List of changes in the revised paper:

This document explains the changes made in the revised manuscript in order to address comments raised by the reviewers. Reviewers' comments are marked in **black**; authors' response is shown in **blue;** while the changes in the revised manuscript are marked in **red.**

Response to Reviewers Reviewer #1

In the study "Integrating multi-hazard susceptibility and building exposure: A case study for Quang Nam province, Vietnam", the authors use an established set of machine learning models to estimate the susceptibility of the Quang Nam province, Vietnam, to floods and wildfires. By creating a comprehensive geospatial database including various historic flood and wildfire events, topographical, geological, hydrological, and climatic features, along with land use and building data, the authors have developed a robust basis for susceptibility mapping regarding the floods and wildfires and offer interesting insights regarding exposure assessment. By combining susceptibility categories for wildfires and floods the study offers a more nuanced perspective on what type of spatially co-occuring multi-hazard events could be expected in different areas of the study region.

The study presents relevant insights into susceptibility factors for floods and wildfires. However, there are several major aspects that require clarification:

Response: Thank you for your helpful and detailed comments and suggestions. They have pushed us to improve the manuscript, and we have tried to incorporate it into our revised version. We have carefully read and addressed all comments, point by point, below.

Specific comment 1: The authors use the term multi-hazard repeatedly in their study. They introduce the term in line 49 to 51 and indicate that "Multi-hazard susceptibility assessment provides insights into the spatial co-occurrence of multi-hazard" (line 53). Further specification in what type of multi-hazard interactions are relevant for the selected hazard pair of floods and wildfires is not provided. Yet, the study would significantly benefit from such a clarification. For instance, the study could benefit from discussing the dynamic interplay between flood probability in wet seasons and wildfire likelihood in dry seasons. Based on previous studies looking at wildfire-flood interactions, most emphasis has been put on the reduction of infiltration/storage capacity in natural systems that have been burnt (see e.g. Mueller et al. 2018). Similarly, it seems physically plausible that a flood might even reduce the risk of wildfires due to the large-scale wetting of vegetation. I am thus wondering whether the current set-up of this study would rather serve the purpose of multiple hazard susceptibility mapping as it neglects the hazard interaction dynamics that are of critical importance for multi-hazard events? This is particularly critical, since the authors want to make the step from susceptibility mapping towards exposure mapping. But due to (temporal) dynamics of multi-hazard events, an assumption of constant exposure might be worth discussing.

Mueller, M., Lima, R. E., Springer, A. E., & Schiefer, E. (2018). Using matching methods to estimate impacts of wildfire and post wildfire flooding on house prices. Water Resources Research, 54, 6189–6201. https://doi.org/10.1029/2017WR022195

Response: Thanks for your comment. We agree that a multi-hazard analysis is not considered in the sense of interactions between hazards. However, the analysis of the two hazards (floods and fires) in our study is the first step towards a fully multi-hazard risk assessment by looking at where there is a spatial overlap. We explained the dynamic interplay between flood probability in wet seasons and wildfire likelihood in dry seasons in Section 1. Introduction, as follows:

"The term "multi-hazard" refers to the fact that hazards often interact in complex ways, and their combined impact might be greater than the sum of individual hazards (Wing et al., 2018). The dynamic interplay between flood probability in wet seasons and wildfire likelihood in dry seasons can be influenced by various factors, including environmental conditions, climatic patterns, topography, vegetation cover, and land use patterns (Skilodimou et al., 2021; Bountzouklis et al., 2022). Wildfires can significantly impact landscape hydrology by destroying vegetation cover and disrupting soil structure, reducing infiltration rates and heightening surface runoff during subsequent rain events (Mueller et al., 2018). Floods can reduce the formation and expansion of wildfire risks by wetting vegetation and soil, temporarily mitigating the likelihood of ignition and fire spread (Papaioannou et al., 2023). However, flood events can disrupt natural drainage patterns, saturate soils, and promote vegetation development, fueling forest fires in dry seasons (Eisenbies et al., 2007). In general, the formation of multi-hazard events often results from dynamic spatial and temporal interactions among various factors (De Angeli et al., 2022); significantly, floods and wildfires can exacerbate or mitigate each other's impacts depending on seasonal fluctuations, environmental conditions or extreme climatic variability (Yu et al., 2023). Broadening the assessment framework for these spatial and dynamic interactions can lead to a more comprehensive and accurate risk evaluation (De Angeli et al., 2022). Thus, multi-hazard susceptibility and exposure assessments are required for efficient disaster risk management (Zhou et al., 2015). Multi-hazard susceptibility assessment provides insights into the spatial co-occurrence of different hazard types (Rusk et al., 2022). Multi-hazard exposure assessment enables the evaluation of the potential impact of multi-hazards on people, buildings, and critical facilities, which supports disaster management activities (De Angeli et al., 2022)."

