Response letter for
“Projecting changes in rainfall-induced landslide susceptibility across China under climate change”
(egusphere-2025-3834)

Response to Editor Comments

Editor: I have carefully read all the comments posted in the open discussion, as well as the original manuscript, and I need to add a few more important issues that need to be addressed in addition to the points raised by the reviewers.:

Thank you very much for your thoughtful and constructive comments on our manuscript. We have carefully considered all of your suggestions and revised the manuscript accordingly, while maintaining its overall framework and core content. We are truly grateful for the time and expertise you devoted to reviewing our work. Your valuable feedback has greatly helped us improve the manuscript.

We have included the comments in this letter and responded to them individually. The revisions are highlighted in yellow in the revised manuscript, and the response is listed below in blue. The in-text citations in our response are marked in orange.

Sincerely,
Jinqi Wang, on behalf of all co-authors.

1. Landslide inventory

To be considered for publication, the manuscript must include a detailed and transparent description of the landslide inventory, addressing at least:

- how each event-based inventory was produced,
- the original purpose of the mapping (e.g. damage assessment vs extensive geomorphological inventory),
- mapping criteria, minimum detectable size, and consistency across events,
- mapping method (remote sensing, field mapping, image interpretation, etc...),
- temporal and spatial coverage and known limitations.
- A study area for each inventory is necessary, as it will allow to prepare a synoptic map showing the

overall areas observed in the 15-year interval.

In addition, a comprehensive exploratory analysis of the spatial distribution of landslides is needed to explain the strong spatial heterogeneity observed in the inventory, with the large majority of landslides mapped in SW and SC regions. The main purpose is to discuss potential reporting biases. Could it be that the strongly inhomogeneous distribution of landslides is due to a sampling bias, i.e. landslide events were mapped in areas where they caused damages to population? This analysis will be especially beneficial in the case no metadata are available to explain how the inventories were prepared.

Response:

Thank you for this important comment. We agree that a detailed and transparent description of the landslide inventory is necessary. In the revised manuscript, we have added a fuller explanation of the inventory source, compilation process, mapping purpose, technical criteria, spatial coverage, and limitations.

Specifically, this study uses the national geohazard records of China for 2008–2023, provided by the Ministry of Natural Resources of the People's Republic of China, as the basic dataset for landslide susceptibility modelling and future trend analysis. This dataset was compiled annually under a unified national reporting framework and covers the whole of China each year, rather than only local areas affected by individual events. Therefore, the study area of each annual inventory is the entirety of China. The dataset records the occurrence time and spatial location of landslides, debris flows, and collapses, which were collectively treated as "landslides" in this study.

The inventory includes both post-disaster event records and geohazard potential sites. The occurred hazard records constitute an event-based post-disaster inventory, which was compiled through post-event field investigations and verification by professional geological survey teams organized by local governments, supported by multiple information sources such as remote-sensing interpretation and UAV surveys, and then reported through the national administrative system. In addition, the dataset also contains geohazard potential sites identified through annual investigation and screening. The main purpose of this mapping and compilation is disaster verification, loss assessment, hazard identification, risk management, and geohazard prevention and control, rather than the construction of a purely geomorphological inventory. As a result, the recorded landslide events are mainly concentrated in areas where landslides may threaten populations, infrastructure, or human activities.

The investigation and compilation procedures followed the industry technical specification, *Specification of Geological Hazard Risk Survey and Assessment (1:50,000)*. According to this standard, the minimum identifiable landslide area in the inventory is approximately 10 m^2. Because the dataset was compiled annually using a generally unified technical framework, the standards for investigation, identification, recording, and compilation were broadly consistent across years. However, as a nationwide operational geohazard dataset, it may still be influenced by regional differences in accessibility, reporting practices, and investigation intensity, which could result in some underreporting in remote areas or for very small events.

To address the reviewer's suggestion regarding spatial coverage, we have clarified in the manuscript that the study area of each annual inventory is the whole of China, and we provide a synoptic overview of the spatial distribution of landslide events in Fig. 1. More detailed information is further provided in Fig. S1 of the Supplementary Materials. The corresponding description has been added to the revised manuscript (Lines 75–100).

