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FRAME v1.0: Advancing Fire Risk Assessment in Tropical Fragmented Forests with a Machine Learning Environment

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Abstract. In this study, we develop a comprehensive Fire Risk Assessment with a Machine Learning Environment (FRAME v1.0) for tropical fragmented forest systems by adding fuel availability and anthropogenic ignition factors to a well-known climate-driven fire hazard assessment model. Our work focuses on the forests of India, a representative example of tropical fragmented forest systems in a densely populated country where fire behavior is complex and influenced strongly by natural and human factors. In this work, we first developed a Fire Danger Rating System (FDRS) based on the Fire Weather Index (FWI) module of the Canadian Forest Fire Danger Rating System (CFFDRS) and machine learning (ML) techniques. The integration of ML techniques increased the FDRS's ability to estimate fire probability by 30-50%. While the FDRS forms the core meteorological component of FRAME v1.0, it does not account for other critical drivers. Hence, we extended this FDRS to a comprehensive fire risk assessment framework by incorporating fuel availability and anthropogenic ignition factors using machine learning predictive algorithms with fire count as the target variable. We observed that the neural network-based model performed best among all algorithms across different forest zones of India. Maximum relevance minimum redundancy analysis revealed spatial heterogeneity in dominant fire drivers, although weather remained a consistently critical factor. FRAME v1.0 provides a scalable operational foundation for fire risk assessment in tropical fragmented forests and demonstrates how machine learning can enhance physically grounded fire danger systems.

1 Introduction

Forest fires are ecologically important phenomena ((Hutto et al., 2016; Pausas & Keeley, 2019). They regulate nutrient cycling, seed germination, and habitat regeneration (Abedi et al., 2018; Carbutt & Kirkman, 2022; Naveh, 1989; Zackrisson et al., 1996). However, in humid tropical forests where natural regeneration is difficult, insufficient recovery rates can pose a threat to forest cover (Scheper et al., 2021). The intensification of climate-related factors is leading to uncontrolled fires in these regions, resulting in not only forest cover reductions and biodiversity loss but also economic losses (Jones et al., 2022; Kalogiannidis et al., 2023; Mohanty & Mithal, 2022; Tyukavina et al., 2022; van Wees et al., 2021; Vancutsem et al., 2021).

Fire risk in tropical fragmented forests is governed by ecological and socio-environmental dynamics that differ substantially from temperate or boreal systems. Fragmentation leads to more exposed forest edges, which are prone to drier microclimates, increased fuel flammability, and higher ignition likelihood (Silva et al., 2018; Silva-Junior et al., 2022). This pattern has been documented in Amazonian forests (Baidya Roy, 2011; Armenteras et al., 2013;

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Broadbent et al., 2008). In India's Dalma Wildlife Sanctuary, fragmented patches with higher edge density exhibited significantly greater fire severity, confirming the link between fragmentation and increased fire impacts and slow post-fire recovery in tropical contexts (Chaudhary et al., 2022).

India is a strong example of a landscape with high forest fragmentation which is characterised by a wide range of climatic and forest types, and intense human–environment interactions. Indian forests also have a large number of uncontrolled fires. The Forest Survey of India (FSI) recorded 2,23,333 forest fires between November 2021 and June 2022 and 2,12,249 between November 2022 and June 2023 (MOEFCC and Press information Bureau https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1946413). Although generally smaller in size than large wildfires in Australia or the Amazon, these fires collectively affect substantial forested areas. As of 2021, 54.40% of India's forests experience occasional fires, 7.49% contend with moderately frequent fires, and 2.40% experience high incidence levels, accounting for a significant land area of 20,074 sq km (ISFR, 2021). In addition to the fire-conducive weather, various socio-economic and fuel related factors affect the occurrence of fire events in Indian forests (Reddy et al., 2012, 2013). India's fragmented forests are interwoven with agricultural lands, grazing areas, and rapidly expanding settlements (Nagendra et al., 2009; Singh et al., 2016; Tripathi et al., 2010). Practices such as crop-residue burning, shifting cultivation, and informal grazing introduce frequent ignition sources along the forest edges (Kandlikar, 2000; Reddy et al., 2019; Singh et al., 2016). High rural population density and dependence on fire for land management further increase anthropogenic ignitions (Li et al., 2009; Vadrevu et al., 2010). With changes in vegetation and weather patterns induced by climate change, many Indian forests are becoming more susceptible to fires (Barik & Baidya Roy, 2023; Mohanty & Mithal, 2022).

Despite the importance of fire in such landscapes, India lacks a nationwide operational fire risk assessment system. Many countries rely solely on fire weather-based Fire Danger Rating System (FDRS) to represent fire danger (Amiro et al., 2004; Bedia et al., 2018; Carvalho et al., 2008; Dowdy et al., 2009). An FDRS is a tool in wildfire management which categorizes fire danger on a scale ranging from "Low" to "Extreme," providing a quantitative measure of the risk and potential impact of fires (Stocks et al., 1989; Vasilakos et al., 2007). Such weather-based approaches may be sufficient for regions with uniform land-use patterns or regulated fire management. To cater to complex interactions in fragmented systems like India requires a comprehensive system that integrates weather, fuel, and socio-economic drivers to accurately assess fire 'risk', which integrates hazard, vulnerability, and exposure factors (Bergonse et al., 2022; Erni et al., 2021). Such systematic approaches enable fire management agencies to proactively allocate resources, plan responses, and implement preventive measures based on the anticipated fire risk level (Júnior et al., 2022; Jolly et al., 2019; Reddy et al., 2017; Taylor & Alexander, 2006).

To address this gap, we developed a unified forest fire risk assessment framework called Fire Risk Assessment with a Machine Learning Environment (FRAME v1.0) tailored for tropical fragmented forest systems. The framework builds upon a meteorologically grounded FDRS based on Canadian Forest Fire Danger Rating System (CFFDRS) Fire Weather Index (FWI) system (Wagner, 1987) using ERA5 reanalyses (Hersbach et al., 2020; Muñoz-Sabater et al., 2021) data and satellite-based fire observations for calibration and evaluation. This characterises the fire hazard component of overall risk. The FDRS thresholds were computed by integrating the classic methods with machine learning (ML) techniques to introduce more data-driven decisions in the process and improve the overall reliability

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of the thresholds (Mitsopoulos & Mallinis, 2017; Satir et al., 2017; Ezugwu et al., 2022; Usama et al., 2019). We then extended this weather-based hazard component by integrating fuel characteristics, topographic controls, and anthropogenic exposure variables within a machine learning–based modeling architecture.