Specific comment 2: While the authors do a great job to explain the significance of each of the single-hazard risks in the study area, the importance of the multi-hazard event remains unclear. Also unclear remains, what type of floods the authors are referring to. In the introduction multiple floods including coastal floods are mentioned. The remainder of this study seems to focus on riverine floods.

Response: You are right; the importance of the multi-hazard events requires more complex hydrological modelling to consider the interactions of these two hazards at the catchment scale. We added this limitation to the discussion section.

The flood hazards in the study area are mainly riverine floods. The research area is in Vu Gia-Thu Bon river basin, one of the largest river basins in Vietnam. We revised the manuscript and also explained this problem in Section 1. Introduction, according to your comment as follows:

"Quang Nam province is characterized by a coastal region with low-lying topography facing high flood risks due to heavy rainfall, typhoons, and potential breaches of dams and levees (Chau et al., 2014). The province has two large river catchment: the Vu Gia - Thu Bon and Tam Ky rivers. Away from the coast, the province is characterized by steep hilly terrains and dense river network. The prolonged heavy rainfall of the monsoon season in this dissected landscape results in yearly riverine floods in the lowland area and along the coast. This issue holds particular significance for the Quang Nam province because flood events pose a direct threat to human lives and cause significant damage to its infrastructure, education, economic development, and health-related services (Lee et al., 2020).".

Specific comment 3: The authors provide a comprehensive list of study aims. However, I am not sure how targets 1 and 4 are covered in this study. The authors describe well the process of deriving the susceptibility maps, yet there's a lack of evidence considering spatially or temporally co-occurring events where hazard dynamics are relevant. Coming back to the previous comment, multi-hazard events are significant because of their interactions which lead to non-linearly altered impacts. It is also unclear how the outputs of the workflow are assessed to determine whether it is a useful assessment tool and provides decision-support (for what exactly?) regarding risk reduction and management.

Response: Thank you for your comments; we revised the target 1 and removed the target 4. The reviewer is right in saying that we model each hazard separately and then look at spatial co-occurrence (combining two different susceptibility maps). We added the limitations into Section 5. Discussion:

"Considering the spatial occurrence of hazards and the associated exposure to build-up environment enables highlighting which areas and which proportion of buildings are exposed to one specific hazard or both, which can already be relevant for risk management. To consider temporal relationships between hazards (i.e. fire during the dry season inducing flood in the next rain season) or non-local dynamic interactions (i.e. wildfire in upper catchment increasing flood occurrence downstream) would require more process-oriented hazard modelling at a more local scale. A more complex physically-based model, typically at the scale of a smaller river catchment, would be required to investigate how the occurrence of one hazard influences the probability of occurrence of another hazard later in time and/or in the same or nearby location (Jenkins et al., 2023). Another significant limitation of this research is the absence of consideration for stakeholder engagement and feedback while developing and applying the multi-hazard exposure estimation model. Interaction with stakeholders in charge of risk management would help to identify further the challenges posed by exposure to multi-hazard, validate the modelling approach proposed in this research and specify how the result of such model can best contribute to strengthening the effectiveness of risk management strategies.”.

Specific comment 4: The method section could benefit from some streamlining. While the overall workflow as presented in Figure 2 is clear and straightforward. Aligning the subsection sequence (and subsection titles) with the workflow presented in Figure 2 would reduce redundancy and improve clarity. Specifically, sections such as 3.3.3 could be embedded in the overall flow (first check multicollinearity, then apply ML model?). Another suggestion would be to present GEE already as part of the methodology flowchart as the overarching framework in which data are combined, the models are set up, tested, and used etc.

Response: Thank you for your suggestions. We adjusted the subsection sequence more clearly according to your suggestions.

Specific comment 5: The process of combining data for the flood and wildfire inventories could benefit from further elaboration (either in the main text or in a supplement). Regarding floods: a) it seems that the flood events point data and map data were combined. How was this done? How were the points prepared for the combination with the maps for the training? To determine the non-flood points, how were the flood markers considered? b) A specification what made the three flood events historic would be interesting. Are those all the same flood type (e.g. fluvial floods)? For wildfires: a) Which period was considered to determine the 1,911 wildfire locations? Was it just within the last year or the past decade or…? B) When selecting non-wildfire locations, it was assumed that built environments cannot burn. However, when it comes to exposure, to wildfires we would assume that the built environment must be exposed to these fires somehow. It would be helpful if the authors could elaborate in this section (or in the section when describing the built environment), how the choice that built environments are non-wildfire locations influence the outcomes of the machine learning training to spot fires that endanger built environment. Also, it would be interesting to learn whether there are any multi-hazard events in the dataset of historic events (potentially to be added to the supplement?)?

