Response to Reviewers Reviewer #1

Specific comment 1: I want to thank the authors for their thorough revision and comprehensive response to my questions. Most of them have been solved. The only remaining question is regarding the title of the study. The authors confirm in their reply that they do not account of multi-hazard characteristics but make a first, crucial step towards multi-hazard susceptibility mapping by developing multiple hazard susceptibility maps. I would suggest that the authors reflect on the title and align it with the key findings/approach of the study (and make some minor adjustments in the introduction, discussion and conclusion sections where necessary).

I enjoyed reviewing this interesting study, learned many new things and hope the authors found the feedback useful and constructive.

Response: We thank you for your kind words and appreciate your insightful comments and suggestions throughout the review process.

Regarding your suggestion on the title of the study, we agree that aligning the title with the focus of our study is important. While our research makes a significant step towards multi-hazard susceptibility mapping, it does not fully address the dynamic interactions between hazards.

We revised the title accordingly to emphasize that the paper primarily develops susceptibility maps for multiple co-occurring hazards rather than fully integrating multi-hazard characteristics.

The revised title is “Integrating susceptibility maps of multiple hazards with building exposure: A case study of wildfires and floods in Quang Nam province, Vietnam”.

Response to Reviewers Reviewer #2

General comment: The paper is well written, and the changes implemented are in the direction of the comments of the previous reviewers. In general, the paper applies two Machine Learning methods (CART and RF) to produce a multi-hazard susceptibility map in the Region of Quang Nam (Vietnam) for floods and wildfires, overlaying the results to create an exposure map for buildings. It describes a robust methodology for spatial co-occurring multi-hazard susceptibility maps, from the creation of a geospatial database of historical wildfires and floods events to the choice of susceptibility factors and the training/testing of ML algorithms for single hazard susceptibility maps. The addition of a building exposure layers to the multi-hazard susceptibility maps is one step towards a multi-risk analysis that can be used to inform used to inform local communities and regulatory authorities. However, there are some aspects that still require some clarification:

Response: Thank you for your positive evaluation of our work and for acknowledging the improvements made based on previous reviewer comments. We are grateful for your constructive feedback, and we will address these aspects thoroughly in the revised version of the paper.

Specific comment 1: The authors added insights on the limitations of the multi-hazard susceptibility mapping, clarifying that the focus of the paper is on spatially co-occurring hazards, and that it does not delve into the analysis of the dynamical interactions between the various hazards. However, it might be important to also discuss more about the choice of exposure layers, (as also stated by Reviewer 1, Comment 1 “an assumption of constant exposure might be worth discussing”). In particular, one important aspect in extending a multi-hazard to an analysis of risk for a specific asset (such as buildings) is the role of vulnerability, which is never mentioned in the paper. This is critical because, for example, the characteristics of buildings might make them more resilient towards one hazard, but more at risk for the second one. The choice of a constant exposure layer for both hazards should then be discussed, and potential limitations/future developments clearly stated.

Response: We thank the reviewer’s insightful comment regarding the need to discuss the choice of exposure layers and the role of vulnerability in the multi-hazard susceptibility mapping. We acknowledge the importance of incorporating vulnerability in extending the analysis from hazard susceptibility to risk, especially in the context of specific assets like buildings, which can exhibit varying resilience depending on the hazard type. In response, we added the explain for chosing the building is a primary exposure layer in section 3.2.3 as follows:

“This study focuses on buildings in terms of elements exposed to a hazards, considering their importance as critical economic assets and reflections of population distribution (Askar et al. 2021). Buildings are essential components of community infrastructure, and damage to them may have big social and economic effects, making them a crucial exposure indicator for risk assessment (Carreño et al. 2007). In addition, buildings often accommodate individuals and vital services; thus, their exposure to hazards and susceptibility to damage directly control the possibility of human fatalities and disturbance to everyday activities. In terms of vulnerability, buildings are not equally at risk from all hazards; their susceptibility varies depending on the hazard type and the structural characteristics of the building, although vulnerability is not considered explicitly in this study (Schneiderbauer and Ehrlich 2004)"

Specific comment 2: There are multiple references to landslide susceptibility mapping, but the paper focuses (and trains ML models) only on wildfires and flood susceptibility mapping. In particular, Chapter 3.2.2 should be changed, to discuss the factors that are relevant for wildfires and floods (now only in the Supplementary material). Also, in Chapter 3.4 ("Experimental process") there are some references to landslide susceptibility, which should be removed. If landslide susceptibility is to be discussed, it should be mentioned in the discussion chapter, as a possible extension.