We then characterised the vulnerability of the forest systems through vegetation and topographic factors. Variables such as Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) serve as proxies for fuel availability and are essential in understanding the potential for fire spread and intensity in forest areas (Gabban et al., 2008; Michael et al., 2021). Topographic variables include slope, aspect, and elevation. Steeper slopes can accelerate fire spread, while aspects facing prevailing winds may experience higher fire risk (Holden & Jolly, 2011; Vadrevu et al., 2010). At higher elevation, changes in local climate, intensified land-atmosphere feedback and other factors further impact fire occurrences (Alizadeh et al., 2023). Exposure layers included factors related to human-environment interactions. We used variables such as population density and the percentage of urban and agricultural areas within a grid as exposure layers. As most fragmented forests are in close proximity to urban built-up and agricultural land-use regions, the percentage of these areas within a grid serves as an indicator of human presence and agricultural activity. By integrating these variables into our assessment at a spatial resolution of 25 km grid cells, we aim to gain comprehensive insights into fire risk dynamics across diverse landscapes. As the Indian landscape is diverse in climate and vegetation types, ranging from the cold, dry Himalayas to the tropical and subtropical humid climate of the Western Ghats and North-East, and the drier deciduous vegetation of Central India, the inter-relationships between the intermediate factors can vary from zone to zone. In this study, we have considered five forest zones separately while calculating risk to accommodate region-specific driver interactions.

Overall, this study advances fire risk assessment in fragmented tropical forests by (1) developing an ML-enhanced fire weather–based hazard system, (2) integrating fuel and anthropogenic drivers within a unified risk framework, and (3) demonstrating spatial heterogeneity in dominant fire controls across diverse forest zones. Although demonstrated for India, the proposed framework is designed to be scalable and transferable to other fragmented tropical landscapes facing similar coupled climate–human pressures. This study not only enhances our understanding of fire dynamics in such ecosystems but also provides a practical tool to identify high-risk areas and support targeted fire management.

2 Study area

India provides a representative example of tropical fragmented forest systems in a densely populated landscape. Forests occupy 27% of the Indian mainland (*India State Forest Report 2021*, 2022). These forests provide a compelling case for studying fire risk in tropical fragmented forests because of high forest fragmentation and diverse climatic and vegetation regimes. To identify the forested regions, we used high-resolution land use land cover data (Roy et al., 2015). The study domain was first divided into 25 × 25 km grid cells. Grid cells with more than 20% of their area classified as any forest type in Roy et al., (2015) were considered forest pixels (Figure 1). Further, we classified these forest pixels into 5 zones as in Barik & Baidya Roy, (2023). These zones are the Himalayan mountainous region (HIM), northeastern India (NE), central India (CEN), the Deccan region (DEC), and the Western

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Ghats (WG). As the range of FWI varied across these zones, development of the FDRS and risk computation was done separately for each zone.

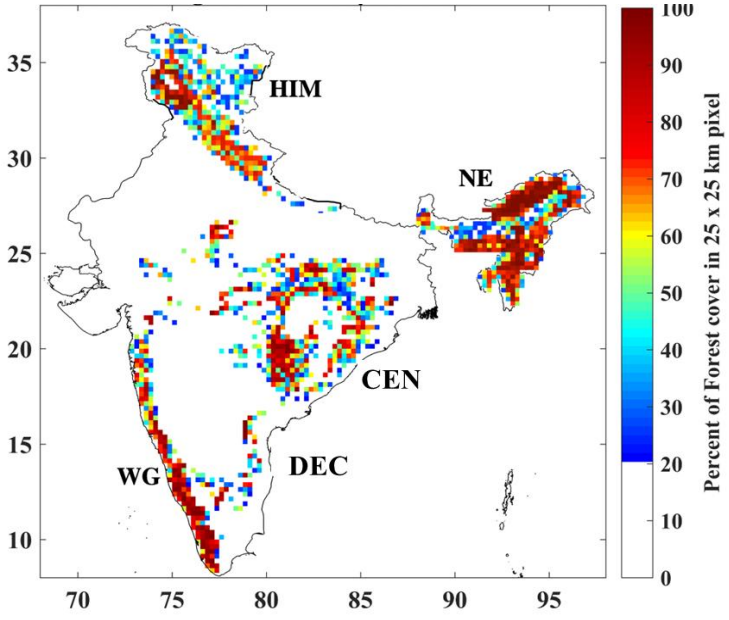

Figure 1: Study area – forest cover percentages over 5 forest zones of India

3 Data and Algorithms

3.1 Meteorological driver data:

To represent the weather component of the fire risk assessment system, we use the CFFDRS-FWI, driven by reanalysis-based meteorological data. Specifically, we used the ECMWF's ERA5-Land and ERA5 single-level reanalysis datasets (Hersbach et al., 2020; Muñoz-Sabater et al., 2021). These datasets perform well in India, are extensively used in various applications (Mahto & Mishra, 2019) and provide continuous records from 1981 to the present through the Copernicus Climate Change Service. (https://cds.climate.copernicus.eu/cdsapp#!/search?type=dataset). We computed daily maximum 2m Temperature and daily averages of relative humidity, and wind speed from the hourly ERA5 single-level reanalysis dataset at 0.25° resolution. For operational fire danger assessments, the values of these variables at 12 Noon local time are used as the inputs to CFFDRS-FWI. However, for climatological evaluations, daily maximum temperature, average/minimum relative humidity and average wind speed are preferable. Daily averages are less sensitive to short-term fluctuations in weather conditions at specific hours of the day (Purcell, 2003), and they offer a more statistically robust assessment of fire risk over extended periods. In the case of relative humidity, there is a general argument as to whether daily minimum or daily mean is more apt for use in CFFDRS. However, a global study, Quilcaille et al., (2023) states that using mean or minimum relative humidity would not change the outcomes much. Daily 24-hour

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accumulated precipitation was obtained from the ERA5-Land dataset at a 0.1° resolution and was regridded to 0.25° resolution.

3.2 CFFDRS-FWI:

The fire weather component of the framework was represented using the Fire Weather Index module of the Canadian Forest Fire Danger Rating System, which quantifies the influence of meteorological variables on fuel moisture and potential fire behavior (Stocks et al., 1989; Wagner, 1987). This system originated in Canada and has since become a widely adopted tool for operational fire weather monitoring across the globe (De Jong et al., 2016; Dimitrakopoulos & Papaioannou, 2001; Jolly et al., 2019; Tian et al., 2011). In this study, FWI was computed using ERA5-based meteorological inputs, and regional adjustments developed for Indian climatic conditions were applied following Barik & Baidya Roy, (2023).

3.3 Fire data:

To evaluate the performance of the simulated Fire Weather Index (FWI) and to develop the modified fire danger thresholds, we used the Moderate Resolution Imaging Spectroradiometer (MODIS) active fire product (Giglio et al., 2003). This dataset also served as the outcome variable in both the FDRS calibration and the machine learning–based fire risk assessment system. We generated a daily fire frequency dataset at a 25 km resolution from MODIS active fire detections. The MODIS tool on Aqua and Terra satellites detects thermal anomalies at 1km resolution at the time of overpass under relatively cloud-free conditions. This product provides spatially extensive fire occurrence information, making it suitable for evaluating fire weather algorithms and training risk prediction systems. The data is publicly available through NASA's Fire Information for Resource Management System website (https://firms.modaps.eosdis.nasa.gov/).