Response: We thank the reviewer for the excellent comments. We agree with the reviewer that this is a bit weird and can lead to reducing the estimated exposure of build-up area to burn. We explained as follows:

* Regarding floods:

We combined the flood locations from 2 sources:

1) 847 historical flood marks of 2007, 2009, and 2013 floods. This data was investigated by the Quang Nam Provincial Steering Committee of Natural Disaster Prevention and Control in 2013 and JICA in 2007 and 2009. These points were recorded with specific measurements of flood depth.

2) 47 new flood locations were detected from Sentinel 1 during 2017-2021. We get 47 points at the centroid of 47 flood area polygons. In reviewing your comments, we have checked all 2007, 2009 and 2013 flood points, and they are also within the 2017-2021 flood zone. Additionally, the non-flood points were determined by overlaying all flood inventory onto the study area. We explained these problems quite clearly in Subsection 3.2.1. Inventories of floods and wildfires are as follows:

“Developing accurate hazard inventories is crucial for susceptibility mapping (Bui et al., 2022). In this study, the flood marker points recorded for all flood events from 2007 to 2023 were considered, as reported by the Quang Nam Provincial Steering Committee of Natural Disaster Prevention and Control. We removed duplicate flood points. A total of 847 historical flood marks were obtained from this database – these correspond mainly to the 2007, 2009, and 2013 flood events with the largest spatial extent. Each flood mark comprises a unique identifier, geographical coordinates (longitude and latitude), flood depth, and provider information. A second source of information was derived from mapping flood extent on SAR data from Sentinel 1 for 2017 to 2023, which we compare with official reports from the Provincial Committee. The flood detection algorithm described in Mai Sy et al. (2023) was implemented in Google Earth Engine. Inundation areas detected on the different Sentinel 1 scenes were overlayed and compared with the flood mark locations to avoid duplicates. 47 new flood sites were detected and integrated as additional points (using the centroid of the flood site), with 847 historical flood marks for the inventory data.

The final flood inventory includes 894 flood locations: 70% of them (626 locations) were randomly selected to calibrate the flood susceptibility model, and the remaining 30% (268 locations) were designated for validating purposes (Figure 3). In addition, 894 non-flood locations were randomly selected across the study area using the “Create random point tool” in ArcGIS software. Non-flood points were chosen only in zones outside the flood-affected zones in our inventory. Additionally, we excluded steep slopes (>10°) or areas of positive relief (such as hilltops) from the selection of non-flood points, as these locations that can not be associated with floods would artificially increase the accuracy of the susceptibility model. The non-flood points were then classified in a ratio of 70/30, mirroring the classification of the flood locations. This process was undertaken to create a comprehensive database for input into the GEE platform, which was utilized for modelling and validation.”

* For wildfires:

For the wildfire inventory, this study involved the collection of 1,911 wildfire locations recorded during the dry season (March to August) from 2020 to 2023 (**Figure 3**), from the National Forest Protection Department's website (available at https://watch.pcccr.vn/thongKe/diemChay). This agency utilizes data from many satellites (AQUA, J1, SUOMI, and TERRA) that are regularly received at the TerraScan receiving station located at the National Forest Protection Department. The use of near-infrared bands from many satellites helps to identify the presence of heat associated with active fires on the ground (Giglio et al., 2008). The website database was checked and filtered to avoid duplicated wildfire locations, dates, and commune data field conditions. The wildfire location data (points) represent the specific fire sites captured by one type of satellite inside a particular commune at a given time. We filtered the database of the National Forest Protection Department to retain only wildfire spots exceeding a minimum size threshold of 2 hectares, as smaller fire areas should be considered human-induced. To determine the non-fire points, we randomly selected points within the zones with forested and natural vegetation land cover, which were not identified as wildfires in the inventory. We excluded residential areas, water, and crop areas from the selection of non-fire points, as these cannot be associated with wildfires corresponding to the criteria selected in this study and would artificially increase the accuracy of our susceptibility model.

We agree with you that although built environments are not typically considered burn points, they can still be exposed to wildfires in various ways. However, Quang Nam is a central coastal province of Vietnam; the population is concentrated in the coastal plain, along National Highway 1A, Vu Gia Thu Bon and Tam Ky plains. In addition, the selected non-fire points have been verified and confirmed through field surveys and local authorities.

Specific comment 6: The authors comprehensively describe what influencing factors are considered. For some of the influencing factors with temporal and/or spatial variability (e.g. precipitation, temperature) it is unclear how the collected data are further processed. For example, precipitation are collected for a period of 10 years, while the considered flood marker cover the periods 2007, 2009, 2013 and 2017-2021. The same applies for the temperature data where data were available only for 3 years. How were the influencing factors considered for wildfires that took place outside of this period (assuming that this is the case, since no specification is made with regards to the time horizon over which the wildfire locations were collected). Same holds for the NDVI index, where it is not clear when this imagery has been produced. Additionally, it would be valuable if the authors could reflect on the interpolation method used to inter/extrapolate between the gauge stations. Are the gauges distributed sufficiently well and do the elevation/similarity characteristics allow for the application of the chosen method?