Response: Thank you for highlighting the inconsistency regarding the references to landslide susceptibility mapping. We fully acknowledge that the paper focuses on wildfire and flood susceptibility mapping and that including landslide susceptibility references may cause confusion. In response, we have made the following revisions:

Chapter 3.2.2: We have revised this section to focus exclusively on the factors relevant to wildfires and floods, ensuring that this section aligns with the central objectives of the paper as follows:

3.2.2 Influencing factors

Several factors significantly influence flood and wildfire occurrences. Low-lying areas are prone to flooding, while elevated regions can hinder fires (Pourtaghi et al. 2016; Bui et al. 2022). Slope, slope aspect, and curvature affect water flow, erosion, and fire spread, with steeper slopes either mitigating or accelerating these hazards (Dottori et al. 2018; Trang et al. 2022). The Topographic Wetness Index (TWI) and Stream Power Index (SPI) help quantify water accumulation and erosion risks. Vegetation density, assessed using the Normalized Difference Vegetation Index (NDVI), impacts both flood absorption and fire fuel availability (Abedi Gheshlaghi et al. 2021; Gonzalez-Arqueros et al. 2018). Road and river proximity also influence flood and fire dynamics, while land cover, lithology, and geohydrology influence water retention and fire susceptibility (Ha et al. 2023; Hosseini and Lim 2022). Rainfall patterns and temperatures, particularly during dry seasons, further contribute to both flood and wildfire risks (Abram et al. 2021; Ahmadlou et al. 2018). These factors are modeled using data from satellite imagery, DEMs, and long-term climate records.

Chapter 3.4 (Experimental Process): All references to landslide susceptibility in this chapter have been eliminated to avoid confusion, as the experimental process is focused solely on wildfires and floods.

Specific comment 3: The formula for GINI impurity (Line 218) is wrong: the factor is the sum of pairwise products of the probabilities for each class, thus the correct formula should be:

$$\sum_{i=1}^{J} P_i(1-P_i) = \sum_{i=1}^{J} P_i - \sum_{i=1}^{J} P_i^2 = 1 - \sum_{i=1}^{J} P_i^2 \quad (1)$$

Moreover, it could be useful for assessing the robustness of the hyperparameter tuning to know which was the range the range of the hyperparameters tested in the Cross Validation and not only the final selection (Table 1), either in the main chapter or in the supplementary materials.

Response: Thank you for pointing out the error in the Gini impurity formula and for your suggestion regarding the hyperparameter tuning process. We have corrected the formula in the manuscript to accurately reflect the sum of pairwise products of probabilities for each class. The updated formula now reads:

$$\sum_{i=1}^{J} P_i(1-P_i) = \sum_{i=1}^{J} P_i - \sum_{i=1}^{J} P_i^2 = 1 - \sum_{i=1}^{J} P_i^2 \quad (1)$$

We added a range of hyperparameters in Table 1 according to your comment. The scikit-optimize's grid search performs iterative assessments using the training data to select the hyperparameter combination that optimizes a chosen performance metric (ROC and AUC) on the testing dataset. The best optimal hyperparameter combinations for each model are determined based on these performance metrics (in the last colum of Table 1).

Table. 1 The hyperparameter values in the optimization process.

Model	Optimized Hyperparameter	Explanation	Lower and upper limits	Optimal value
CART	max_Nodes	The maximum number of leaf nodes in each tree.	2-500	150
	minLeafPopulation	Only create nodes whose training set contains at least this many points.	1-10	2

RF	numberOfTrees	The number of decision trees to create.	100 – 1000	200
	minLeafPopulation	Only create nodes whose training set contains at least this many points.	1-10	1
	bagFraction	The fraction of input to bag per tree.	0.1 – 1.0	0.7
	seed	The randomization seed.	0 - 42	23

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