3.4 Topography data:

We incorporated topographic information from the Famine Early Warning Systems Network Land Data Assimilation System (FLDAS; McNally et al., 2017; https://ldas.gsfc.nasa.gov/fldas/elevation) at 0.1° resolution as part of the fire risk assessment framework. This dataset is derived from a combination of satellite observations and the FLDAS-global surface modelling system. It incorporates input data from NASA's Shuttle Radar Topography Mission (SRTM 30m) for elevation with digital elevation models for slope and aspect calculations. These topographical features including slope steepness, elevation gradients, and orientation relative to the sun are used to define the terrain morphology and are important vulnerability layers in fire risk computations. These topographic features affect local microclimates, fuel distribution, and fire spread potential, and are thus important vulnerability layers in the risk assessment.

3.5 Vegetation data:

We used the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) derived from the MODIS sensor aboard NASA's Terra and Aqua satellites (Didan & Munoz, 2015); https://lpdaac.usgs.gov/products/mod13a3v061/) to characterize vegetation in the risk framework. NDVI and EVI are calculated using reflectance measurements from visible and near-infrared bands, providing valuable insights into vegetation health, density, and phenology. These indices are indicators of vegetation stress, biomass, and fuel

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availability. Within the fire risk assessment framework, lower values of these indices indicate higher fire vulnerability and exposure in forests.

3.6 Population Data:

To represent human exposure to fire risk, we quantifying the population density living within the forest regions. The gridded population dataset from the Socioeconomic Data and Applications Center (SEDAC; Doxsey-Whitfield et al., 2015; https://sedac.ciesin.columbia.edu/data/collection/gpw-v4/sets/browse) integrates census data, administrative boundaries, and satellite imagery to estimate population distribution at a global scale at a resolution of 1 km. Utilizing advanced spatial modeling techniques, it provides fine-grained population density information across various geographic regions. We used the annual data for 2003, 2005, 2010, 2015, and 2020 to create an aggregated 25km dataset.

3.7 Land Use Land Cover data:

Agricultural and urban land use types are often linked to ignition sources and human activities near forests. To capture this influence in the fire risk framework, we calculated the percentage of land under agriculture and urban use within each 25 km grid. For this, we derived the percentage of land in each 25 km grid under agriculture and urban land use type from the MODIS Land Use Land Cover (LULC). The MCD12Q2 product (Gray et al., 2022; https://lpdaac.usgs.gov/products/mcd12q2v061/) is available annually at a 1 km spatial resolution. We used the standard IGBP classes of agriculture/cultivated land and urban built-up areas to compute the percentage datasets at 25 km resolution.

4 Methods

4.1 Approach

The flowchart of the methods used to develop the structured framework to assess forest fire risk is illustrated in Figure 2. We begin by computing daily FWI using meteorological inputs from ERA5 data through the CFFDRS system at 25 km resolution. Fire observations from MODIS active fire data are used to evaluate the FWI output and generate a gridded forest fire count dataset. This fire count was used to develop the FDRS and as the target variable in the risk model. FDRS thresholds were derived using an ensemble of four statistical approaches integrated with machine learning. This system defined thresholds for fire danger levels to capture the relationship between fire weather and observed fire activity. The resulting FDRS represents the weather-driven hazard component of the FRAME v1.0. To estimate overall fire risk, the hazard component was combined with fuel characteristics (slope, elevation, aspect, NDVI, and EVI) and ignition factors (agriculture, urban area, population density). Seven machine learning algorithms were tested, and an Artificial Neural Network (ANN) was selected based on its predictive performance. The model was trained using 70% of the dataset and validated using the remaining 30%.

Details of the datasets and modelling steps of FRAME v1.0 framework are described in the following subsections.

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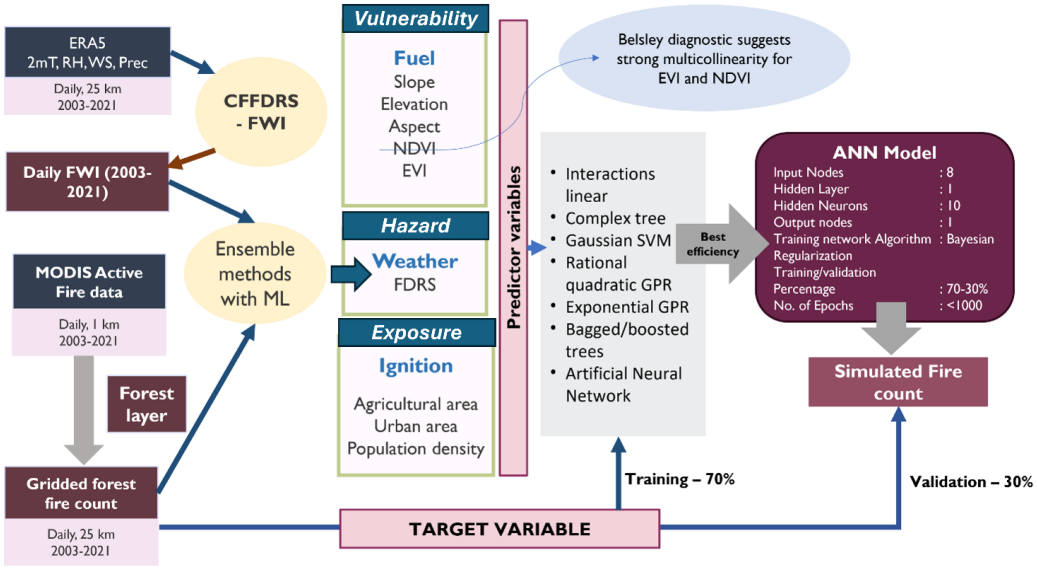

Figure 2: Overview of the FRAME v1.0 framework

4.2 Fire frequency dataset development

We used MODIS active fire data in FRAME v 1.0 for three purposes, as described in detail below. With the fire data, we evaluated the simulated FWI from CFFDRS, calibrated the FDRS thresholds for each zone, and used them as a target variable in fire risk assessment. For this, we converted the spatial and temporal information in the active fire data to a gridded daily fire count dataset at 25 km resolution. To do this, we used the MODIS fire data from January 1, 2003, to December 31, 2021. We then retrieved only those fires occurring in the forest zones of India. This step is critical, as it removes all fires set in farmlands to burn crop residues to clear the field for the next crop, a practice widely prevalent in many parts of India. Then, we aggregated the filtered forest fire data into a daily count of fires within a grid with 25 km spacing, matching the ERA5 weather data and the simulated FWI information. We also computed zone-wise daily and monthly aggregated climatological fire datasets from this daily fire frequency information for risk calculations.

4.3 CFFDRS-FWI configuration

The CFFDRS calculates the FWI, which is a numerical measure used worldwide by researchers to understand how weather conditions affect forest fuels and fires, and to study patterns of fire severity (Wagner, 1987). This index comprises of three moisture codes: the Fine Fuel Moisture Code (FFMC) to quantify surface moisture, the Duff Moisture Code (DMC) for moisture below the surface, and the Drought Code (DC) for deeper soil levels. It then calculates two intermediate indices: the Initial Spread Index (ISI) indicating fire spread rate and the Buildup Index (BUI) indicating available fuel for combustion. The FWI is calculated from ISI and BUI.