Response: For some of the influencing factors with temporal and/or spatial variability (e.g. precipitation, temperature), we used the IDW interpolation method to extract the rainfall and temperature for the study area. In the manuscript, we explained the collected time and processing technique for these data:

“Daily rainfall data was recorded from 2003 to 2023 and collected from 33 rain gauge stations in Quang Nam province. This study used the *Inverse Distance Weighted* technique to separately generate average yearly cumulated rainfall maps for the rainy and dry seasons.”

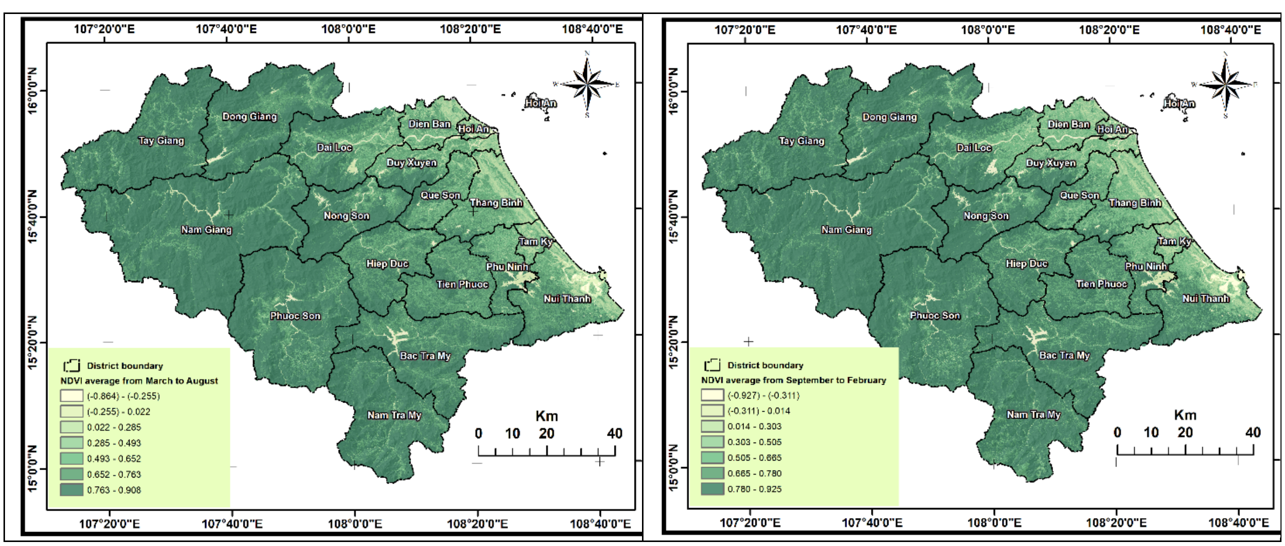
and

“The daily temperature data were collected from March to August between 2020 and 2023 (dry seasons) at https://power.larc.nasa.gov/data-access-viewer/. This research used the Inverse Distance Weighted approach to produce a temperature map specifically for dry seasons (March to August).”.

In this study, the historical flood marker points have been considered continuously from 2007 to 2023. However, we collected, synthesized, and removed duplicate flood points, so there were 847 historical flood marks of 2007, 2009, and 2013 historical flood events obtained from the Quang Nam Provincial Steering Committee of Natural Disaster Prevention and Control and 47 flood points explored from Sentinel 1 for 2017 to 2023. We added the information into Subsection 3.2.1 Inventories of floods and wildfires.

We also explained the NDVI calculation for this research: “This study calculated the NDVI index from the Landsat 8 imagery. The NDVI index is the average value for the rainy and dry seasons separately from 2020 to 2023 – the same period over which the fire dataset is available.”.

We revised the NDVI index for flood hazard and wildfire hazard modelling. The NDVI for flood hazard is from September to February (rainy season), and wildfire hazard is from March to August (dry season) as follows:



Specific comment 7: While the authors do well in qualitatively describing the algorithm and underlying principles, key information regarding the hyperparameter tuning (and final chosen ones) and pruning techniques are not provided. As such it is difficult to reproduce the results. The results of the tests for the hyperparameter tuning could be useful additions as supplemental information. On a similar note, further quantitative information regarding the bootstrapping (e.g. number of bootstrapped samples) could be relevant as well. Furthermore, it would be helpful for readers less familiar with ML methodology (like me) to link the parameters used in the equations to the inputs used in this specific study. For example, what are D, N, X and Y in the CART?