2. In addition, a comprehensive exploratory analysis of the spatial distribution of landslides is needed to explain the strong spatial heterogeneity observed in the inventory, with the large majority of landslides mapped in SW and SC regions. The main purpose is to discuss potential reporting biases. Could it be that the strongly inhomogeneous distribution of landslides is due to a sampling bias, i.e. landslide events were mapped in areas where they caused damages to population? This analysis will be especially beneficial in the case no metadata are available to explain how the inventories were prepared.

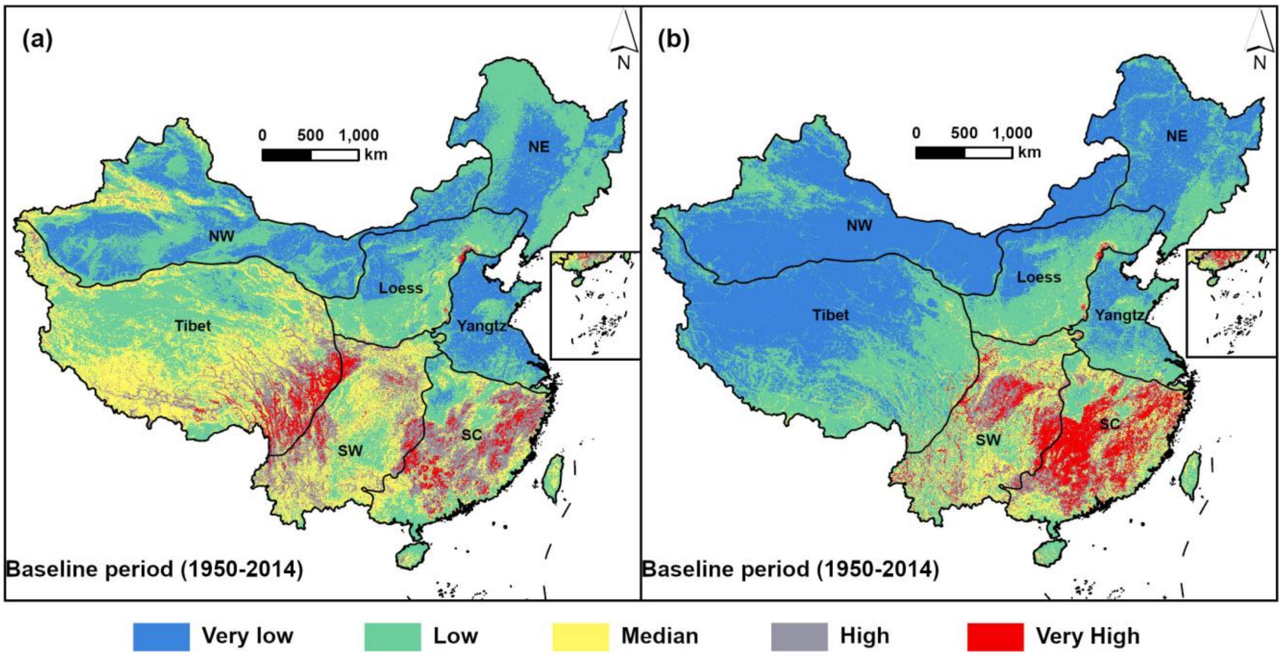
Such a spatial heterogeneity provides the authors with a valuable opportunity to explicitly address the issue of inventory incompleteness and its implications for susceptibility modelling. Given the aims of the Special Issue, the manuscript would strongly benefit from a discussion on how to assess and deal with spatial biases in landslide inventories, susceptibility estimates, and model performance evaluations.
If such biases are present, the authors must either (i) propose and justify strategies to mitigate their effects (e.g. sampling strategies, weighting schemes, spatial constraints), or (ii) explicitly acknowledge these limitations and constrain the scope and interpretation of the susceptibility results accordingly.
Without a critical discussion of inventory incompleteness and its propagation into the models, the validity of the susceptibility analysis is undermined.