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We wrote the code for this algorithm in MATLAB using the equations described in Wagner, (1987) *(https://github.com/anasuya993/CFFDRS-FWI_India/blob/main/CFFDRS_FWI_year_ABiitd.m)*. We then provided gridded (25km) ERA5 meteorological inputs to the algorithm. We implemented the latitude adjustments as in Barik & Baidya Roy (2023) and performed experiments to deduce the spin-up required (Refer to Supplementary Annexure 1) and tested the compatibility of the CFFDRS with Indian weather (Refer to Supplementary Annexure 2).

4.4 Association between FWI and fire frequency

To test the association between fire data and the simulated ERA5-based FWI, we used three non-parametric statistical tests as in Barik & Baidya Roy, (2023). These tests include the Chi-square test of association/ independence (McHugh, 2013), Yule's correlation (Yule, 1897), and Fisher's exact test (Upton, 1992). These tests are best applied over nominal or ordinal variables. Hence, we converted the FWI to a nominal variable by introducing data bins. FWI values lesser than the 40th percentile were considered to be zero and the rest values to be 1. We chose this threshold of the 40th percentile based on the observation that the curve of the percentile ranks showed maximum change in slope with 97.9% of fires occurring beyond this threshold. The presence and absence of fire were denoted as 1 and 0 respectively.

In addition, we also plotted the Epanechnikov Kernel Density Estimations (KDE; Epanechnikov, 1969; Samiuddin & El-Sayyad, 1990) to compare the distribution of FWI values corresponding to fire and no-fire events. This approach demonstrated the distinct differences in FWI spread, suggesting that it is an effective metric for identifying conditions conducive to fire occurrence.

4.5 Developing FWI thresholds for fire danger classes

Fire danger rating is a necessary tool for the quantitative assessment of fire danger in a systematic way (Stocks et al., 1989; Vasilakos et al., 2007). It is a medium to communicate with all stakeholders including the public about potential threats. In FRAME v1.0, we chose five classes Low, Medium, High, Very high, and Extreme because they adequately represent the FWI spread over the zones. To compute the upper FWI thresholds for these danger classes, we selected 4 methods from Barik & Baidya Roy, (2023). These 4 methods are based on logistic regression, percentile-based, percentage of fire-based and K-means clustering (Refer to Supplementary Annexure 3). We excluded the geometric progression method in Barik & Baidya Roy, (2023) as it did not include the fire count in the threshold computation. We then introduced machine learning techniques like Receiver Operating Characteristics (ROC) and hierarchical clustering to reduce subjective decision-making in these methods and computed modified thresholds in terms of percentiles. The range of FWIs varied across zones. So, we calculated specific thresholds for each zone.

We calculated the Critical Success Index (CSI) of the methods against the newly developed thresholds to assess the extent of improvement achieved by including ROC and clustering techniques. More details on the evaluation and robustness check of the developed FDRS thresholds are in Supplementary Annexure 4. The ensemble of the thresholds from all the updated methods formed the FRAME v1.0 FDRS component.

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4.6 Fire risk computation

The final objective of FRAME v1.0 was to estimate spatial fire risk by integrating the hazard component derived from FDRS with additional vulnerability and exposure indicators. These components were calculated using various predictor layers and machine learning algorithms. The fire weather severity or FDRS rating formed the hazard factor. Exposure factors consisted of population density data, where higher densities indicated increased exposure to fires. Additionally, layers representing agricultural land and urban built-up percentages also served as proxies for exposure. Vulnerability was characterized by fuel condition, for which we used NDVI and EVI as proxies for vegetation health. Lower values of these indices denoted greater fuel availability and hence more fire vulnerability. We initially considered both NDVI and EVI, as there is no consensus amongst existing literature regarding which variable is better suited to represent the state of vegetation over fragmented forest systems of India. Topographical features such as elevation, slope, and aspect are standard variables considered in fire risk assessment studies and they are also considered in this study as vulnerability factors. Together, these variables represent the weather, fuel, terrain, and anthropogenic components incorporated in FRAME v1.0 to capture hazard, vulnerability and exposure conditions influencing fire occurrence.

After aggregating/ resampling all the input layers at 25 km resolution, we first tested the multicollinearity with the Belsley collinearity diagnostic (Belsley, 1991). It evaluates the degree of collinearity among predictor variables in any regression model. The criteria to denote multicollinearity using the Belsley collinearity diagnostic typically involve examining condition indices (CI) and variance decomposition proportions (VDP) of each variable in the input data. In this study, multicollinearity is considered to be present if CI is greater than 30 and the VPD exceeds the default tolerance of 0.5. NDVI and EVI returned CI>30 and high VPD in CEN and DEC regions where forests are most scattered thus, suggesting strong multicollinearity. We retained EVI as a predictor variable in FRAME v1.0 as EVI showed overall better linear correlation with the fire count than NDVI.

Next, we normalized all our predictor variables namely FDRS, EVI, elevation, slope, aspect, percentage of cultivated land, percentage of urban built-up area, and population density using standard minimum-maximum method. Then, 70% of the predictors, randomly selected, were used to train various machine learning based models to simulate fire count. The simulated fire count is representative of probable fire occurrence and hence proxy to fire risk. We evaluated 7 methods such as interactions linear, complex tree, gaussian support vector machine, rational quadratic GPR, bagged boosted trees and ANN with the remaining 30% of the predictor dataset using parameters like coefficient of determination, RMSE and time taken to train the model. We found that the ANN model outperformed all others, achieving the highest coefficient of determination (R^2) and the shortest training time (Annexure 2: Table S1). Therefore, the ANN model was selected for subsequent fire count simulations. The trained ANN model for every zone was then used to compute simulated probable fire count information from the gridded predictors at monthly scale. These simulations represent the spatially distributed fire risk outputs generated by FRAME v1.0.

Then, we used a popular method called the Maximum Relevance Minimum Redundancy (MRMR) algorithm to determine the zone wise analysis of dominant factors causing forest fires. The MRMR ranks predictors by maximizing their mutual information with the target fire count (relevance) while minimizing mutual information

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among the predictors themselves (redundancy), then normalizes these relevance scores as weights. We computed these weights pertaining to each variable in causing changes in the target fire count. The weighted predictors were additively aggregated to compute a risk index which was finally scaled between 0 and 1 to maintain uniformity and give relative risk information in between the zones. This normalized index represents the final fire risk output of FRAME v1.0.