Response: We thank the reviewer's comment. We explained the used parameters in the equations in Subsection 3.3.2 Machine learning approach for hazard susceptibility modelling. Additionally, we also explained key information regarding the bootstrapping, the hyperparameter tuning (and final chosen ones), and pruning techniques in Subsection 3.4 Experimental process, as follows:

This study employed the GEE cloud computing platform for the pixel-based CART and RF algorithms to build susceptibility maps for flood and wildfire hazards separately. The input data was collected from various sources and formats. First, we pre-processed and converted these data into raster format with 30-meter spatial resolution in a GIS environment. Then, these data were uploaded into the GEE platform. Hyperparameter tuning technique was used to optimize the performance of ML algorithms, as they significantly affect the accuracy, efficiency, and generalization ability of ML models (Schratz et al., 2019). Various hyperparameter tuning methods have been used in landslide studies, such as grid search, random search, gradient-based optimization, and Bayesian optimization (Sameen et al., 2020; Rong et al., 2021; Abbas et al., 2023; Sun et al., 2024; Ma et al., 2023). This hyperparameter tuning process of grid search was used for the modelling in this study, including the following steps:

1. Set up the environment: install Python packages in the Google Earth Engine (GEE) Application Programming Interface (API) to handle geospatial data and scikit-learn to develop ML models.
2. Data preparation: upload fifteen landslide-affecting factors to the GEE environment to build the landslide susceptibility map. The training and testing datasets have also been uploaded to this platform.
3. Hyperparameter tuning: use scikit-learn to develop various ML models (CART and RF) and define the hyperparameter search spaces for a grid search. This step involves setting reasonable value ranges for each hyperparameter in each model, for CART model (*max_Nodes, minLeafPopulation*) and RF model (*numberOfTrees, variablesPerSplit, minLeafPopulation, bagFraction, max_Nodes, seed*), described in **Table 1**. Then, 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 validation set. The best hyperparameter combinations for each model are determined based on these performance metrics.

4. Model assessment: optionally, the final evaluation involves retraining the predictive models with the chosen hyperparameters on the training data. The performance of these retrained models is then assessed using the ROC curve and AUC value on the validation dataset to gauge their effectiveness.

Table. 1 The hyperparameter values in the optimization process.

Model	Hyperparameter	Explanation	Lower and upper limits	Established value
CART	max_Nodes	The maximum number of leaf nodes in each tree.	Integer, default: 1	150
	minLeafPopulation	Only create nodes whose training set contains at least this many points.	Integer, default: 1	2
RF	numberOfTrees	The number of decision trees to create.	Integer	200
	variablesPerSplit	The number of variables per split. If unspecified, use the square root of the number of variables.	Integer, default: null	null
	minLeafPopulation	Only create nodes whose training set contains at least this many points.	Integer, default: 1	1
	bagFraction	The fraction of input to bag per tree.	Float, default: 0.5	0.7
	Mmax_Nodes	The maximum number of leaf nodes in each tree. If unspecified, defaults to no limit.	Integer, default: null	null
	seed	The randomization seed.	Integer, default: 0	23

Specific comment 8: The discussion section could benefit from some critical reflection on the decisions made in this study set-up and discuss some of the limitations that come with it. This is particularly critical since the authors claim, that this workflow could be extended by including different hazards and applied in different regions. For example, with reference to Line 458: Both in terms of inputs as well as in terms of how multi-hazard has been defined and conceptualized. The aspect of dynamics has been neglected and it has mostly been looked at spatially co-occurring (without temporal memory) hazard events. Or with reference to Line 489: From the results it seemed that multi-hazard seems to be a less prominent problem (both in terms of susceptibility as well as the exposure). So, a planner could also read the results as mentioned by the authors: “flood risk is much more of a problem, we should focus on that!”. I would suggest specifying that with these exposure maps, further analysis into the impacts of multi-hazard events can be made that ultimately can inform multi-hazard risk assessment and thus effective DRM.

Response: We thank the reviewer's comment, we agree that this research still lacks evidence of interactions between forest fires and floods in the study region. We cannot confirm that there have been more floods in the years with many wildfires or in the catchments that have experienced large fires. One issue overlooked so far is that wildfires and floods do not have to occur at the same location to interact - burned areas can happen in the upland and generate/influence floods in the lower basins. We added the limitations of this research in Section 5. As per your advice, the discussion follows:

"Considering the spatial occurrence of hazards and the associated exposure to build-up environment enables highlighting which areas and which proportion of buildings are exposed to one specific hazard or both, which can already be relevant for risk management. To consider temporal relationships between hazards (i.e. fire during the dry season inducing flood in the next rain season) or non-local dynamic interactions (i.e. wildfire in upper catchment increasing flood occurrence downstream) would require more process-oriented hazard modelling at a more local scale. A more complex physically-based model, typically at the scale of a smaller river catchment, would be required to investigate how the occurrence of one hazard influences the probability of occurrence of another hazard later in time and/or in the same or nearby location (Jenkins et al., 2023). Another significant limitation of this research is the absence of consideration for stakeholder engagement and feedback while developing and applying the multi-hazard exposure estimation model. Interaction with stakeholders in charge of risk management would help to identify further the challenges posed by exposure to multi-hazard, validate the modelling approach proposed in this research and specify how the result of such model can best contribute to strengthening the effectiveness of risk management strategies.".

