Response to Reviewer #1

We sincerely thank the reviewer for the careful evaluation of the manuscript and for the constructive and insightful comments. The reviewer's original comments are reproduced below in bold black, our responses are provided in blue, and the corresponding modifications made in the manuscript are indicated in orange.

The manuscript presents a solid and well-structured analysis of the impact of extreme rainfall events on landslide rainfall thresholds and susceptibility modelling. The dataset is comprehensive, and the methodological framework (CTRL-T and Random Forest) is appropriate and carefully implemented. The results are clear and provide meaningful insights into how extreme events can alter statistical models used for landslide prediction. Overall, the manuscript is suitable for publication after moderate revisions. However, several aspects could be further strengthened to improve clarity, robustness, and broader applicability.

First, the discussion section should be slightly expanded to better generalize the findings beyond the study area, particularly addressing whether similar effects of extreme rainfall events on thresholds and susceptibility can be expected in other climatic and geomorphological contexts.

Response:

We thank the reviewer for this suggestion. In response, we have expanded the discussion by adding a paragraph at the end of section *6.4 Changes in susceptibility maps due to Storm Alex landslides* to explicitly address the potential generalization of our findings to other climatic and geomorphological contexts, supported by literature.

Modifications:

- ➔ The following paragraph has been added at the end of the section 6.4 :

"Beyond the specific case of the Alpes-Maritimes region, our results suggest broader implications regarding the role of extreme rainfall in landslide triggering. The observed activation of areas with lower pre-event susceptibility supports the hypothesis that extreme hydrometeorological forcing can partially override the usual controls exerted by soil and terrain properties on slope stability. Similar effects may occur in other regions exposed to short-duration, high-intensity rainfall events, particularly in Mediterranean and tropical environments. However, the magnitude of these effects likely depends on both the return period of the rainfall event and the local geomorphological context.

Achu et al. (2024) investigated the impact of landslides triggered during extreme rainfall events on the performance of machine learning models and susceptibility maps using a Deep Neural Network approach in the southern Western Ghats (Kerala, India), a humid tropical region affected by recurrent *high-intensity monsoon rainfall. Their results showed that a model trained without landslides associated with extreme events remained capable of identifying landslides triggered during such events. Nevertheless, incorporating these landslides into the susceptibility modelling increased the spatial extent of low and extreme susceptibility classes (+120% and +32%, respectively), while the moderate and high susceptibility classes decreased (-15% and -42%, respectively).*

Our results partially agree with those of Achu et al. (2024). Similar to their observations, the inclusion of landslides triggered during Storm Alex leads to an increase in the area associated with low susceptibility values (0.1–0.2) and a decrease in the area associated with intermediate susceptibility values (0.2–0.6) (Fig. 10). However, the magnitude of these variations remains less pronounced than that reported by Achu et al. (2024), while the area associated with high susceptibility values (>0.6) remains largely unchanged in our case.

These differences may be partly due to methodological and contextual factors. First, the two studies rely on different modelling approaches, as Achu et al. (2024) used a Deep Neural Network, whereas our susceptibility assessment is based on a Random Forest model. In addition, the influence of extreme rainfall events on susceptibility patterns likely depends on both the regional geomorphological context and the rarity of the triggering event. While Achu et al. (2024) only indicate that their extreme rainfall events were associated with return periods exceeding 100 years, Storm Alex was characterized by a millennial-scale return period. Nevertheless, both studies consistently show that incorporating landslides triggered during extreme rainfall events modifies susceptibility patterns"

Second, the limitations of the study should be more explicitly acknowledged, especially regarding the spatial representativeness of the Storm Alex landslides, the temporal inconsistency of the inventory, and the assumptions made in rainfall–landslide matching (e.g., fixed occurrence time).

Response:

We have revised the manuscript to better highlight the limitations of the study. Regarding the spatial representativeness of the Storm Alex landslides, we have expanded the discussion in Section *6.1 Quality of landslide inventory* to better highlight their strong spatial clustering and the fact that they are concentrated within a limited area. The issue of the inconsistency of the inventory is also addressed.

Finally, the question of the use of a fixed occurrence time, is already discussed in the section *5.1 ED threshold*. This paragraph has been slightly expanded to further address this point and to explicitly account for the reviewer's comment.

Modifications:

➔ The following paragraph has been added to the section 6.1 :

"A potential temporal inconsistency in the inventory may arise from the progressive improvement in landslide detection over time, with more recent periods benefiting from systematic orthophoto coverage and improved reporting. This may result in a lower completeness of older landslide records. However, this effect is expected to remain limited in the present study, as the analyses primarily rely on post-1997 events and on recent landslides documented with relatively homogeneous acquisition methods. In addition, the main objective of this work is to compare modelling results obtained with and without Storm Alex landslides within the same inventory framework, which reduces the influence of potential temporal biases on the comparative interpretation.