5 Results and discussion

5.1 Association between FWI and fires

The Chi-square goodness of fit test (Cochran, 1952) shows that the FWI dataset belongs to a normal distribution, whereas the fire occurrence dataset does not. Hence, we cannot assume a normal distribution and use Pearson's correlation coefficient and simple linear regression between the two variables. Hence, we used three non-parametric statistical tests. All three tests demonstrate consistent results, indicating a significant association between FWI and fire occurrences. The Chi-square test of association/ independence test returns a value of 8968.6 which is greater than the critical decisive test value. Thus, the association between the two variables was established at a 95% significance level. For computing Yule's correlation (Q), the concordant cells consist of two favorable scenarios wherein low FWI and high FWI correspond to no fire and fire scenarios respectively. The discordant pair consists of unfavorable outcomes for FWI and fire datasets. Q yields a value of 0.803 indicating a strong positive association. Fisher's exact test over FWI and fire data yields a value of h=1 at a 95% significance level and an odds ratio of 9.18 (8.54-9.87). This test also suggests a significant non-random association between the fire occurrence and its corresponding FWI value. The odds ratio of 9.18 suggests that the odds are 9.18 times higher that a fire will occur at low FWI values compared to high FWI.

From the KDE analysis of FWI corresponding to that of fire-occurring grids and no-fire grids (Figure 3), we observed that in all the zones the FWI corresponding to the fire points spread towards higher values. The peak of FWI spread corresponding to no-fire points occurs at comparatively lower FWI values. Also in all the zones, the median of FWI at the fire points curve is at a higher value than that of no-fire points. This confirms that fire occurrences are accompanied by comparatively higher FWIs. The difference between the KDE curves is prominent in HIM, NE and DEC regions. In the CEN and WG regions, although the FWI in fire points extends towards higher values, there is also a notable peak of fire point FWIs at lower values. This can be attributed to the higher fragmentation of forests in these regions, with some grids exhibiting as low as 20-30% forest cover. Consequently, a grid with lower forest cover may exhibit fewer fires compared to a grid with higher forest cover, despite the latter having a lower FWI.

This demonstrates the strong association of FWI with observed fire counts and hence establishes that the subsequently developed FWI-based FDRS is a strong hazard component for the FRAME v1.0.

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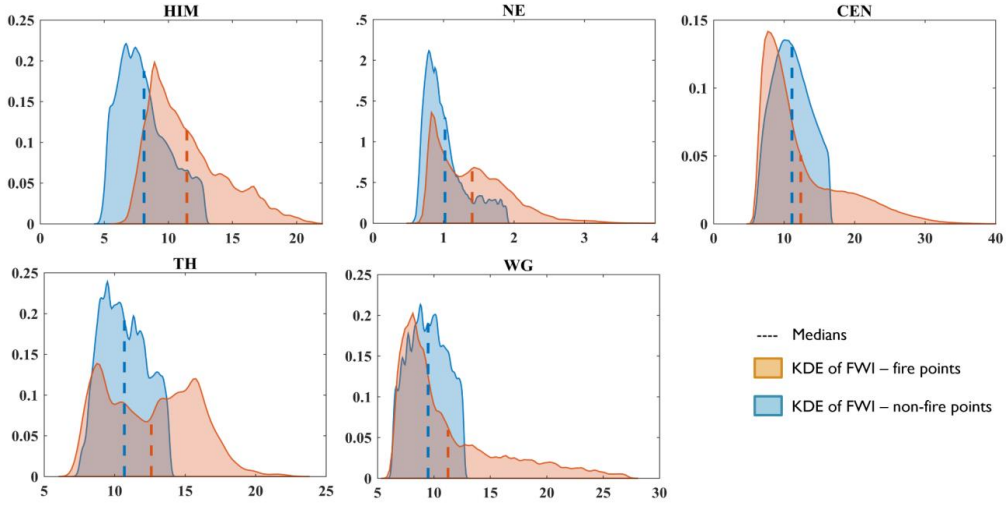

Figure 3: Kernel Density Estimation of FWI corresponding to that of fire-occurring grids and non-fire grids for different zones.

5.2 Evaluation of FDRS

We calculated the FDRS system threshold in FRAME v1.0 using the methods described in Annexure 3 of the Supplementary material. The thresholds in (Barik & Baidya Roy, 2023), relying on subjective threshold numbers, were tailored to specific regions and applications. This limits their usage as potential thresholds for operational usage for India with all kinds of datasets. To ensure the robustness of these danger classes, we recalibrated the initially chosen numerical thresholds. The incorporation of clustering and ROC curves provided a more adaptive and data-driven framework for threshold computation. We used the CSI metric to compare the new thresholds with the previous ones. CSI is a comprehensive metric that factors in true positives, false positives, and false negatives. The results show consistently higher CSI values for the thresholds derived from machine learning methods (Figure 4). This suggests an improvement in the classification to predict fire danger accurately. We observe an overall improvement of 30-50% in the CSI in all the zones except WG where we observe that Low and Medium class thresholds show no significant improvement. However, there is a 23% improvement in the CSI of the Very high danger class. The highest improvement is in the DEC zone followed by CEN with CSI increasing by 49.5% and 43% respectively in the newer thresholds than the older ones. In the Low and Medium classes, we observe the most significant improvement in the NE zone. In higher danger classes, DEC and CEN zones show maximum improvement. In summary, the overall CSI of new thresholds shows an increase of 28% across all classes and zones in Indian forests. This evaluation shows that the inclusion of objective decision-making approaches significantly improves the overall performance of the resulting fire danger threshold computation.

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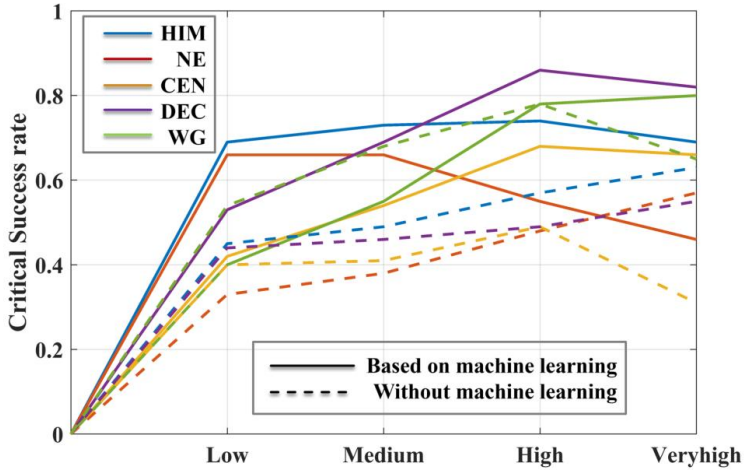

Figure 4: Critical Success Rate (CSR) of thresholds for each danger class developed without machine learning (dashed lines) and with machine learning (solid lines) for different zones.

We developed the upper thresholds for the five fire danger classes in terms of percentiles of FWI (Table 2). Barik & Baidya Roy, (2023) defined FDRS class thresholds using fixed FWI values specifically for Indian forests and the datasets and time periods they analyzed. This made those thresholds highly specific to the input data, time period and region. To ensure that our danger classes remain valid across different tropical zones, and temporal spans, we instead defined class boundaries in terms of percentiles of the FWI distribution (Table 2). By expressing the thresholds in terms of percentiles, they become adaptable for use with any dataset, gridded or station data, facilitating a more versatile and operationally relevant threshold classification. This approach makes the thresholds applicable across different forest regions, time periods, and FWI datasets, contributing to a robust fire danger assessment framework. The range of thresholds in terms of percentiles in all the zones is similar with the Low class threshold ranging around the 40th percentile to the Extreme class beyond the 95th percentile. These percentile thresholds are directly transferable to other regions with matching the forest and climate characteristics of the 5 zones.