Response:

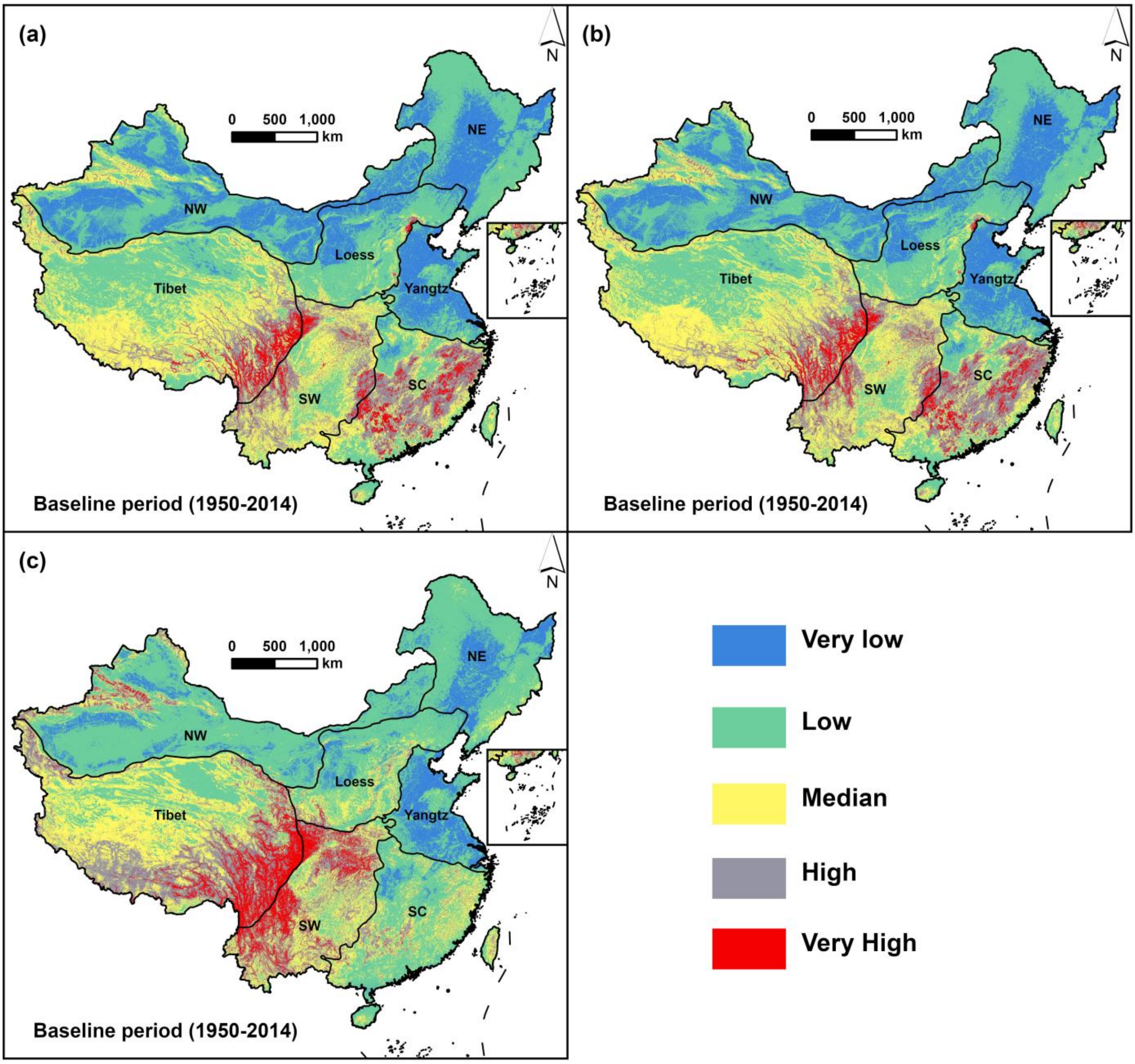
Thank you for this important comment. We agree that the strong spatial heterogeneity of the landslide inventory provides an important opportunity to explicitly address inventory incompleteness and its implications for susceptibility modelling. In the revised manuscript, we therefore added further discussion and analyses on spatial bias in the inventory, its propagation into susceptibility estimates, and possible strategies to mitigate its effects.

