Referee comments 1

The study presents and evaluates a globally applicable machine-learning framework for integrated landslide and flash flood susceptibility mapping, demonstrated in the multi-hazard-prone Liguria region of Italy, with the aim of supporting effective risk management. The topic is relevant and promising; However, several parts of the manuscript require further modifications and improvement before it can be considered for publication in the journal

Comment 1:
Title: I understand that the study area is well presented within the Mediterranean context. However, a minor change to the title would improve clarity and better specify the case study. Consider replacing "Mediterranean" with "Liguria region, Italy."

Response 1:
Good suggestion, the title will be updated to:

A single framework for assessing flash flood and landslide susceptibility: an application to the Liguria region, Italy

<u>Introduction Section:</u>

Comment 2:
Line 41: The distinction between land cover and vegetation, is unclear. For instance, is vegetation considered part of land cover, or are you referring to a vegetation index such as NDVI?

Response 2:
This section will be rewritten – see below in Itlaics - to clarify what the study in Tehrani et al. 2021 included and what our study has added.

Our starting point is Tehrani et al., (2021) which originally developed a landslide detection ML model, and subsequently adapted it to a landslide susceptibility mapping framework. The latter has been extended in this study with (i) the inventory construction, (ii) the systematic inclusion of input layers relevant to flash floods and landslides, (iii) the assessment of multicollinearity between the layers, and (iv) the study of behaviour similarity between both hazards resulting in a unified susceptibility framework.

Comment 3:
Lines 46–47: "…due to high susceptibility…landslides." How is this demonstrated? Please cite at least one study to support this statement and make it more precise.

Response 3:
References will be added.

Comment 4:
Study Area: Please provide information on recorded damage and economic losses in the region, if available.

Response 4:
A reference including the economic losses reported by Liguria only for national emergency events and hydrogeological disasters will be added.

Comment 5:
Line 61: "…period of 1910–2010…1990." Is more recent meteorological data available, or is it excluded from the modeling? Also, is the inventory data collected for the same period, or how was it determined?

Response 5:
We were looking to include trends in precipitation data for Liguria specifically and that was the only study to our knowledge. We have added another more recent reference that studies the temporal change in rainfall for the

whole of Italy and extracted information for Liguria.
The inventory data dates from 1940 to 2024 with gaps (Figure 3) the period is defined by the availability of open data sources.

Comment 6:
Line 68: Please rephrase, as the term "hydrology" is too general and should be more specific in this context.

Response 6:
Will do.

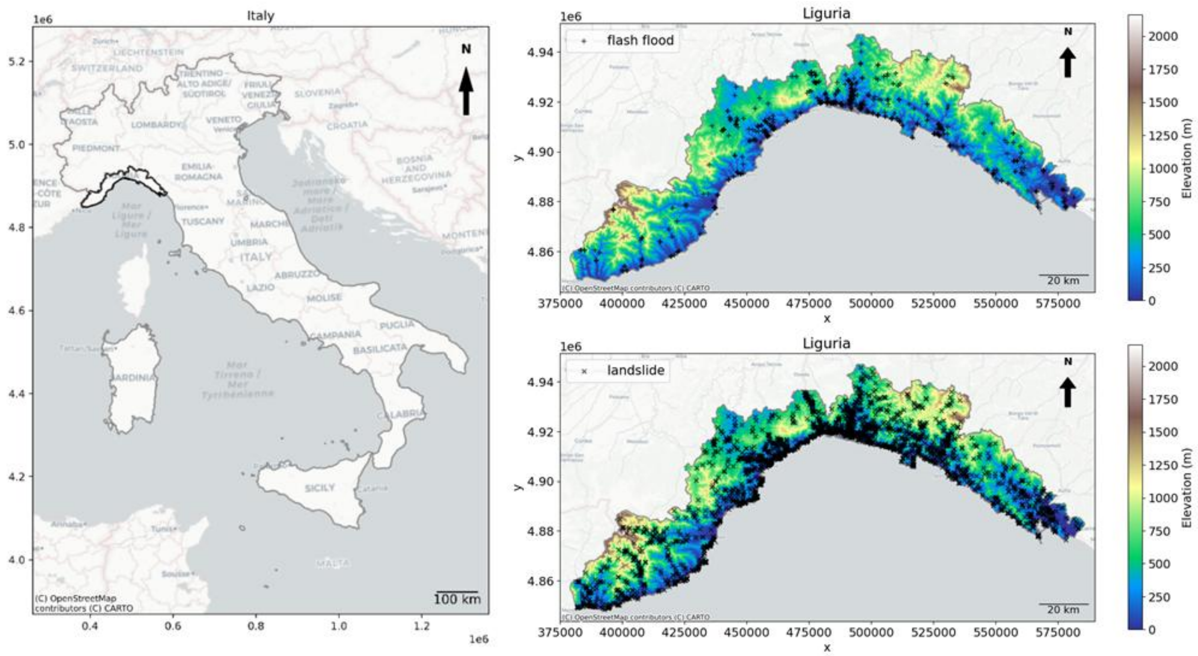
Comment 7
Line 69: "…from 1 to 5 hours." Please provide a citation.

Response 7:
Will be removed, as it originally appeared in Silvestro et al. (2018). Instead, we are citing two other papers that indicate the formulae rather than the actual value. It seems that the authors had computed the response time within their research. Instead, we added the runoff ratios which were explicitly computed in that paper.

Comment 8:
"Figure 1: The map requires the following improvements:

• Add scale bars for both the left and right panels.
• Include a north arrow.
• The black lines and rectangle are somewhat confusing. I suggest either removing the two lines (currently only indicating flash floods) or adjusting them to also indicate landslide areas.
• Consider using the term "Elevation" instead of "DEM" in the legends for both flash flood and landslide maps. While it is technically a DEM, "Elevation" would be clearer for the reader.
• Ensure that the coordinates (longitude and latitude) are consistent across all maps."

Response 8:
The figure 1 and the term DEM have been updated.



Data Section:

Comment 9:
Line 84: "(1) the AVI…Italia)" requires a proper citation and/or a link to the data source.

Response 9:
The link will be added to the text.

Comment 10:
Line 89: "OpenStreetMap" needs to be cited.

Response 10:
Citation will be added.

Comment 11:
Line 90: "(2) ARPAL" also requires a citation.

Response 11:
The link will be added to the text.

Comment 12:
Line 99: Replace "didn't" with "did not."

Response 12:

Will be replaced

Comment 13:
Figure 2: Include the year(s) of both inventories in the figure caption.

Response 13:

Will be added

Comment 14:
Lines 126–128: "…coarse-resolution…finer resolution." Please clarify precisely what do you mean and provide details. This statement can also be supported with a reference.