Specific comment 9: Have the authors considered to deposit input data maps, algorithms, and model code in FAIR-aligned repositories/archives in alignment with the ambition of NHESS to support open data?

Response: Thanks for your comment. We will provide input data maps, algorithms, and model code supporting the findings of this study according to your comment.

Specific comment 10: Minor comments

1. The introduction generally includes all relevant elements. The overall story for the introduction could be refined, e.g. by avoiding duplication (compare lines 91 to 99 with lines 32 to 45). Similarly, lines 60 to 88 provide in depth introduction to the ML and previous practice. At the same time, the authors mention multiple information which are quite interesting, but seem to be not relevant for this study

(e.g. line 61 to 63; 63 to 65; 68 to 70). I would also suggest trying to integrate lines 60 to 77 with the current practice described in lines 78 to 88).

Response: We improved paragraphs in the Introduction section to avoid duplication.

2. The methodological flow is described nicely. However, it seems that there is a lot of overlap in lines 135 to 139 compared to line 139 to 147. Streamlining the text could help the reader.

Response: We rewrote the text in the Subsection 3.1 Methodology flowchart to avoid duplication.

3. Figure 2: The flowchart is very nice. Couple of questions:
   - What is the importance of different colors used in this figure? I tried to understand why certain boxes were colored in different colors (e.g. flood influencing factors vs floods, same colors for e.g. ML vs Testing…). If there is a reason for specific colors, I would suggest making it clearer (e.g. explaining in the figure description) or otherwise reduce the number of colors used.
   - I was expecting that the susceptibility maps would be built after the validation exercise. The flow suggest that they were created directly from the training dataset?

Response: We reduced the number of colors used in the flowchart and adjusted the order to build susceptibility maps.

4. Line 174 to 175: I don't understand this sentence. Is that the method to determine whether a wildfire has occurred?

Response: That is the method to determine whether a wildfire has occurred in the Quang Nam province by the National Forest Protection Department (available at https://watch.pcccr.vn/thongKe/diemChay)

5. Line 176 to 177: This sentence seems unclear to me. What filter has been applied to filter what?

Response: A file with the Excel format was explored and downloaded from the website of the National Forest Protection Department (available at https://watch.pcccr.vn/thongKe/diemChay), which is collected from many satellite image sources, so it was necessary to check and filter to avoid duplicated wildfire locations, dates, and positions.

6. Line 180: it is not clear whether areas larger than 2 ha were assumed to be human caused.

Response: Wildfire areas smaller than 2 ha were interpreted as induced by human activity based on annotations provided in the statistical data of the National Forest Protection Department. This information was represented in our manuscript as follows:

"We used a filtration process only to retain wildfire spots that exceed a minimum size threshold of 2 hectares, as smaller fire areas should be considered human-induced according to the National Forest Protection Department."

7. Figure 4: I would suggest to either add a bit more text to explain the different maps as part of the influencing factors or place Figure 4 in the appendix. In the appendix, individual plots could also be resized so that legends are better readable.

Response: We moved Figure 4 to the appendix.

8. Line 188: How was this set of influencing factors determined? For flooding, proximity to coast could also be a determinant of (coastal) flooding?

Response: The set of influencing factors was determined based on their relevance and the data availability within the research area. In this study, we mentioned riverine floods in the Quang Nam province, so we did not use the proximity to the coast.

9. Line 301 to 302: What does these choices of filtering for confidence interval mean? What type of buildings are more likely to be disregarded with the chosen confidence intervals?

Response: The type of building and confidence intervals are presented in the study of Sirko et al. (2021) (https://arxiv.org/abs/2107.12283). We cited this work in the manuscript. We also based on the province population to find the appropriate confidence intervals for the research area. The population is 1.5 million, and the total buildings with 80% confidence intervals are 442,220. Assume that about 3-4 people per building on average is realistic. We also randomly manually check building accuracy on Google Earth for the appropriate confidence intervals.

10. Line 354 to 366: This section seems almost identical with the workflow presented and discussed alongside figure 2. I would suggest streamlining the method section and remove Section 3.2.2 and add relevant information in previous sections. For example, the information that CART and RF work cell-based is quite a relevant information given that the flood and wildfire inventories are point information.

Response: We agree with you. We removed Subsection 3.2.2 and added relevant information to explain how CART and RF models work.

