives. It also contributes to increasing temperatures, fluctuating precipitation patterns, and altering land use dynamics. This study thoroughly assessed Forest Fire Risks using advanced tree-based machine learning methods. The findings indicate that temperature, precipitation, wind speed, and elevation exert the most significant influence on forest fire occurrence, whilst other factors demonstrate little to insignificant impacts. The AdaBoost algorithm demonstrated the highest predictive accuracy among the considered models, with an AUC of 0.82, effectively classifying risks zones into high, moderate, and low categories. Future fire risks projections were conducted for the years 2040, 2060, 2080, and 2100 under several Representative Concentration Pathways (RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5). Research suggests that the risks associated with forest fires would escalate over time, with high-risk regions expected to comprise 15.39 % of the total region under the most extreme climate scenario (RCP 8.5) by the year 2800. These estimates highlight the imperative of implementing adaptive fire control strategies, including real-time monitoring systems, firebreak building, and community-focused fire mitigation programs. Despite the robustness of the modeling system, significant limitations must be acknowledged, including uncertainty in climate predictions and dependence on current information. Nevertheless, the study's findings have significant implications for sustainable forest management and disaster mitigation strategies in Bangladesh. The findings align with global climate adaption goals and promote the Sustainable Development Goals (SDGs), including "Climate Action" (SDG 13), "Life on Land" (SDG 15), and "Sustainable Cities and Communities" (SDG 11). Policymakers and forest management authorities may leverage our findings to formulate data-driven fire prevention policies, integrate climate-adaptive strategies into land management practices, and enhance regional resilience to escalating fire risks. Future research should explore deep learning models and incorporate additional ecological factors, such as vegetation dynamics and soil moisture variability, to improve assessments of forest fire risk and increase forecasting accuracy. This understanding is essential for preserving the abundant resources provided by forests and for protecting human lives.

Ethical Approval

The authors declare No ethical approval required. Ethical approval for this type of study is not required by our institute.

CRediT authorship contribution statement

Mafrid Haydar: Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Al Hossain Rafi:** Writing – original draft, Methodology, Formal analysis, Data curation. **Md.Kamran Hasan Khan:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Sakib Hosan:** Writing – original draft, Methodology, Formal analysis, Data curation. **Halima Sadia:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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