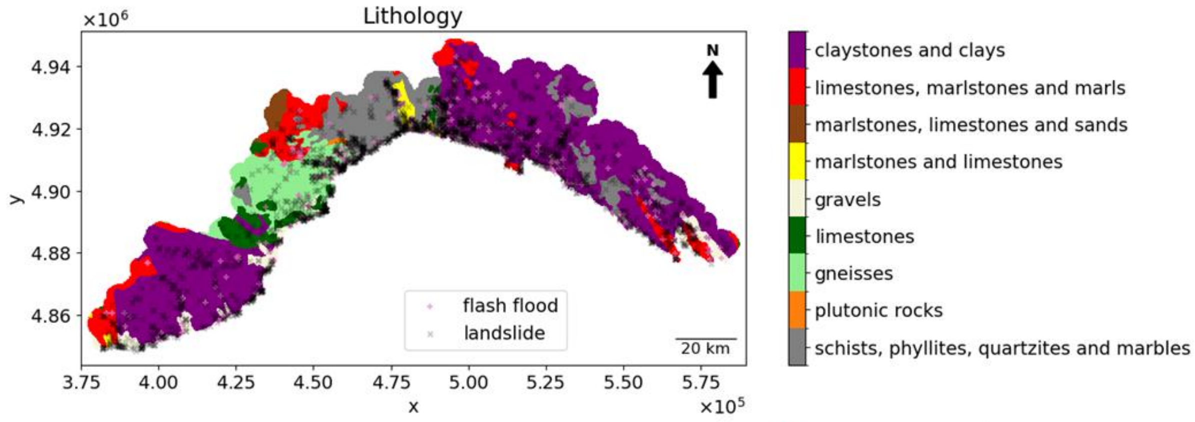
Response 14:
We've specified that coarser is meant by coarser than 4 km and finer resolutions from 30 to 250 m. We've also included examples of global precipitation datasets.

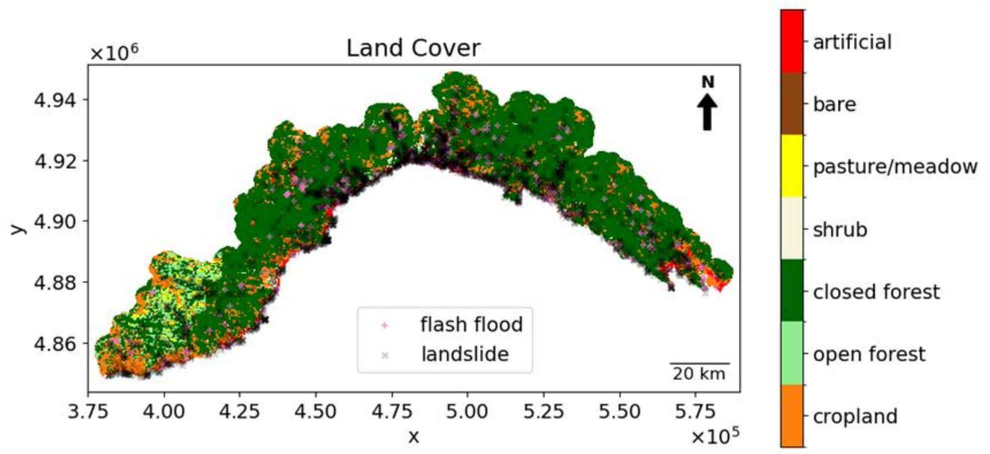
Comment 15:
Table 1:
• Land cover: Have you checked for newer, higher-resolution data (e.g., ~50 m) to better match your DEM and improve consistency? JRC has recently updated their datasets.
• Distance to roads: You mention "There is no…resolution," but it is possible to provide the resolution or scale of OpenStreetMap.

Response 15:
• Good suggestion, we will not rerun the whole framework now, but will consider it in future work. We believe it will have a limited impact on the results due to the many layers considered. Additionally, not all input layers have such a high resolution.
• The resolution is not fixed since it is a vector layer but ~~it is likely to be high in Liguria due to high population density and thus high inclusion of crowd sourced information.~~we have added an approximate resolution ~50 m for the derived proximity raster maps.

Comment 16:
Figure 3: Apply the same suggestions as for Figure 1, and:
• Remove shadows from the background of each variable map, as they make the study area polygon misaligned with calculated areas. Alternatively, remove the borders.
• Adjust font sizes for clarity.

Response 16:





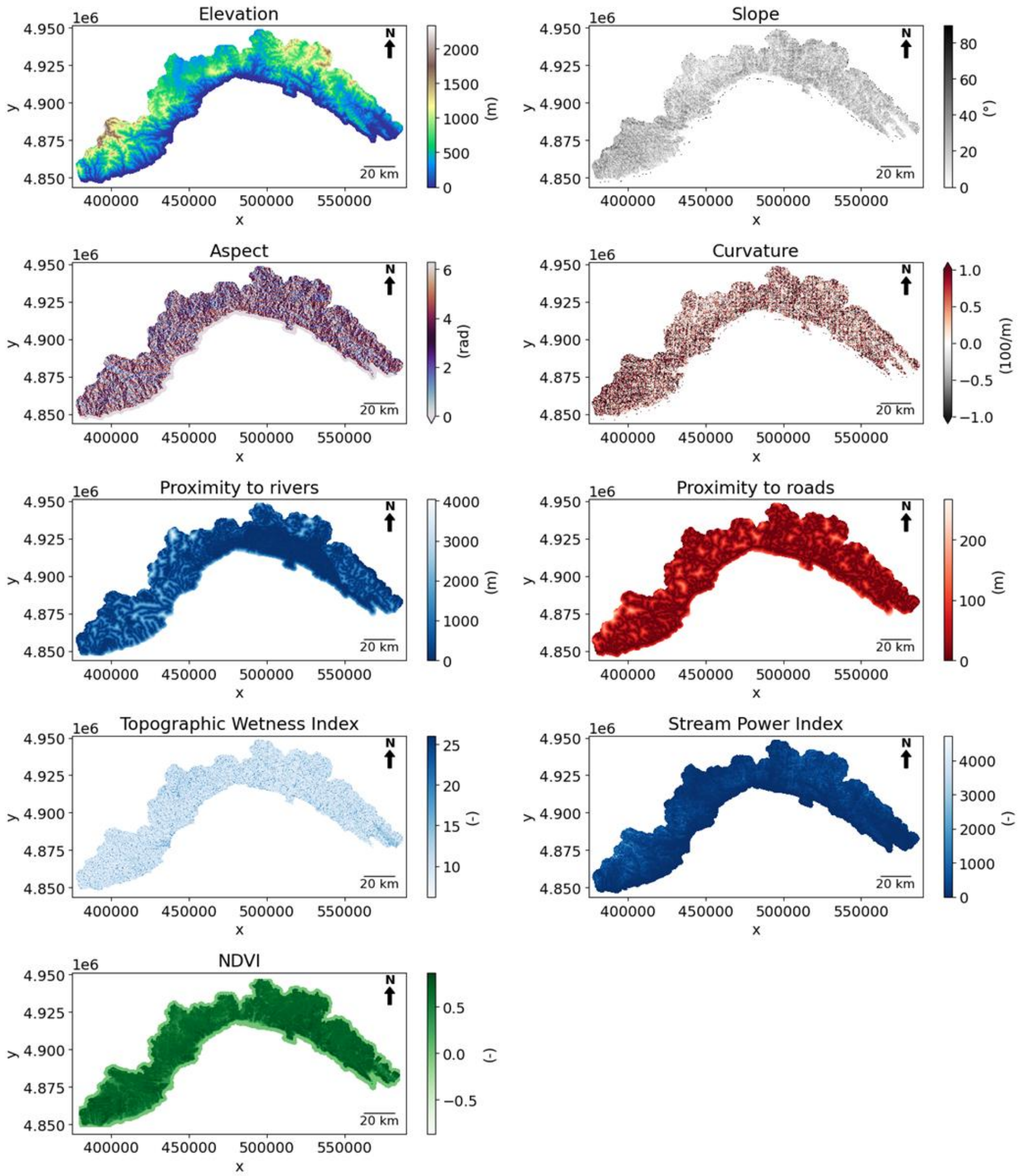
Comment 17:

Figure 4: Apply the same improvements as above.

Line 141: Replace “DEM” with “elevation.” While elevation is extracted from a DEM, the DEM itself is not a topographic factor, elevation is. I also suggest overlaying the landslide and flash flood inventories on these maps to visually examine the factors prior to modeling.

Response 17:

DEM has been replaced by elevation and Figure 4 has been updated.



Methods Section (3.2):

Comment 18:
Please specify the versions of any software used (e.g., GIS, modeling tools).

Response 18:
We have specified it in the methods section*: "Hence, we used the Variance Inflation Factor (VIF), specifically the variance_inflation_factor from Statsmodels statistical modelling and econometrics in Python (Josef Perktold et al., 2024) […] we used the Jenks natural breaks classification (George F. Jenks, 1967) via the Jenkspy: Fast Fisher-Jenks breaks for Python (Viry, M. et al., 2024) […] These were computed using the LogisticRegression, RandomForestClassifier and the svm modules respectively from Scikit-Learn Machine Learning Python library (Pedregosa, F. et al., 2011)."*

Comment 19:
Lines 191–192: "Only for…the results." Could you clarify this statement further, and explain how it was determined?

Response 19:
We have clarified that the manual classification was applied to aspect and curvature and have specified the classes*: i.e. aspect was divided between flat, NE, SE, SW, NW while curvature was separated into concave, flat, and convex.*

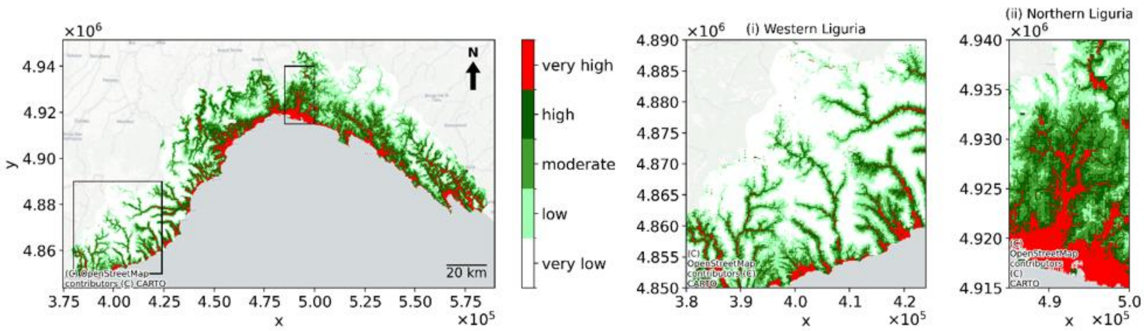
Comment 20:
Model Calibration: Please provide more details on the calibration phase to enhance clarity and reproducibility. Include references or studies that guided your calibration approach.

Response 20:
We have added the references to Scikit-Learn and the module names (see above). We will include the parameters tested and the ones selected for each ML algorithm in the Appendix B.

<u>Results Section</u>

Comment 21:
Results Section: This section should be more comprehensive, with a clearer descriptive analysis of the findings. Currently, the maps are too small to allow independent interpretation; consider adding zoomed-in areas or inset maps.

Response 21:
Figure 10 and 11 will be expanded to include zoomed-in areas of Western and Northern Liguria for all susceptibility maps.



Comment 22:
Additionally, the distinction between the Results and Discussion sections should be strengthened. The Results should focus on presenting outcomes and facts, while interpretation and comparison with other studies should be reserved for the Discussion to improve the overall flow. For example, Lines 276–279, 295–297, and 300–306 should be rephrased or moved to the Discussion; please review the manuscript accordingly.

Response 22:
The section 4.2 Frequency Ratio Analysis will be split leading to a new section 5.1. Frequency Ratio Analysis in which the results are clearly separated from the discussion. Similarly, comparison with other studies initially included in 4.4 will be moved to 5.2

Comment 23:
Figures 7 and 8: The threshold values of the factors (variables) are not optimally aligned with the desired thresholds and appear slightly shifted to the right. Redesigning their positioning and size is recommended to improve clarity and facilitate interpretation of the results.

Response 23:
Figure 7 and 8 will be improved.

Comment 24:
Line 307: "proximity…relationship." Please specify the figure from which this information is derived (e.g., Figure 8) to improve clarity.

Response 24:
Figure 8 will be added to the sentence.

Comment 25:
Figure 10: Apply the same suggestions as for Figure 1. I strongly recommend adding zoomed-in inset maps to better highlight key results. This will allow a clearer visual interpretation and more effective discussion of the findings, as relying solely on numerical assessments does not fully convey the spatial patterns of the study.

Response 25:
Figure 10 and 11 have been improved (see the example above).

Comment 26:
Table 2: Please provide more details on how the confusion matrix was generated. Are all numbers based on points or polygons? If polygons were used, an area-based accuracy assessment might be more appropriate, and showing the full spatial representation would be more informative than only the numerical summary.