11. Line 386: Can the authors explain how the importance sampling can inform which factors have the highest impact on multi-hazard formations? The algorithm used is applied to single hazards (either floods or droughts) but not the multi-hazards?

Response: This is the relative importance of variables in modelling single-hazard and not multiple-hazards.

12. Figure 5: Aligning terminology (either testing or validating dataset) would help the readability. Also, what does the Se stand for?

Response: We fixed all texts with training and testing datasets. We added the note in the figures that ''Se'' term stands for standard error.

13. Line 453 to 455: Can the authors clarify what they mean when they claim that floods and wildfires have 'similar spatial extent' and frequency?

Response: In this study, we synthesized and collected flood and wildfire inventory based on historical data, satellite imagery, and reports from relevant authorities. While the frequency of floods and wildfires occurs separately, the occurrence of both hazards depends on the season or year.

14. Line 483 to 485: How is this finding affected by the choice to define built-up areas as non-wildfire areas when creating the training data set? It seems that seeing less fires in built up areas could also be influenced by the fact that the ML algorithms were taught that wildfires just don't occur in more densely populated areas?

Response: We agree with you. We do NOT select non-fire points in the build up environment.

15. Line 486: How do the authors derive the claim, that the chosen method works well with recurring hazard events? The applied methods seemed not to account for the changes in the physical system induced by either floods or wildfires.

Response: We thank the reviewer for your excellent comment. We added this limitation into Section 5. Discussion: "Our findings suggest that ML models such as CART and RF should be used to analyze multi-hazard exposure for various geographical areas particularly susceptible to recurring incidents of wildfire and floods. Our data has shown these tools to model risk and exposure effectively. However, the applied methods in this study did not account for the changes in the physical system induced by either floods or wildfires.".

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List of changes in the revised paper:

This document explains the changes made in the revised manuscript while adressing the comments raised by the reviewer. Reviewers' comments are marked in **black**; authors' response is shown in **blue;** while the changes in the revised manuscript are marked in **red.**

Response to Reviewers Reviewer #2

General comment: While the paper is generally well-written, there could be improvements in organizing the content to enhance readability and flow, particularly in presenting the methodology and results sections.

Response: We thank the reviewer for helpful and detailed comments and suggestions. They contributed to further improving our manuscript. The methodology section has been significantly restructured to avoid duplication and improve readability.

Specific comment 1: It would be beneficial to include a more detailed discussion on the validation process and uncertainty analysis of the models to ensure the robustness and reliability of the findings.

Response: The validation is embedded in our susceptibility model (but does not account for the exposure aspect). There are several sources of uncertainty, including models and exposure data. Future research might modify and enhance the exposure and susceptibility groups.

Specific comment 2: It is not entirely clear from the paper how the multiple hazards (floods and wildfires) are integrated into the multi-hazard exposure estimation. The methodology section should provide a more detailed explanation of the approach used to combine and assess the compound risk arising from different hazards. Clarifying this aspect would help readers better understand the synergistic effects of multiple hazards and how they contribute to overall risk.

Response: Thanks for your comment. We clarify that the hazard susceptibility maps were produced separately for flood and wildfires, and then combined in a multi-hazard susceptibility maps that consider only the spatial co-occurrence of these hazards, without considering dynamic interactions. We explained the approach used to combine and assess the compound risk arising from different hazards in Section 3.1 Methodology flowchart, as follows:

3.1 Methodology flowchart

The multi-hazard exposure assessment process comprises seven main stages, as follows: (1) Inventory maps of each hazard were created based on historical data collection; (2) Factors potentially influencing the spatial distribution of floods and wildfire were collected, including topography, geology, hydrology, climate (temperature, wetness, wind), and land use based on their relevance and data availability (Luu et al., 2018; Pham et al., 2021); (3) The influencing factors of each hazard were tested for multicollinearity to enhance the reliability and stability of the model's predictions, (4) CART and RF models were developed on the GEE cloud computing platform to construct susceptibility maps of floods and wildfires separately, (5) The Area Under the ROC Curve (hereafter, AUC) was utilized to assess the predictive performance of the susceptibility maps to choose the best model for each hazard and validate it, (6) The flood susceptibility map and the wildfire susceptibility map were combined to build a multi-hazard susceptibility map, and (7) this multi-hazard susceptibility map was overlaid with the building data to create a multi-hazard exposure map for the study area (**Figure 2**).

