Response to Reviewer Comments

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

Journal: Natural Hazards and Earth System Sciences (NHESS)

We thank the reviewer for their careful reading of the manuscript and for the constructive and insightful comments. The reviewer's feedback will help us improve the clarity and scientific rigour of the paper. We have addressed each comment below. Reviewer comments are shown in blue italics, our responses are in black, and proposed changes to the manuscript text are indicated in red with the relevant line numbers.

Fire risk computation based on several inputs, including the FWI, needs further elaboration in the paper. The relevance of hazard component i.e FWI and other vulnerability and exposure indicators, such as altitude, slope, aspect, population density, fuel availability, is well factored by the authors but the manner in which these have been integrated across the regions is not clear. This is an important challenge which needs to be dealt in more detail, including its theoretical basis.

We thank the reviewer for highlighting this important point. We agree that the integration methodology needs clearer articulation. The risk computation in FRAME v1.0 follows the well-established conceptual framework of fire risk as a function of hazard, vulnerability, and exposure (Bergonse et al., 2022), which is consistent with frameworks used in international fire risk assessment literature.

To improve clarity on the theoretical basis of the hazard-vulnerability-exposure framework and the subsequent fire risk computation, we propose the changes highlighted in red in the introduction section (Lines 69-95 in the original manuscript)

“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 conceptual basis of FRAME v1.0 follows the widely adopted risk framework in natural hazard studies, where risk is characterised by the interaction between hazard, vulnerability, and exposure components (Bergonse, Oliveira, Santos, et al., 2022). In the context of forest fires, hazard represents the probability of fire-conducive atmospheric conditions, vulnerability represents the susceptibility of the landscape and fuels to ignition and fire spread, and exposure characterises the presence of human systems and activities that can both influence and be affected by fire events. 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 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. In this framework, vulnerability captures how landscape structure, fuel condition, and terrain properties modulate fire behaviour once hazardous weather conditions are present. 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). Lower vegetation moisture and degraded vegetation conditions increase fuel flammability and therefore increase environmental vulnerability to fires. 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). These terrain variables therefore influence the spatial susceptibility of landscapes to fire propagation and are treated as environmental vulnerability indicators.

Exposure layers included factors related to human-environment interactions. Within FRAME v1.0, exposure represents the degree of interaction between human activities and fire-prone landscapes. 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. These factors increase the likelihood of anthropogenic ignitions and intensify human–fire interactions across fragmented forest edges. By integrating these hazard, vulnerability and exposure components 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.

In Section 4.6 (Lines 282-326 in the original manuscript), we propose the following additions

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.

All predictor layers were aggregated/resampled to a common spatial resolution of 25 km and spatially aligned grid-wise before model development. Thus, each grid cell contained simultaneous information on fire-conducive weather conditions, vegetation state, terrain characteristics, and anthropogenic influence corresponding to the observed fire count. 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. The normalization ensured that all variables contributed comparably within the machine learning framework despite differences in units and value ranges. 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. Rather than assigning predefined weights to hazard, vulnerability, and exposure variables, FRAME v1.0 uses machine learning algorithms to learn the relationships between the combined predictor conditions and observed fire occurrence patterns directly from the data. Thus, the integration of weather, fuel, terrain, and anthropogenic factors emerges from the model training process itself.

Although the same predictor variables were used across all zones, the relationships among hazard, vulnerability, and exposure components were learned independently for each region using separate ANN models. This accounts for the strong climatic and ecological heterogeneity across India and captures interactions of weather, fuel, terrain, and anthropogenic factors that vary spatially depending on the regional fire–environment relationships represented in the training data. 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 among the predictors themselves (redundancy), then normalizes these relevance scores as weights. The MRMR analysis was performed separately for each forest zone. This enabled the relative contribution of individual predictor variables to vary regionally, across contrasting forest systems, according to the relationships learned by the ANN models. 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.

The linearity between the FWI values and fire occurrence is established by the authors in 5.1 (lines 330–357). However, the association of FWI and fires is expected to significantly vary during the fire season based on my personal experience. Towards the end of the fire season during an average fire season (avoiding both extremes), the subsequent peaks in the FWI value towards the end of the fire season are not accompanied by fires due to fuel exhaustion. This is generally expected across the regions, with some exceptions where fires trigger increased needle shedding in Pinus roxburghii forests in the western Himalayas. Fuel exhaustion is an important factor which can explain some of the exceptions noted in the paper.

We greatly appreciate this ecologically nuanced observation from the reviewer. The reviewer's point about fuel exhaustion is well-taken and we propose to integrate in the Section 5.1.

Moreover, our analysis spans a long climatological period (2003–2021) and uses daily FWI values which includes the within-season fluctuations including the fuel exhaustion effect noted by the reviewer. The non-parametric association tests (Chi-square, Yule's Q, and Fisher's exact test) used in Section 5.1 assess the overall statistical association between FWI and fire occurrence across all days and zones, rather than within any strict period. The KDE also plots similarly to reflect overall distributional differences.

The reviewer's specific point regarding Pinus forests in the western Himalayas is an interesting exception that further shows the value of a zone-specific framework like FRAME v1.0 rather than a uniform national approach. We acknowledge that the FWI–fire relationship is not linear and is modulated by fuel dynamics within and across seasons. We propose to clarify this in Section 5.1 to acknowledge the role of fuel exhaustion and within-season variability.