Response 26:
Pixels were used. This has been added. The text in section 4.4 will be extended:

The confusion matrix, which summarizes how many pixels (as defined in the reference dataset) were correctly predicted, is shown in the Appendix B for the training dataset and in Table 2 for the testing dataset. The RF, exhibited the best results (flash floods, landslides) with the highest number of TP (593, 3318) and TN (591, 2967), and the lowest number of FP (96, 690) and FN (80, 381), followed by the SVM. The highest accuracy is achieved by the RF with values 0.87 and 0.85 for flash floods and landslides respectively.

Comment 27:
Suggestion:
• The table could be presented more concisely by combining both flash flood and landslide into a single row. Including the percentage of each category alongside the numbers would provide a clearer picture of the proportions in addition to the overall accuracy.
• Including confusion matrix results for the training dataset, in addition to the test dataset, would also help readers better understand the model's performance and allow for a more meaningful comparison between the datasets.

Response 27:
The suggestions have been incorporated.

The table below is the confusion matrix and accuracy for each ML model derived from the testing dataset. Another table similar to this one but for the training dataset has been added to the appendix.

	Flash floods						**Landslides**					
	LR		**RF**		**SVM**		**LR**		**RF**		**SVM**	
	pixels	**%**	**pixels**	**%**	**pixels**	**%**	**pixels**	**%**	**pixels**	**%**	**pixels**	**%**
TP	537	39	593	44	544	40	3077	42	3318	45	3173	43

FP	147	11	96	7	131	10	1041	14	690	9	932	13
TN	540	40	591	43	556	41	2616	36	2967	40	2725	37
FN	136	10	80	6	129	9	622	8	381	5	526	7
Accuracy	0.79		0.87		0.81		0.77		0.85		0.80	

Discussion

Comment 28:
Discussion: Please discuss the transferability of this model (workflow), including any modifications that may be needed. Could you also clarify whether you would recommend its application at local scales and what improvements would be necessary for such use?

Response 28:
This will be included in section 5.6 Role of inventories and data completeness in framework transferability:

This will affect the training of the ML algorithm and its accuracy, limiting the transfer of the framework to other data rich regions, or the transfer of the trained framework to regions with similar terrain, meteorological conditions, land cover, soil types, and land use including degree of urbanization. To overcome the latter, transfer learning for landslides susceptibility modelling in dissimilar areas was applied by Wang et al. (2022) by using Domain Adaptation (DA) in which a latent feature space is defined where the source and target areas have the same distribution. In particular, we expect physics-informed predictors like TWI, SPI, slope, curvature to be more easily transferable (after aligning their distributions) to other regions. On the other hand, elevation, proximity to roads, proximity to rivers, NDVI, land cover, and lithology are region dependent and could be transferred to similar regions using e.g. Case-Based Reasoning (CBR) (Wang et al., 2022). Alternatively, they may be harmonized to represent properties rather than classes e.g. grain size instead of lithology classes. Aspect on its own is not an informative variable but could be rederived into Windward-Leeward Index (WLI) that incorporates the influence of orographic precipitation. Still, there may be other aspects like wetness, seasonality and variability of precipitation that are not similar between regions affecting the accuracy of the transferred framework. This will affect the training of the ML algorithm and its accuracy, limiting the transfer of the framework to other data rich regions or transfer of the trained framework to regions with similar terrain, meteorological conditions, land cover, soil types and land use including degree of urbanization. Wang et al. (2022) applied transfer learning for landslides susceptibility modelling in dissimilar areas by using Domain Adaptation (DA) for which a latent feature space is defined where the source and target areas have the same distribution. In particular, we expect physics-informed predictors like TWI, SPI, slope, curvature to be more easily transferable (after aligning their distributions) to other regions. On the other hand, elevation, proximity to roads, proximity to rivers, NDVI, land cover, and lithology are region dependent and could be transferred to similar regions using e.g. Case-Based Reasoning (CBR) (Wang et al., 2022). Alternatively, they may be harmonized to represent properties rather than classes e.g. grain size instead of lithology classes. Aspect on its own is not an informative variable but could be rederived into Windward-Leeward Index (WLI) that can incorporate the influence of orographic precipitation. Still, there may be other aspects like wetness, seasonality and variability of precipitation that are not similar between regions affecting the accuracy of the transferred framework.

Comment 29:
It would be helpful to provide a brief explanation regarding the confusion matrix in Table 2, here in the Discussion. The findings look promising, and adding this context would help readers better understand the practical significance of the observed differences.

Response 29:
We have included an explanation on the confusion matrix and added additional context – see response 26

Comment 30:
Line 269: “The results…study” better to support this by providing table, map, figure, then continue.

Response 30:
We will replace “The results” by the figure numbers.

Comment 31:
Figure 12: First, please include information similar to the previous figures and use the maximum size allowed by the journal to improve readability. For Figure 12, the map could be presented to better support visual assessment of the results alongside the statistics. While the overall map is good, its usefulness is limited without zoomed-in views (inset maps) of key locations. If you overlay the inventories (which I recommend), consider showing them only on these zoomed in subsets to avoid excessive density and maintain clarity, rather than overlaying everything on the main map.

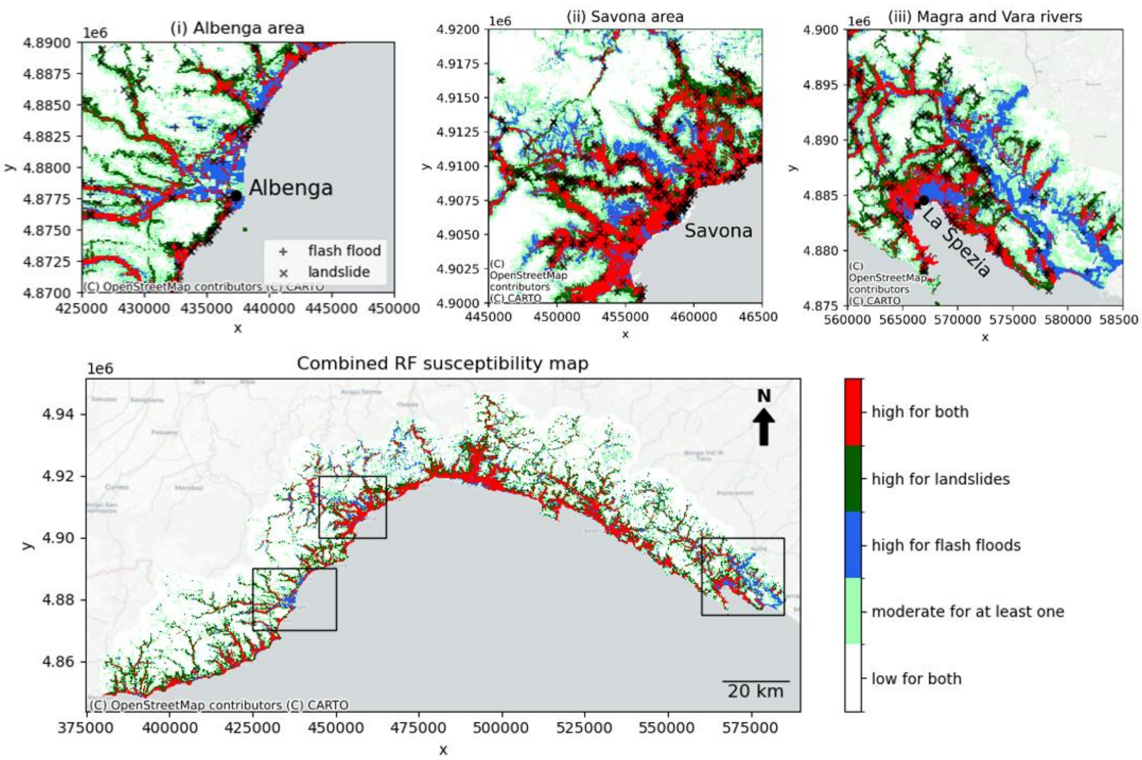
Response 31:
Figure 12, now 13, has been updated with zoomed-in locations. We’ve not been able to find a maximum figure size established by the journal.