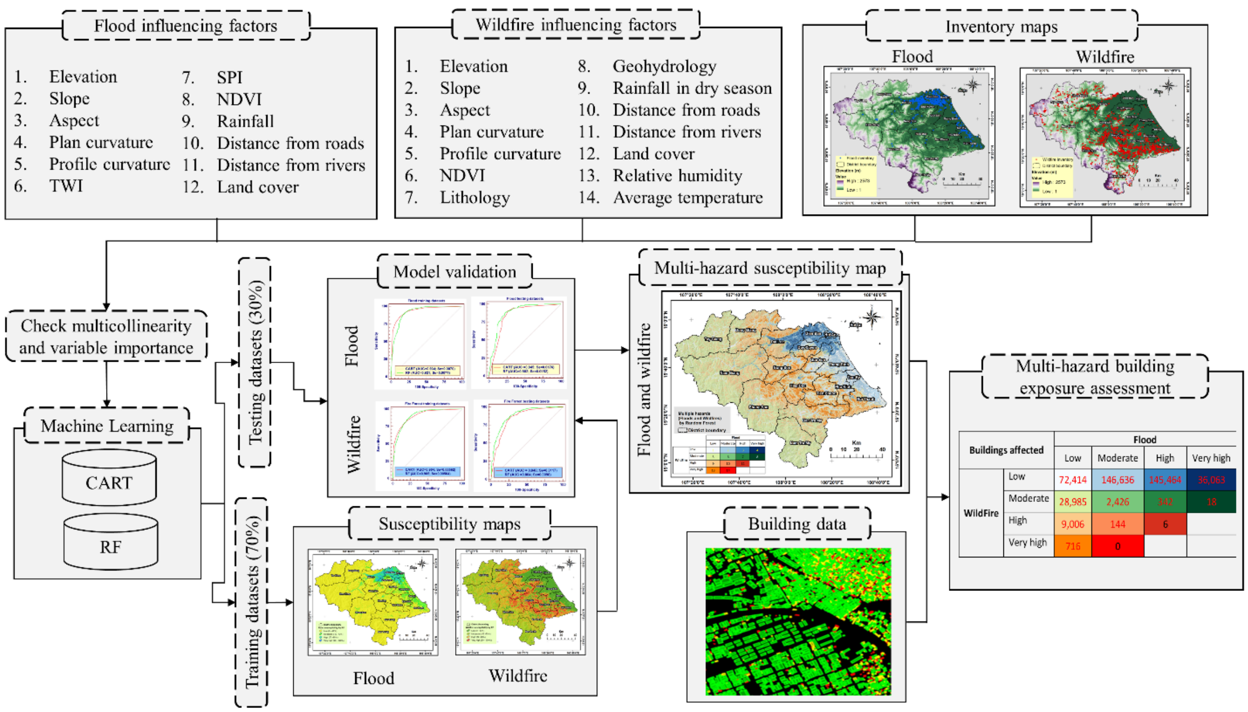

Figure 1. Methodology flowchart for multi-hazard exposure assessment and mapping in this study.

Specific comment 3: My previous comment is of special relevance when the two hazards analyzed are common to happen in different hydrological seasons. Exploring the interactions, dependencies, and cumulative effects of floods and wildfires would provide valuable insights into the complex nature of multi-hazard scenarios. A comparative analysis of the combined risk versus individual hazards would further highlight the significance of considering multiple hazards in risk assessment and management.

Response: We agree with you. To highlight the significance of considering multiple hazards in risk assessment and management, we explained the dynamic interplay between flood probability in wet seasons and wildfire likelihood in dry seasons in Section 1. Introduction. We acknowledge that your assessment is limited to spatial co-occurrence without considering temporal links or dynamic interactions, so we added the limitations to Section 5. Discussion:

"Considering the spatial occurrence of hazards and the associated exposure to build-up environment enables highlighting which areas and which proportion of buildings are exposed to one specific hazard or both, which can already be relevant for risk management. To consider temporal relationships between hazards (i.e. fire during the dry season inducing flood in the next rain season) or non-local dynamic interactions (i.e. wildfire in upper catchment increasing flood occurrence downstream) would require more process-oriented hazard modelling at a more local scale. A more complex physically-based model, typically at the scale of a smaller river catchment, would be required to investigate how the occurrence of one hazard influences the probability of occurrence of another hazard later in time and/or in the same or nearby location (Jenkins et al., 2023). Another significant limitation of this research is the absence of consideration for stakeholder engagement and feedback while developing and applying the multi-hazard exposure estimation model. Interaction with stakeholders in charge of risk management would help to identify further the challenges posed by exposure to multi-hazard, validate the modelling approach proposed in this research and specify how the result of such model can best contribute to strengthening the effectiveness of risk management strategies.".

Specific comment 4: Consideration of stakeholder engagement and feedback in the development and application of the multi-hazard exposure estimation model could enhance the relevance and applicability of the research to real-world scenarios.

Response: We agree that consultation with the stakeholders is very important. We will consider stakeholder engagement and feedback in the next stage of our GeoSciRe project. At this stage, we only present some potential results and approaches in this paper. We added this limitation to the Discussion section.

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