Table 2: Upper thresholds of fire danger classes in percentiles of FWI for the different zones

Fire danger classes	**HIM**	**NE**	**CEN**	**DEC**	**WG**
Low	40	36	38	40	34
Medium	61	57	65	66	58
High	85	82	87	90	87
Very high	95	96	97	98	98

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Extreme	>95	>96	>97	>98	>98

To ensure the robustness of our developed thresholds, we implemented three key criteria. Firstly, we ensured that there was no overlap between classes when considering different methods. For example, if the low threshold in method 1 surpasses the medium threshold of method 2, then there would be an overlap and it would be inappropriate to use the methods in an ensemble threshold computation. To assess this, we observed the spread of FWI in each class for different methods using a violin plot (Figure 5). This plot combines the aspects of a box plot and a kernel density curve and displays the distribution of data across different categories or groups. The violin shapes convey information about the kernel density of the data in the category, highlighting characteristics such as skewness and multimodality. The black and the red lines indicate the mean and the median of data in that category which provides measures of central tendency.

From this, we observe that the mean and median thresholds in each method consistently do not overlap with the thresholds of the previous class. This shows agreement between the methods in threshold development, which is essential for their ensemble use. Also, the pattern of kernel densities, including the shape of the kernel density curve, skewness, and relative frequency magnitudes, are in agreement across the chosen methods. This uniformity also shows coherence within the methods and develops confidence in our approach. Another observation is that the spread of kernel densities is more pronounced in the very high class in all the zones. This ensures a broad range of values in the class denoting high fire danger, effectively minimizing the occurrence of true negatives. This strategic emphasis on a comprehensive range in the Very High class enhances the sensitivity of our fire danger thresholds, crucial for accurate risk assessment and management strategies. The observed skewness in the distribution of some methods towards lower values can be attributed to the lower prevalence of highly fire-conducive conditions compared to moderate fire weather conditions. In some zones, the kernel densities in the Low class exhibited skewness towards higher values.

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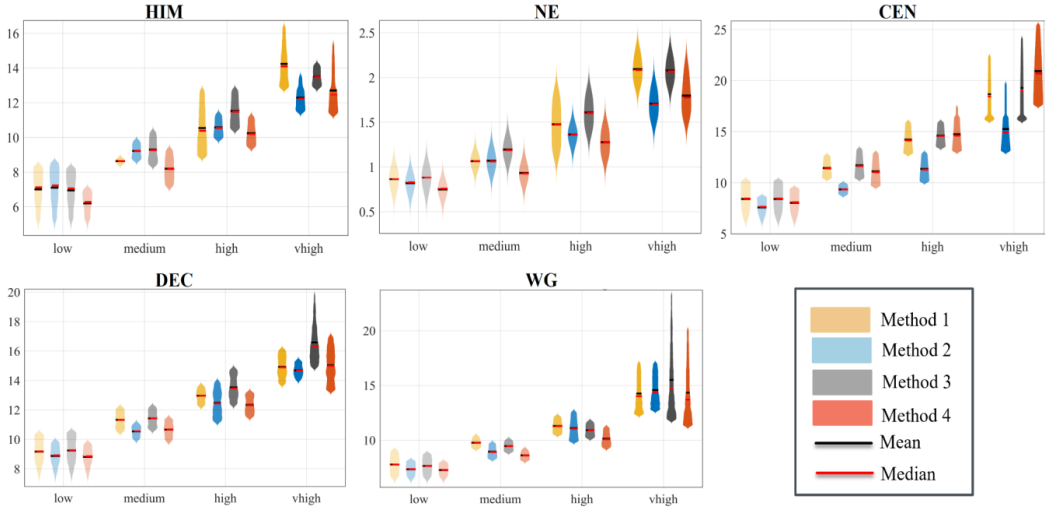

Figure 5: Violin plots for danger class thresholds developed using logistic regression, percentile-based, percentage of fire-based and K-means clustering methods integrated with machine learning, with the mean and median marked for different forest zones of India

In assessing the second criterion concerning the increasing probability of fire occurrence within each danger class (Figure 6), we computed the probability as the ratio of favorable events—in this case, instances of fire occurrence—to the total number of events in each class. As anticipated, the results show that lower fire danger classes exhibit a correspondingly lower fire probability and the higher fire danger classes demonstrate a higher fire probability. The significance of this probability criterion lies in its role in ensuring the reliability of the established danger classes. If, for instance, a high fire danger class were associated with a low fire probability, it would introduce a contradiction and diminish the practical utility of the thresholds. Therefore, incorporating this probability criterion is essential for developing thresholds that make the delineated danger classes acceptable. Moreover, the violin plot in Figure 5 also illustrates a clear progression of thresholds showing the increase in the spread of FWI values from low to high classes in all the methods. This agreement between fire danger classes and the associated fire occurrence likelihood provides a robust foundation for the developed thresholds.

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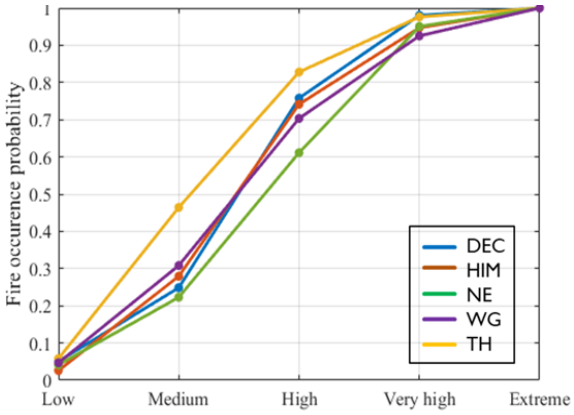

Figure 6: Fire occurrence probability at fire danger classes for different forest zones of India

Next, in our evaluation of the defined danger classes, we used evaluative parameters to ensure the reliability of the classification. The results reveal a consistently high hit rate across all zones, with the highest value in HIM. This high hit rate indicates the effectiveness of the defined danger classes in capturing true positive events. Hits due to chance are consistently low across all zones. This ensures that the observed hits are not merely coincidental but are due to the model's ability to accurately predict fire occurrences. Correct rejection rates vary within the range of 15-35% across zones, representing the proportion of instances where the model correctly identifies non-fire events. The moderate values in this parameter indicate a balanced classification performance. An interesting observation is the relatively high False Alarm Ratio (FAR), especially in CEN, DEC, and WG zones. This metric is the ratio of false alarms to the total positive predictions. Within these zones, the prevalence of hot and dry conditions during the pre-summer monsoon months contributes to a large number of days having high FWI. However, the presence of high FWI does not necessarily result in fires unless there is an ignition source. This behaviour reflects the conceptual design of FRAME v1.0, where the weather-driven hazard component alone does not determine fire occurrence and must interact with vulnerability and exposure factors to produce actual fire risk.