Comment 32:
Lines 389–390: “…in the city… (e.g., La Spezia).” These locations are difficult to identify on the map. Consider highlighting them on the existing map or preparing a separate figure showing all locations discussed in the text. This would visually strengthen the analysis and improve the clarity and quality of the results (see the previous comment on Figure 12).

Response 32:
We’ve added Albenga, Savona, and La Spezia cities to each of the zoomed-in maps.

Comment 33:
Line 399: “areas and…Liguria” may be difficult to locate for readers unfamiliar with the study area. These should be highlighted on the map or provide a zoomed-in one, as suggested previously, to improve clarity and reader understanding.

Response 33:
Zoomed-in maps with each of those areas have been added to the Figure 14 (previously Figure 12).

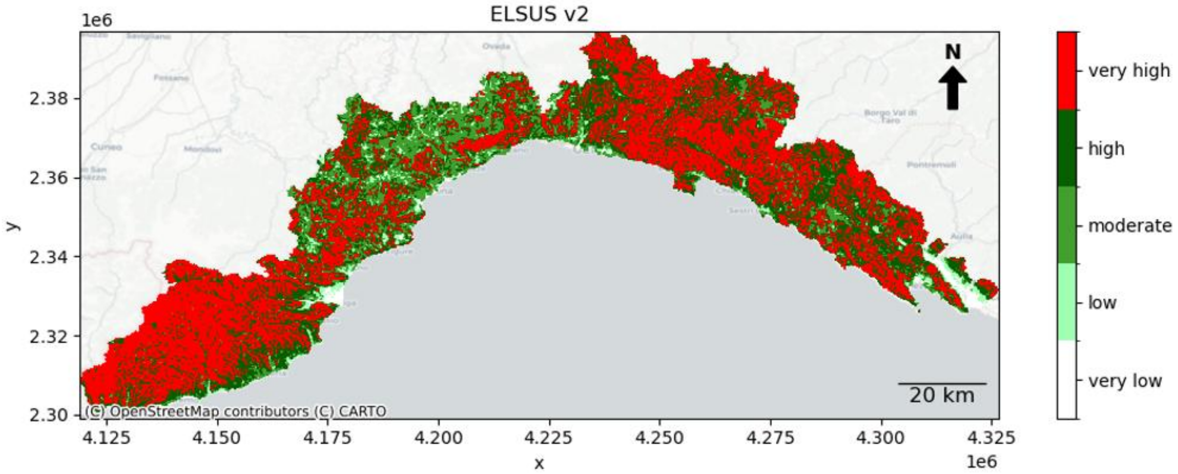


Comment 34:
Line 417: The reference to “ELSUS” should be properly cited.

Response 34:
The ELSUS reference in the figure has been updated to include the full list of references.

Comment 35:
Figure 13: Please add a scale and other map elements as before. Additionally, indicate the original scale at which ELSUS v2 was mapped.

Response 35:
The elements have been added to Figure 15 (previously Figure 13) and the original scale has been added to the caption.



Comment 36:
Lines 444-445: “..,consequently…excludes.” Have you documented this? Please provide the number of cases that were excluded.

Response 36:
1149 entries with dates and without duplicates were excluded.