First, to reduce the influence of spatial bias during model training, we revised the non-landslide sampling strategy. We compared susceptibility maps produced using two different non-landslide sampling strategies: random sampling across the whole study area and sampling restricted to areas with human presence. The results revealed substantial differences between the two approaches. When non-landslide samples were randomly generated across the whole of China, susceptibility tended to be overestimated in densely recorded regions, such as SC and SW, while being underestimated in sparsely recorded regions, such as NW and Tibet (Response Fig. 1). This is likely because the landslide inventory used in this study was compiled by integrating post-disaster investigations and annual geological hazard potential-site surveys, and these records are relatively more concentrated in areas with human settlements and activities. Under such conditions, randomly generating non-landslide samples across the entire study area may incorrectly treat poorly surveyed or uninhabited regions as true negatives, thereby amplifying the effect of spatial inventory incompleteness and increasing the uncertainty and spatial bias in susceptibility mapping results (Reichenbach et al., 2018). Therefore, we revised the non-landslide sampling strategy by restricting non-landslide sample generation to areas with human presence, as a practical strategy to mitigate the uncertainty and spatial bias introduced by inventory incompleteness.

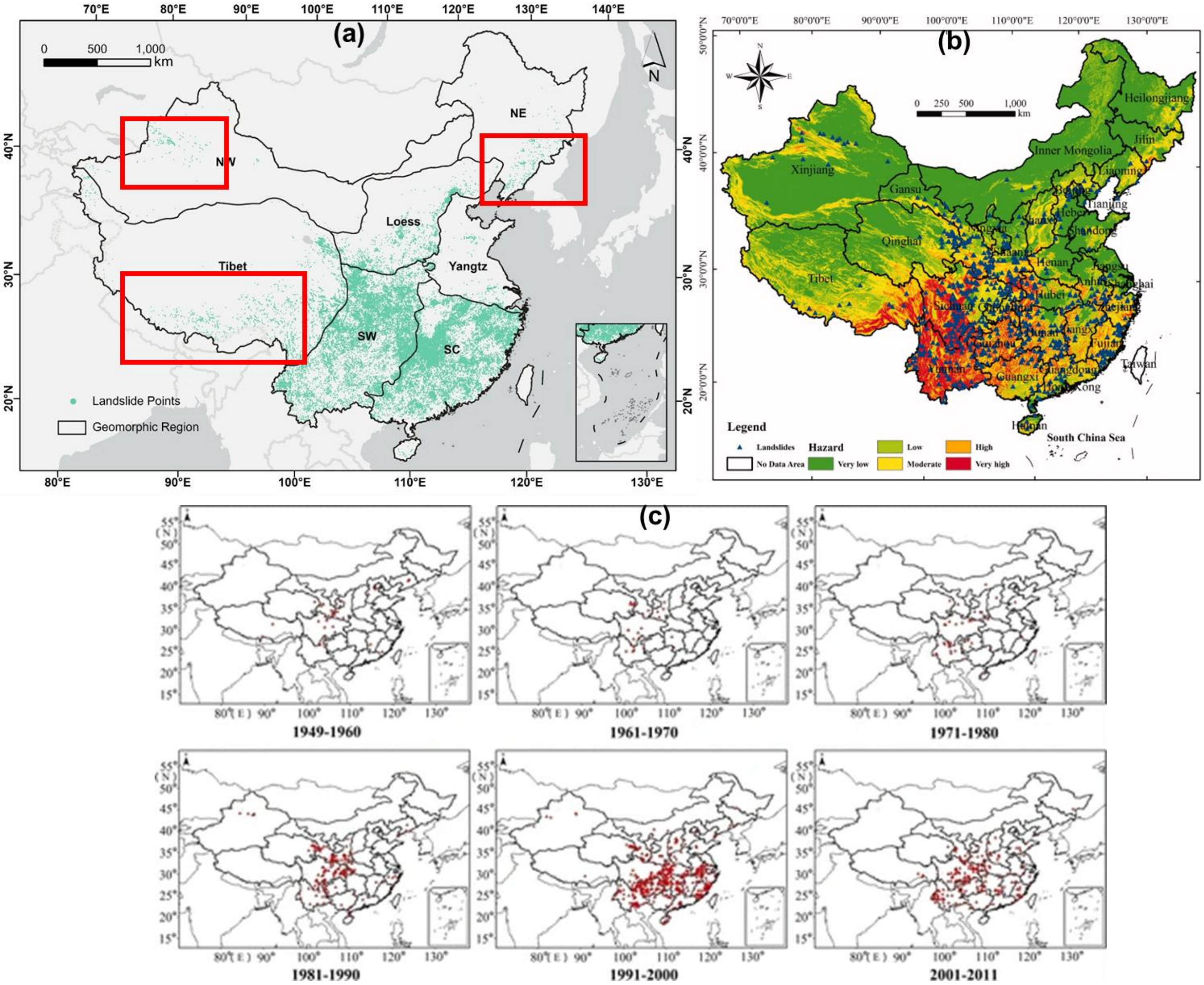
Second, to further examine how inventory incompleteness may affect susceptibility estimates, we carried out a set of sensitivity experiments. Specifically, modelling and mapping were performed for China after randomly removing 50% and 100% of the small-landslide samples, respectively (Response Fig. 2). Relative to the results based on the complete inventory, the exclusion of small-landslide records had a pronounced effect on susceptibility: susceptibility decreased markedly in SC, whereas it increased markedly in Tibet and SW. When only 50% of small landslides were removed, the overall susceptibility pattern remained highly consistent with that from the complete inventory. In addition, considering that inventory completeness is likely to vary regionally, we further tested sample reduction in NW, NE, and Tibet, where landslide samples are relatively scarce because of terrain constraints, limited accessibility, and weaker monitoring capacity (Response Fig. 3) (Liu et al., 2013; Liu and Miao, 2018). We randomly removed 50% and 75% of the samples in these regions and then repeated the modelling and mapping (Response Fig. 4). Relative to the complete-inventory results, these sample-poor regions showed an overall decrease in susceptibility as more samples were removed, whereas regions with relatively sufficient samples changed little. These results indicate that inventory incompleteness can indeed propagate into susceptibility estimates, especially in regions with sparse records. The corresponding description has been added to the revised manuscript (Lines 428–440, 483-499).