Despite the elevated FAR in these zones, the overall classification remains acceptable as it does not compromise the accurate identification of true negatives. The comprehensive CSI combines various performance measures and indicates high values in HIM and NE. In other zones, the CSI is comparatively lower because of high false alarms. In summary, the defined danger classes demonstrate coherent values for evaluative parameters, with a consistently high hit rate, low hits due to chance, moderate correct rejections, and an acceptable FAR. This evaluation confirms that the FDRS thresholds provide a robust hazard representation within FRAME v1.0 and can therefore be reliably used as the weather-driven input for the subsequent fire risk modelling framework. The rigorous evaluation of these thresholds makes the designed danger classes suitable for operational fire management use.

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Table 3: Evaluative parameters to test the skill of the developed system in fire prediction

	HIM	NE	CEN	DEC	WG
Critical success rate (CSR)	0.52	0.56	0.26	0.22	0.18
Probability of detection/ hit rate	0.92	0.76	0.56	0.7	0.56
False alarm ratio (FAR)	0.45	0.31	0.67	0.75	0.78
Hits due to chance	0.22	0.36	0.23	0.12	0.13
Correct rejection	0.25	0.15	0.24	0.32	0.33

5.3 Evaluation of risk assessment

Out of all the models used in the study, we found that the ANN model performed the best with least training time and maximum coefficient of determination that is R^2 values - up to 0.89 in the CEN zone and an average R^2 of 0.73 across all zones - while maintaining competitive RMSEs (Annexure 2: Table S1). The performance of the ANN model to capture nonlinear interactions made it the most robust performer among the seven tested methods. The final ANN architecture, which was selected to be the risk assessment tool in FRAME v1.0, comprised of eight input nodes (one for each predictor), a single hidden layer with ten neurons, and one output node for fire count. We trained the network using Bayesian regularization, with a 70 %–30 % train/validation split and under 1,000 epochs.

Figure 7 shows the simulated and actual fire counts against every predictor variable. Overall, the simulated counts closely mirror the observed ones, confirming the model's ability to capture fire occurrence signals. We observe that higher FDRS values indicate elevated fire hazard thus demonstrating a direct relationship between FDRS and fire occurrence. The vulnerability layers consist of topographical features like elevation, slope, and aspect. Steeper slopes and certain aspects may exacerbate fire spread. Higher elevations influence the temperature and fuel moisture conditions. In addition to these the vulnerability layers also contain indicators such as EVI from which we obtain the fuel availability information. Lower EVI values suggest dryer vegetation and increase in fire vulnerability. Increase in agricultural activities and urban built-up area and population increases the chances of human ignition while agricultural activities may also lead to landscape modifications affecting fire behavior. Overall, the simulated fire counts match well with the actual fire counts. It is important to note here, the simulated target variable is not an indicator of absolute fire count per say. Rather a high simulated fire count denotes a higher probability of fire occurrence.

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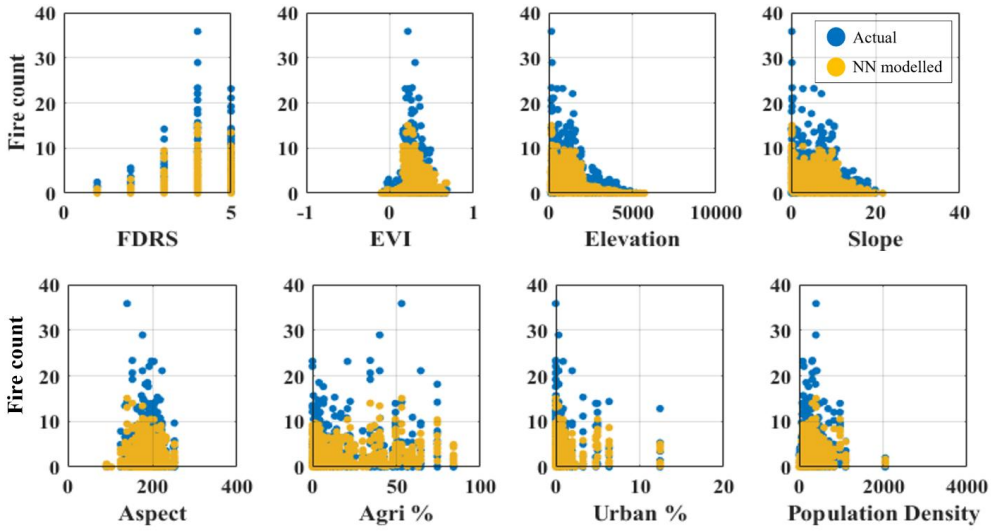

Figure 7: Evaluation of actual and NN simulated fire counts against all the hazard, vulnerability and exposure factors

5.4 Drivers of fire risk

Figure 8(a) shows the relative contribution of individual predictor variables in simulating the target fire variable. The red and the blue dots denote positive and negative relationships between the protector variable and the target respectively. It is clear from the figure that FDRS has a positive relationship with fires in all the zones. The relative importance of this variable is also more than the other variables.

In the mountainous regions of the HIM, elevation plays the most important role (Figure 8a). With increasing elevation, the fire susceptibility reduces. This is followed by equal contribution from metrological and fuel availability factors. The exposure factors also contribute positively to the overall fire risk in this region. In NE and CEN, FDRS is the most important governing fire risk. The risk is also prominently higher in the central and southern NE. The contribution of percentage of urban built-up area is high though the nature of this relationship is less significant. However, weather and a high built-up area is primarily the reason for higher fire risk in this zone. In CEN, weather hazard, urban area percentage and population density increases the fire risk. Elevation and EVI factors counter this, because of which the overall risk is relatively low in the CEN region (Figure 8b). In the DEC region, fire risk increases with variations in slope and aspect of the landscape. The fuel availability contributes negatively, and FDRS contributes positively but with low statistical significance. Human influence factors particularly do not contribute positively to the fire risk in this region. In WG, all the risk factors contribute positively to increasing fire risk. Fire weather hazard, elevation, and agricultural land percentage are the major reasons behind the fire risk in western ghat.

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Overall, fire weather hazard is the most important factor contributing positively to fire risk in all regions. Another interesting thing to note is that regions where the urban built-up area contributes positively to the overall fire risk, population also contributes in similar direction to the fire risk. For example, in CEN and HIM, more built-up area within the forest zones translates to more population density and hence increased exposure of these regions to forest fires.

Figure 8 (b) shows the final, normalized fire risk index as computed by FRAME v1.0 across India, combining weather hazard, fuel conditions, topography, and ignition factors. High-risk values (>0.8) cluster in the Northeast, where shifting-cultivation (jhum) burns (Heinimann et al., 2017) and pre-monsoon humidity drops combine to dry fuels rapidly and sustain frequent ignitions. These regions also have steep slopes and south-facing aspects that dry fuels quickly. Dense human settlements and agricultural edges further raise ignition probability. The Western Ghats also show high risk, as semi-evergreen and semi-deciduous forests experience dry pre-monsoon conditions along with recurring land-clearing burns and accidental ignitions (Renard et al., 2012). Moderate risk (0.4–0.8) spans forests in the CEN zone, where mixed fuel loads and variable rainfall create intermittent fire windows. In these areas, fuel continuity is broken by patches of open land. Low risk (<0.4) is found in wet evergreen and high-altitude zones, where persistent moisture, thick canopy cover, and limited human access keep fuels damp and ignition sources rare. The fire risk map matches well with the spatial patterns of actual fire occurrence over these zones. This spatially explicit risk map shows how local climate regimes, terrain morphology, vegetation type, and socio-economic practices jointly drive fire risk.