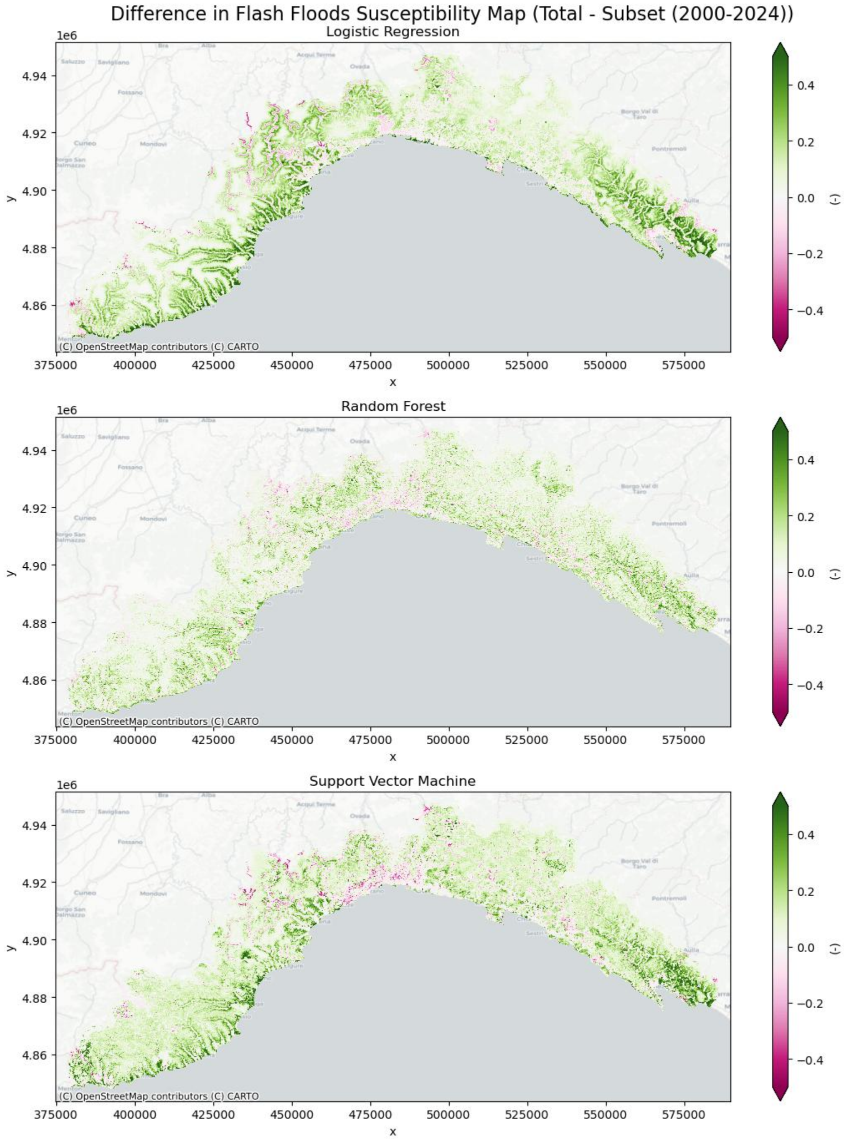
Referee comments 2

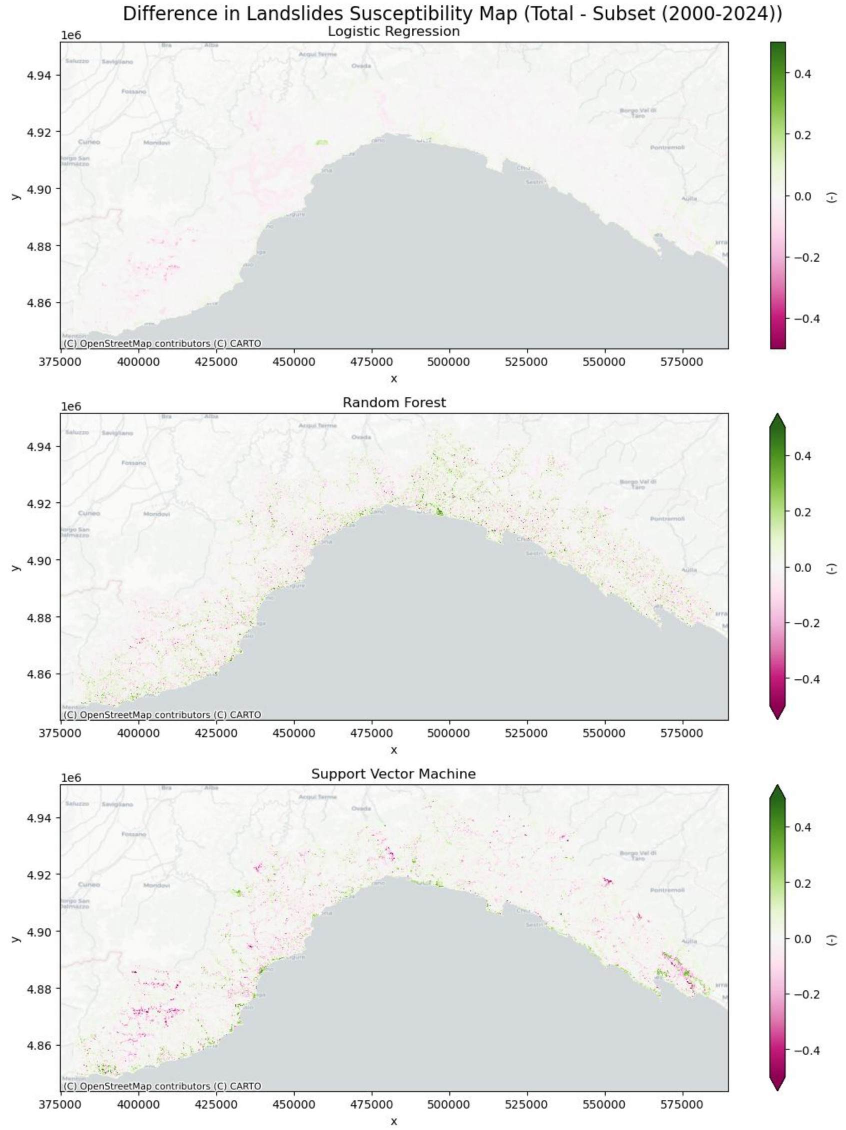
This manuscript investigates flash flood and landslide susceptibility using a unified machine-learning framework applied to the Liguria region in Italy. The study addresses an important topic in the context of multi-hazard risk assessment and benefits from the use of multiple event inventories, a consistent modelling framework across hazard types, and a careful discussion of several limitations. Overall, the paper is technically sound and clearly written, and it has the potential to make a valuable contribution to regional-scale multi-hazard susceptibility analysis. The comments below are intended to help strengthen the methodological clarity, interpretability, and positioning of the contribution.

Comment 1:
The flash flood inventory spans a very long time period (approximately 1950 to present), whereas the susceptibility modelling relies on present-day static conditioning factors (e.g. land cover, river network, road networks, …). Over this period, substantial changes have occurred in Liguria, particularly related to urbanisation, river modification, and land-use change, which may violate the assumption of stationarity between past events and current susceptibility conditions. While the long inventory improves statistical robustness, it may also introduce temporal inconsistencies that affect the interpretation of the resulting susceptibility maps, especially in urbanised valleys where many early events predate current conditions. This issue is particularly relevant for flash floods, which are highly sensitive to anthropogenic hydrological modifications. The authors are encouraged to (i) acknowledge this limitation more explicitly, and/or (ii) demonstrate that it does not substantially affect the results. Possible approaches could include comparing susceptibility maps derived from a more recent subset of events (e.g. post-1990) with the full inventory-based map, or applying temporal weighting to events based on their distance from present-day conditions.

Response 1:
This is a valid point. We can indeed relate high hazard susceptibility to urbanized areas (Section 4.3) and the level urbanization increased over time, especially for the area of Genoa (Faccini et al., 2015 and Lanza, 2004). We have added a comment to section 5.6 Role of inventories and data completeness in framework transferability. "*In addition, the framework has been applied and trained on the full period of data availability at once (only excluding scattered events from before 1940), while especially land use changes such as urbanization may have affected the landslide susceptibility in the region over time. To verify that the long inventory does not introduce temporal inconsistencies that may affect our conclusion, we derived new susceptibility maps for both hazards using only the more recent events (2000-2024) (refer to Figure 3). We found no significant changes in the susceptibility maps with more limited changes for landslides than for flash floods (figures not shown).*"

We found no significant changes in the susceptibility maps especially for landslides. As for flash floods there are some more differences but least pronounced for Random Forest. Figures will not be included in the manuscript for conciseness. Overall, the maps based on only the period 2000-2024 shows a somewhat lower susceptibility, which is most likely a result of the lower number of events included in the training.