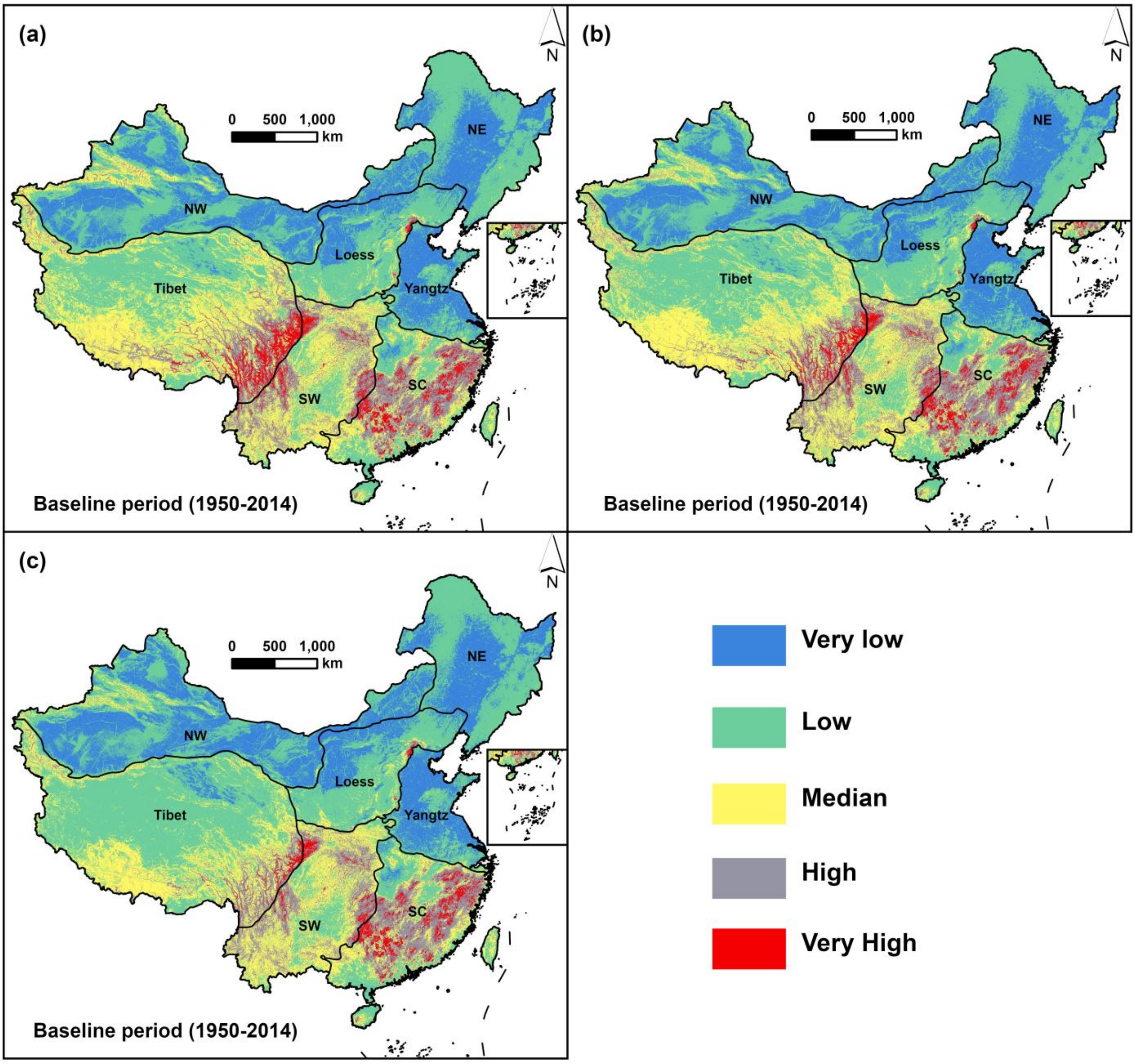
Response Fig. 1: Landslide susceptibility mapping in China for the baseline period (1950–2014) under different non-landslide sampling strategies. (a) Susceptibility map generated using non-landslide points sampled only from areas with human presence (AUC = 0.96). (b) Susceptibility map generated using non-landslide points sampled across the whole of China (AUC = 0.97).