Proposed addition in Section 5.1: *"It is important to note that high fire weather conditions do not necessarily translate into fire occurrence throughout the fire season. Following periods of active burning, depletion of available fuels (fuel exhaustion) may limit subsequent fires even when FWI remains high. Such fuel-limited conditions provide a plausible explanation for the non-linearity in FWI-fire association and further justify the inclusion of vegetation- and fuel-related variables in the comprehensive FRAME v1.0 risk assessment framework."*

FWI and FDRS appear to be used interchangeably across the paper, which creates some confusion in the reader's mind. Some examples are 5.2 (lines 363–396); 356–357; Figure 7. Also, please check lines 343–344; 556–557 for accuracy.

We thank the reviewer for identifying this terminological inconsistency. In the manuscript we intend to use FWI as a continuous numerical index derived from meteorological inputs, whereas the FDRS as the categorical danger classification system that assigns FWI values to danger classes (Low, Medium, High, Very High, Extreme).

For the specific sections pointed out by the reviewer (lines 342–344, 356–357, 363–396, Figure 7, and lines 556–557), we verified that the terminology is being used in its intended context and made changes wherever required. In lines 342–344 and 356–357, the discussion pertains directly to the relationship between observed fires and the raw FWI values, and therefore the use of "FWI" is appropriate. To increase clarity, we propose a revised version as follows.

Proposed change *(Addition before lines 356–357): "Higher FWI values correspond to greater fire weather hazard, and when these values exceed the zone-specific thresholds, they are translated into higher FDRS danger classes.*

In Figure 7 and Section 5.2, the discussion concerns the classified fire danger categories derived from FWI, and therefore the use of FDRS is intentional.

Nevertheless, to avoid any potential ambiguity for readers, we have carefully reviewed all sentences throughout the manuscript to distinguish between the meteorological FWI component and the derived FDRS hazard classification framework.

Please check the effect of elevation in lines 512–513, as elevation is not expected to significantly influence fires in the Central Indian region, which is mostly a level plateau without much ruggedness, relatively speaking.

We thank the reviewer for this important observation and for bringing in the regional geomorphological perspective, which helped us refine the interpretation and strengthen the discussion in the manuscript.

We agree that the Central Indian (CEN) region is predominantly characterized by plateau terrain with relatively limited topographic variability compared to the Himalayan and Western Ghats regions. In our analysis, elevation shows a negative relationship with fire occurrence in the CEN region. A positive relationship indicates that fire occurrence increases with increasing parameter value. Therefore, a negative relationship implies that significant number of fires occur in the lower-elevation portions of the region.

This relationship does not imply that elevation is a dominant controlling factor on fire behaviour in the region. Instead, it likely reflects the greater concentration of deciduous forests, human accessibility, and anthropogenic activities in relatively lower-elevation areas of Central India. We have revised the corresponding discussion in the manuscript to clarify this interpretation and avoid overstating the role of elevation in the CEN region.

We propose to replace lines 511–513 with the following text.

Proposed change "*In CEN, weather hazard, urban area percentage and population density increase the fire risk. Elevation and EVI exhibit negative relationships with fire occurrence, thereby counteracting the positive influence of these factors. The negative relationship with elevation indicates that, relative to higher elevations, fire occurrence is greater in the lower-elevation portions of the Central Indian plateau. This should not be interpreted as elevation being a dominant control on fire risk in the region, but rather as reflecting the greater concentration of deciduous forests and human activities in these lower-elevation areas, resulting in an overall lower risk across the CEN region (Figure 8b)."*

I suggest looking into the explanation of the results discussed in the last para of 5.4. The interpretation can be improved by looking into the data and correlating it to the ground conditions.

Authors' Response:

We thank the reviewer for this suggestion. The last paragraph of Section 5.4 discusses the spatial distribution of the normalised fire risk index across India as produced by FRAME v1.0, including high-risk values in the Northeast and Western Ghats, relatively moderate risk in CEN, and low risk in wet evergreen and high-altitude zones.

We propose to revise the final paragraph of Section 5.4 accordingly to more explicitly anchor the model outputs to verifiable ground conditions and literature.

Proposed change : *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. The spatial pattern of fire risk index aligns closely with known ground-level fire conditions across India's forest zones. 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. This is also consistent with ISFR (2021) reporting the highest national fire* *incidence in this region and with previous studies in the states of Manipur (Puri et al., 2011), Meghalaya (Dhar et al., 2023), Mizoram (Chakraborty et al., 2026), and Nagaland (Arunima et al., 2023). 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). The calculated high risk in the Western ghats is consistent with regional studies of high risk and fire occurrences across the region. For example, high fire risks are reported by previous studies in the Western Ghat parts of Kerala (Ajin et al., 2015, Ajin et al., 2016) and Maharashtra (Bhuyan et al., 2015). Kodandapani et al., 2004 has listed fragmentation as a major reason for fire risk in a sanctuary in the Western Ghats. The temporal trends in these forests suggest that the dry deciduous forests are at more risk than the moist deciduous forests (Kodandapani et al., 2009). 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. In spite of relative risk in this zone being lesser than Western Ghats and North East India, some studies have reported fire risk in parts of Madhya Pradesh and Orissa (Ahmad et al., 2018, Sahu et al., 2024). 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. Overall, the spatial distribution of the risk index is well-corroborated by observed fire occurrence patterns and ecological ground conditions across India's diverse forest types. This spatially explicit risk map shows how local climate regimes, terrain morphology, vegetation type, and socio-economic practices jointly drive fire risk.*

We hope that the revised manuscript and the detailed responses above adequately address the reviewer's concerns. We remain open to further discussion and are grateful for the opportunity to improve the manuscript.

Added references:

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