Difference in Flash Floods Susceptibility Map (Total - Subset (2000-2024))
Logistic Regression
Random Forest
Support Vector Machine
1e6
4.94
4.92
4.90
4.88
4.86
y
375000
400000
425000
450000
475000
500000
525000
550000
575000
x
0.4
0.2
0.0
−0.2
−0.4
(-)
(C) OpenStreetMap contributors (C) CARTO



Comment 2:
The Introduction states that this study transfers the framework of Tehrani et al. (2021) to flash flood susceptibility and applies it within a unified multi-hazard context. However, the precise methodological and conceptual advances beyond the original framework are not sufficiently articulated. The authors are encouraged to clarify more explicitly what aspects of the framework are novel (e.g. unified hazard treatment, inventory construction, comparative analysis), and how this work differs from or extends Tehrani et al. (2021) beyond a change in hazard type and study area. Strengthening this framing would help readers better appreciate the innovative potential of this study.

Response 2:
We have clarified the text in the introduction: "*Our starting point is Tehrani et al. 2021 which originally developed a landslide detection ML model, and was subsequently adapted it to a landslide susceptibility mapping framework. The latter has been extended in this study with (i) the inventory construction, (ii) the systematic inclusion of input layers relevant to flash floods and landslides, (iii) the assessment of multicollinearity between the layers, and (iv) the study of behaviour similarity between both hazards resulting in a unified susceptibility framework.*"

Comment 3:
The title emphasises a Mediterranean-scale application, while the analysis is conducted at a local/regional scale focused on Liguria. While Liguria is representative of Mediterranean hydro-geomorphic settings, the current title may overstate the spatial scope of the application. The authors may wish to consider revising the title to better reflect the local-scale case study, while still acknowledging Mediterranean relevance.

Response 3:
We've adjusted the title:

A single framework for assessing flash flood and landslide susceptibility: an application to the Mediterranean Liguria region, Italy

Comment 4:
In the Methodology section, the manuscript states that hyperparameters were calibrated using grid search and cross-validation, but the specific parameter ranges and final selections for each algorithm (LR, RF, SVM) are not described in detail. For transparency and reproducibility, the authors are encouraged to provide: the tested hyperparameter ranges, and the final selected values for each model, possibly in an appendix or supplementary material. This would strengthen the methodological clarity of the paper.

Response 4:
The parameter ranges and the final selected values for each model and hazard will be added in the Appendix B.

Comment 5:
Class imbalance: the flash flood and landslide inventories differ substantially in size, and the binary classification problem is inherently unbalanced (event vs non-event pixels). While model performance metrics (AUC, accuracy, confusion matrices) are reported, the role of class imbalance in influencing false positives and false negatives is not explicitly discussed. The authors are encouraged to either: discuss how class imbalance may affect the reported performance metrics, or justify the decision not to apply balancing techniques (e.g. class weighting, SMOTE). Explicitly addressing this point would improve confidence in the interpretation of model performance.

Response 5:
Since the susceptibility mapping for the two hazards is done independently, the impact of the imbalance between inventories will be limited. However, we do recognize that the imbalance in the number of events in the inventories over time can have affected the accuracy of the model. A comment on this has been added to section 5.6 of the discussion and a figure with events over time in the inventory section.