Response Fig. 2: Landslide susceptibility maps illustrating the effect of thematic accuracy (i.e., completeness of small landslide records) on model results. (a) Baseline map constructed from the complete inventory (AUC = 0.96); (b) Map after removing 50% of the small landslides from the inventory (AUC = 0.94); (c) Map after completely excluding small landslides from the inventory (AUC = 0.94).



Response Fig. 3: Comparison of landslide inventories. (a) Landslide points used in this study; (b) National-scale landslide inventory from Liu and Miao (2018); (c) National-scale landslide inventory from Liu et al. (2013).



Response Fig. 4: Landslide susceptibility maps generated from inventories with different levels of completeness in Northwest (NW), Northeast (NE), and permafrost region of the Qinghai-Tibet Plateau (Tibet) (AUC = 0.96). (a) Baseline map using the complete inventory; (b) Map after randomly removing 50% of landslide points in the target regions (AUC = 0.96); (c) Map after randomly removing 75% of landslide points in the target regions (AUC = 0.95).

3. Re-evaluation of the susceptibility modelling framework

The training of the model is done with no-landslide data generated outside the buffer around the landslide data. This even enforces the effect of the incompleteness and trains the model to reproduce the data. When dealing with potentially incomplete and spatially biased inventories, such a strategy is dangerous as it forces the incompleteness to propagate rather than being mitigated.