It should also be noted that Alex-induced landslides exhibit a strong spatial clustering, mainly concentrated within the Vésubie, Tinée and Roya valleys. This clustering primarily reflects the actual spatial extent of the storm impacts, as these valleys correspond to the areas that experienced the most intense rainfall during Storm Alex (Fig. 2). Most Alex-induced landslides were identified through orthophotography comparison using the post-Alex orthophoto, which specifically covered these heavily affected sectors (Fig. 3). Although it is possible that a limited number of Alex-induced landslides located outside the orthophoto extent were not identified, such cases are expected to remain minor given the localized nature of the storm and the concentration of the most extreme rainfall within the surveyed valleys. Consequently, the strong spatial clustering of Alex landslides is considered to mainly reflect the actual spatial distribution of landslide occurrence during the event rather than an artefact of the mapping procedure. To further limit the influence of this clustering, the analysis of the distributions of predisposing factors (Fig. 8) was restricted to the spatial extent covered by the post-Alex orthophoto for both Alex and non-Alex landslides. Despite this spatial restriction, clear differences between Alex and non-Alex landslides were still observed, suggesting that the identified contrasts are not only related to the spatial concentration of the Alex inventory but also reflect differences in the geomorphological conditions under which landslides were triggered during the storm ."

➔ The section *5.1 ED threshold* has been completed as follow:

"Recall that the default hour of occurrence is set at 12:00 in the CTRL-T algorithm. This simplification may introduce uncertainties in the estimation of the rainfall conditions associated with each event, particularly for short-duration or high-intensity rainfall, where the timing of the triggering rainfall relative to the landslide occurrence can significantly affect the calculated event duration and cumulative rainfall. To assess the influence of this arbitrary choice, sensitivity tests were performed by changing the assumed landslide occurrence time (00:00, 06:00, 12:00, 18:00, and 23:00) (Fig. A4). This resulted in noticeable changes in the obtained thresholds. However, in all cases, the threshold including the Alex landslides remained higher than the threshold computed without them, by a factor of 1.2 to 2.4 "

Third, a brief perspective on future research directions would be valuable, for example the need for non-stationary modelling frameworks, event-based calibration strategies, or hybrid approaches distinguishing between ordinary and extreme triggering conditions.

Response:

The subject of non-stationary modelling frameworks, i.e. dynamic susceptibility varying with actual precipitation conditions, is already addressed in the perspectives section. The conclusion has nevertheless been expanded to include additional future research directions, in line with the other suggestions raised in this comment.

Modifications:

- ➔ The following paragraph has been added in the conclusion

"In addition, event-based calibration strategies, distinguishing between ordinary and extreme triggering conditions, could help improve the robustness and transferability of predictive models. Hybrid approaches combining separate parameterizations or models for different magnitude of rainfall events may represent a promising direction to better capture the different mechanisms highlighted in this study."

Finally, moderate clarifications could be added regarding the influence of non-landslide sampling strategy and the potential uncertainty introduced by converting landslide polygons into points. With these moderate improvements, the manuscript will be further strengthened and make a valuable contribution to the field.

Response:

We have addressed these points in the revised manuscript. Clarifications regarding the influence of the non-landslide sampling strategy are provided in section *4.2.2 Non-landslides samplings*, as well as the potential uncertainty introduced by converting landslide polygons into points, have been added respectively to the section *6.1 Quality of the landslide inventory*.

Modifications:

- ➔ The section 4.2.2 has been revised as follow:

"In the context of supervised landslide susceptibility modelling, the selection of non-landslide samples is a crucial step that can strongly influence model performance and final results (Fu et al., 2025). In particular, it controls the statistical contrast between landslide and non-landslide conditions used to train the Random Forest (RF) model. Sampling strategies that preferentially select non-landslide locations in clearly stable areas may increase class separability and produce more contrasted susceptibility patterns. In contrast, sampling designs that rely on a broader or less constrained selection of non-landslide locations may include areas close to past landslide locations.

A commonly adopted approach in landslide susceptibility studies is to generate non-landslide points outside a buffer zone around known landslides (Gu et al., 2024, 2023). Building on this principle, and aiming to capture the geomorphological variability of the study area without imposing deterministic assumptions on terrain stability, we adopted a random sampling approach within a spatially constrained domain. This domain was designed to ensure comparable reporting conditions and reduce potential bias. Specifically, it was defined as a 1 km buffer around major roads, while excluding areas located within a 150 m radius of recorded landslides (Fig. A32). This design reduces potential reporting bias, as landslides occurring near infrastructure are more likely to be documented, while maintaining a data-driven and non-deterministic selection of absence locations.

Within this constrained domain, non-landslide points were generated using random sampling, ensuring an unbiased representation of non-landslide conditions while preserving spatial realism. To account for variability in non-landslide selection, 50 distinct datasets were generated for each scenario (i.e., with and without Alex landslides), keeping landslide points fixed while randomly generating non-landslide points within the valid domain. A balanced 1:1 ratio between landslide and non-landslide points was maintained to avoid class imbalance.

Non-landslide points were first generated for the WSAL datasets (i.e. including Alex landslides). Each dataset therefore includes 4,200 landslide points and 4,200 non-landslide points. To generate the corresponding WoSAL datasets (i.e. excluding Alex landslides), we started from the WSAL datasets. In each dataset, the 1,319 Alex landslides were removed, and an equal number of non-landslide points was randomly excluded. This approach avoids regenerating non-landslide points, which could otherwise introduce spatial inconsistencies, and ensures maximum comparability between WSAL and WoSAL datasets. The full procedure is summarized in Fig. 5."

- ➔ The following paragraph has been added at the end of the section 6.1:

"Finally, landslides, originally mapped as polygons, were simplified as single points for the RF modelling. This simplification neglects the spatial extent and internal heterogeneity of landslides, and may introduce some uncertainty in the attribution of predisposing factors, especially in areas with strong spatial variability. However, this approach remains consistent with common practices in large-scale susceptibility modelling and allows for a homogeneous treatment of the inventory."