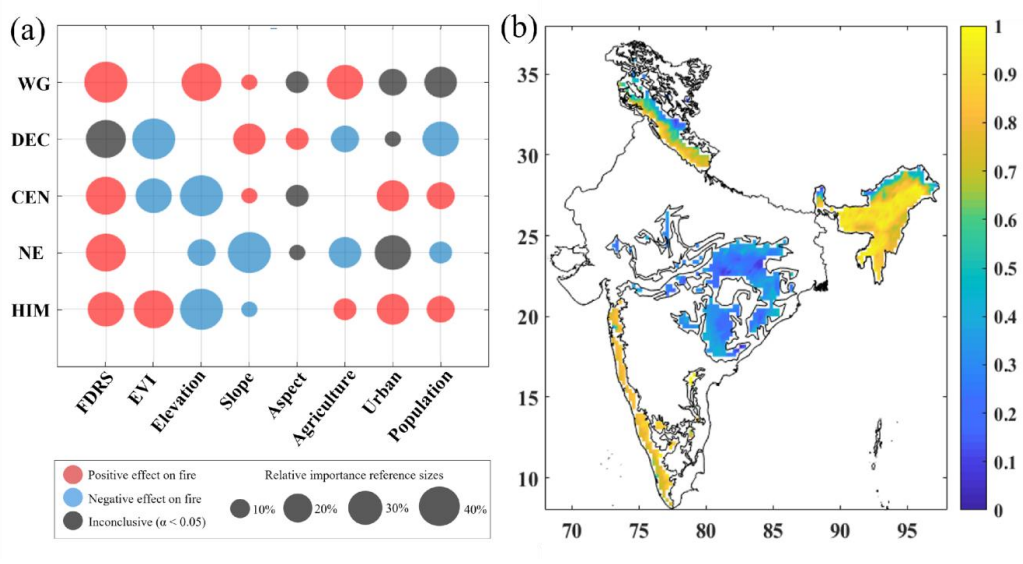

Figure 8: (a) Contribution of individual variables calculated by maximum relevance minimum redundancy algorithm and (b) overall relative fire-risk in FRAME v1.0 over Indian forests

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6 Conclusion

This study presents a comprehensive fire risk assessment framework, FRAME v1.0, tailored for tropical fragmented forest systems, using India as a representative case. We analyzed the complex interplay of biophysical, climatic, and anthropogenic factors in tropical landscapes. As the first step to developing the FRAME v1.0, we developed an adaptable FDRS framework using the CFFDRS. The framework integrates region-specific fire-weather thresholds and uses machine learning to refine thresholds and reduce subjectivity in the fire weather hazard computation. The integration of machine learning techniques, such as ROC curves and clustering, increased the reliability of developed fire danger thresholds for better forest fire prediction and management practices. The developed FDRS framework can independently serve as a reliable indicator of fire weather hazard, helping to understand how weather and climate variables interact to create fire-conducive conditions. However, focusing only on weather-driven hazards provides an incomplete representation of fire risk. Effective fire management requires understanding not only where fires are likely to ignite, but also where ignition is most likely to occur. The integrated risk in FRAME v1.0 identifies areas where high fire hazard coincides with high vulnerability or exposure, highlighting truly high-risk zones. So, we developed the comprehensive FRAME by integrating hazard with key vulnerability and exposure factors, enabling spatially explicit assessment of relative fire risk across tropical fragmented forest systems. We employed ANN to model fire occurrence based on gridded environmental and socio-economic predictors and used the Maximum Relevance Minimum Redundancy (MRMR) algorithm to identify dominant drivers of fire risk across zones. The resulting FRAME v1.0 fire risk index integrates hazard, vulnerability, and exposure dimensions in a scalable manner, which enables comparisons within and across tropical forest regions.

While FRAME v1.0 was applied in the Indian context in this study, its structure and methodological design are transferable to other tropical forest regions facing similar fragmentation and climate pressures. Gridded assessments such as ours provide a valuable tool for strategic fire management, particularly in data-scarce environments. However, we acknowledge that finer-scale applications would benefit from incorporating additional socio-economic and ecological variables, including detailed fuel composition and localized ignition sources.

A key methodological advancement is the development of a risk framework that integrates hazard, vulnerability, and exposure into a single, spatially explicit index. We created a workflow that combines FDRS outputs, fuel and socio-economic layers, and machine learning weights in one reproducible pipeline. In addition, the zone-specific calibration of the FDRS builds distinct fire-danger models for each forest zone to account for local climate regimes and vegetation types, unlike one-size-fits-all systems that apply uniform thresholds across diverse landscapes. By coding this end-to-end process, we provide a clear, transferable method for generating comprehensive fire risk maps in tropical fragmented forests.

Scientifically, these results reveal that fire risk in tropical fragmented forests is controlled by a shifting hierarchy of drivers rather than a single dominant factor. Across all areas, fire weather hazard sets the baseline risk. In mountain zones, higher elevation reduces risk by keeping fuels cooler and moister. In plains and fragmented forests, human factors increase chances of ignition. Fuel availability and terrain shape risk in between. By using machine learning

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to weigh these zone-specific drivers, we demonstrate that accurate fire risk prediction needs models tailored to local climate, landscape, and human influences.

Ultimately, this study contributes to the evolving global discourse on fire risk in tropical forest systems by combining operational hazard indicators with machine learning–based risk estimation. FRAME v1.0 provides a foundational step toward scalable and data-driven fire management strategies that can be adapted to similar regions globally, particularly under the increasing pressures of climate change and land use transformations.

7 Author contributions

A.B. and S.B.R. conceptualized the study and designed the overall methodological framework. A.B. developed the analysis workflow, implemented the model framework, and performed the data analysis and simulations. S.B.R. supervised the research and provided guidance on methodology and interpretation of results. A.B. prepared the original manuscript draft. S.B.R. reviewed and edited the manuscript. Both authors contributed to the discussion of results and approved the final manuscript.

8 Competing interests

The authors declare no competing interests.

9 Acknowledgements

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10 Financial support

This research is not funded.

11 Data availability

The datasets used in this study are available from the authors upon reasonable request.

12 Code availability

The modifiable MATLAB code used to compute the Fire Weather Index is available on the GitHub repository (https://github.com/anasuya993/CFFDRS-FWI_India/blob/main/CFFDRS_FWI_year_ABiitd.m,, and the frozen version 1 is archived on Zenodo (https://doi.org/10.5281/zenodo.10047237). The code used for the neural network modelling and fire risk simulations can be made available from the authors upon reasonable request.

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