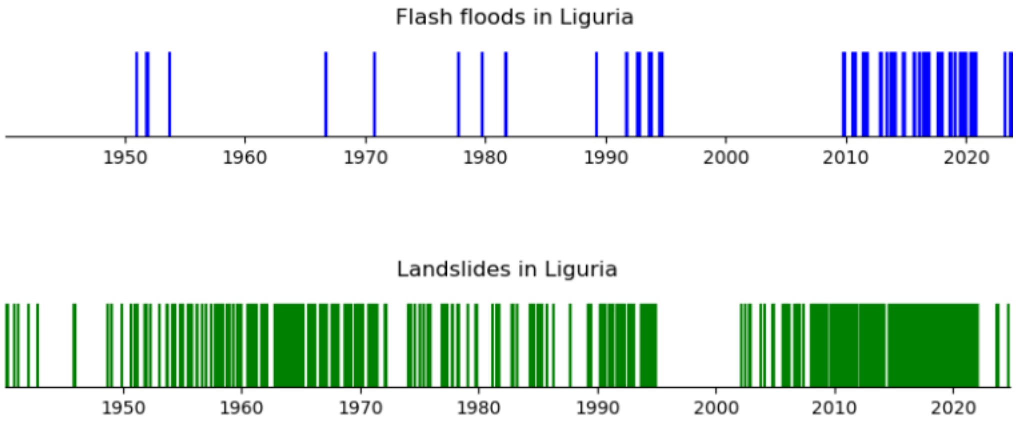


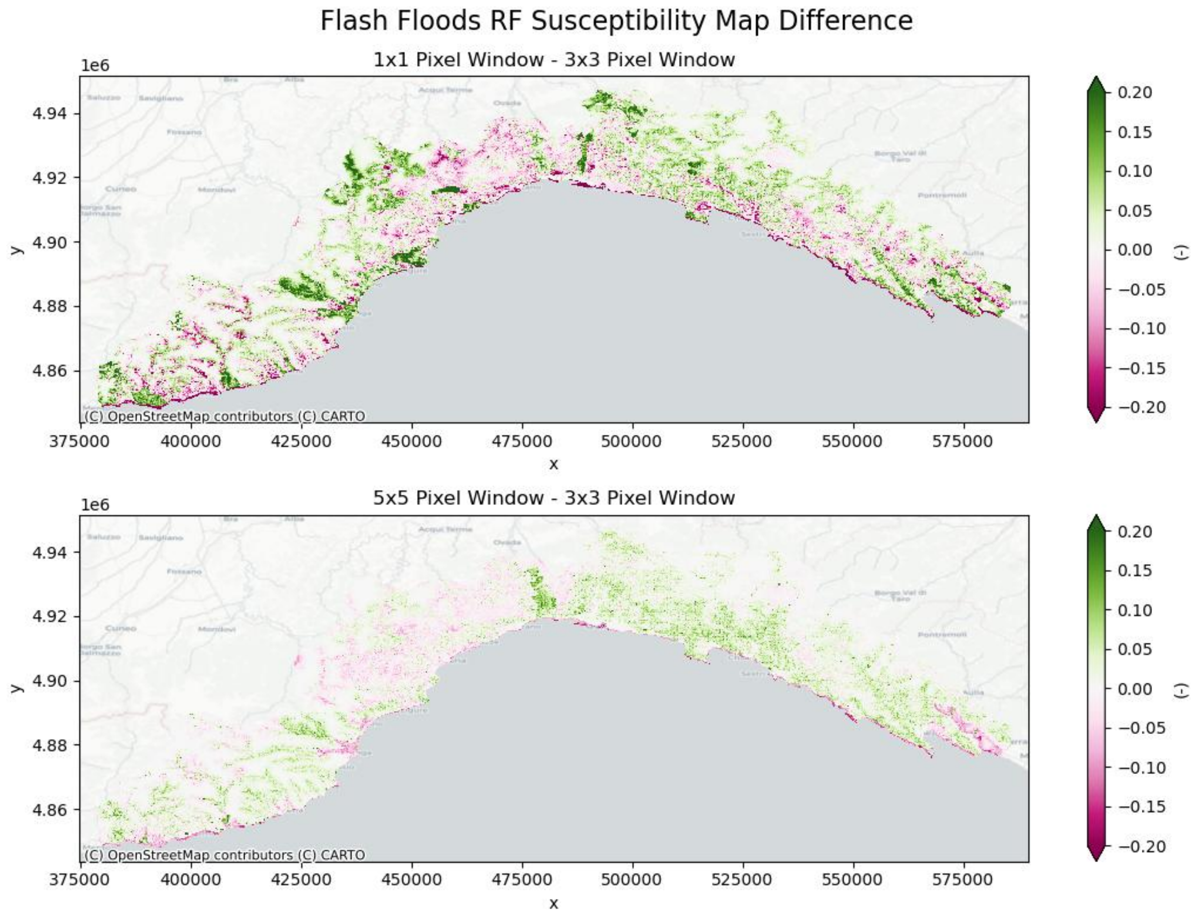
Figure 3: Flash flood (top) and landslide (bottom) events distribution from 1940-2024

We have added a comment on the inherently balanced binary classification in section 5.8: "*The fewer occurrences of events –whether landslides or flash floods– with respect to non-events lead to a class imbalance which can cause bias in the ML model by predicting the event (majority class) more often. One approach to handle this imbalance is to under sample the majority class and/or oversample the minority class, the latter is the more common in hazard mapping. A popular method is the synthetic minority oversampling technique (SMOTE) which for each event finds the k nearest neighbours and generates a random event at the chosen neighbour creating new events along the segment between the original event and the chosen neighbour. Han and Semnani (2025), who confirm the challenges of addressing class imbalance in landslides, found the best overall results for gridded hyperspace even sampling with a variant of SMOTE. However, this method can potentially create physically unrealistic events. Another approach is to apply class weights or cost sensitive weighting (Chen, C. et al., 2004) in which the model is penalized for misclassifying the minority class. This means that by balancing the classes, a trade-off occurs: an increase of TP to the detriment of creating more FP. As previously indicated, our confusion matrix results are quite positive, limiting but not removing the need of applying a trade-off which could be studied in future work.*"

Comment 6:
To account for location uncertainty in point-based inventories, a 3x3 pixel window is used around each event. While this is a reasonable approach, it may introduce spatial smoothing that blurs the influence of certain conditioning factors, particularly for landslide susceptibility in steep terrain. As already partially acknowledged by the authors, this may contribute to unexpected results (e.g. landslides associated with gentler slopes). The authors may consider discussing alternative or complementary strategies, such as: exclusion or buffer zones around event pixels to reduce spatial autocorrelation, or sensitivity tests on window size. If considered too technical for implementation, a clearer discussion of the implications of this choice would still be valuable.

Response 6:

We have added in the methods a sentence on this and in the results. We reran the ML models for both 1x1 and 5x5 pixel window sizes. There are only minor differences, though not significant, for the flash floods susceptibility maps. There are no differences in the susceptibility maps for landslides. The figures will not be included for conciseness.



Comment 7:

The framework is described as globally applicable; however, its performance depends strongly on the availability and quality of local hazard inventories. The authors are encouraged to expand the discussion on spatial and temporal transferability, particularly regarding:

- data-rich versus data-scarce regions;
- which conditioning variables may be problematic when transferring the model (e.g. the authors mention aspect -southward facing slopes- dependence, how would that change in regions with different dominant exposure?);
- the potential role of high-resolution dynamic inputs (e.g. convection-permitting reanalysis and future projections) in improving applicability across regions and time periods.

Response 7:

We will extend the discussion on this in section 5.6 that specifically links the data completeness to transferability of the framework:

Previous studies (Free et al., 2022; Modrick and Georgakakos, 2015; Uwihirwe et al., 2022) have shown that in many other, especially remote, regions of the world the number of recorded events is substantially lower. Global inventories can fill some gaps but are often coarse, incomplete or inconsistent in spatial and temporal coverage. This will affect the training of the ML algorithm and its accuracy, limiting the transfer of the framework to other data rich regions, or the transfer of the trained framework to regions with similar terrain, meteorological conditions, land cover, soil types, and land use including degree of urbanization. To overcome the latter, transfer *learning for landslides susceptibility modelling in dissimilar areas was applied by Wang et al. (2022) by using Domain Adaptation (DA) in which a latent feature space is defined where the source and target areas have the same distribution. In particular, we expect physics-informed predictors like TWI, SPI, slope, curvature to be more easily transferable (after aligning their distributions) to other regions. On the other hand, elevation, proximity to roads, proximity to rivers, NDVI, land cover, and lithology are region dependent and could be transferred to similar regions using e.g. Case-Based Reasoning (CBR) (Wang et al., 2022). Alternatively, they may be harmonized to represent properties rather than classes e.g. grain size instead of lithology classes. Aspect on its own is not an informative variable but could be rederived into Windward-Leeward Index (WLI) that incorporates the influence of orographic precipitation. Still, there may be other aspects like wetness, seasonality and variability of precipitation that are not similar between regions affecting the accuracy of the transferred framework.*

The potential role of high-resolution dynamic inputs will be included in 5.7 Framework applications:

In this study all conditioning factors were static. Including these dynamic parameters would enhance the capacity of the models to capture transient conditions and could potentially even allow the framework to update susceptibility in near real time. Moreover the framework holds the potential to be applied in early warning applications, as we previously explored in Uwihirwe et al. (2022), using high-resolution forecasted, or even now-casted precipitation (short-term). The same holds for future climate change assessments using high resolution precipitation projections from convection-permitting climate models (Zander et al., 2022). The framework would anyhow benefit from higher resolution precipitation products as these capture better the effect of the high spatial variability in heterogeneous terrain (Lee et al., 2022).