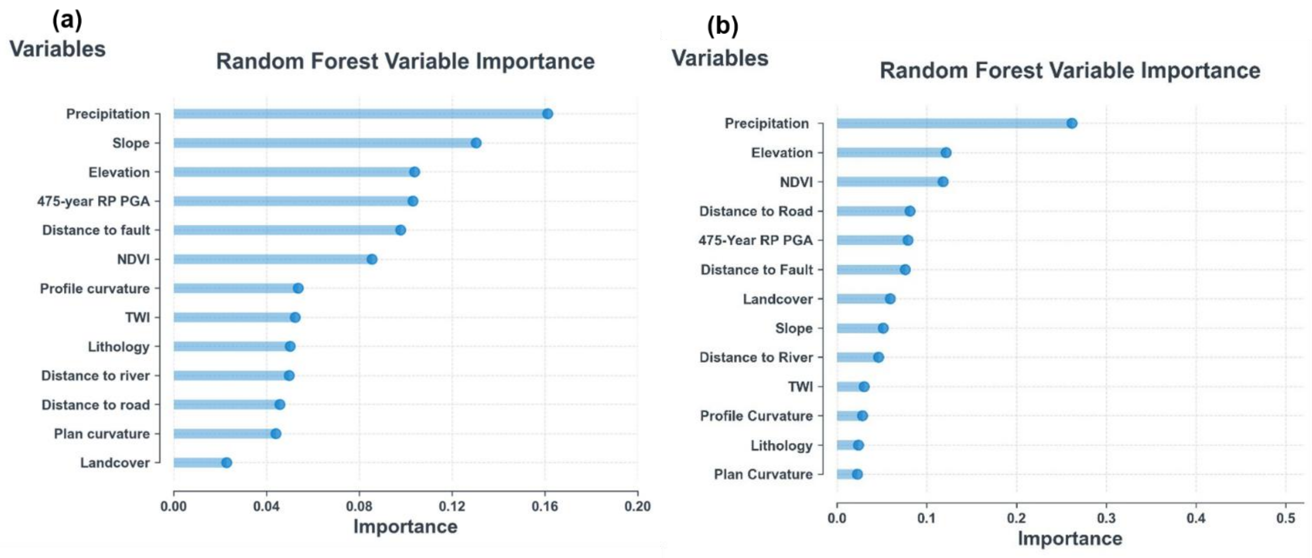
The validation strategy requires careful reconsideration too. Unlike the Yangtz region, where it is reasonable to expect very few to no landslides due to the largely flat topography, in the other regions (e.g., Tibet) the inventory is likely to be rather incomplete. In such contexts, validation metrics may be strongly biased and inflated by the true negatives, which are an artifact. As a result, model performance reflects the spatial structure of the inventory and the mapping efforts rather than a true prediction of landslide

spatial distribution. Reicenbach et al., (2018) showed that if training needs statistically representative inventories, susceptibility model validation needs complete inventories.
The authors should therefore explicitly address how inventory incompleteness affects model training and validation, and discuss whether the adopted entire modelling strategy (training and validation) is appropriate given the spatial heterogeneity of the data.

Response:
Thank you for this important comment. We agree that, when landslide inventories are potentially incomplete and spatially heterogeneous, generating non-landslide samples outside landslide buffers across the entire study area may propagate inventory incompleteness rather than mitigate it. In response to this concern, we revised the non-landslide sampling strategy in the susceptibility modelling framework.

Specifically, all landslide records were first spatialized in ArcGIS Pro, resulting in 93,935 landslide points. A 3 km buffer was then established around each landslide point. Outside all buffers, non-landslide points were randomly generated at a ratio of 2:1 relative to the number of landslide points, but only within areas with human presence rather than across the whole of China. Human presence was identified using the WorldPop R2025A version v1 population dataset, from which the annual mean population for China during 2015–2023 was calculated at 1 km resolution (Bondarenko et al., 2025). To maintain temporal consistency, each non-landslide point was randomly assigned a year between 2008 and 2023 to match the temporal distribution of the landslide points.

To assess the impact of this revised sampling strategy, we compared susceptibility maps produced using two different non-landslide sampling strategies: random sampling across the whole study area and sampling restricted to areas with human presence. The results revealed substantial differences between the two approaches. When non-landslide samples were randomly generated across the whole of China, susceptibility tended to be overestimated in densely recorded regions, such as SC and SW, while being underestimated in sparsely recorded regions, such as NW and Tibet (Response Fig. 1). This was also reflected in the feature-importance results, where whole-area random sampling led to lower importance of geomorphological and lithological factors (Response Fig. 5). This is likely because the landslide inventory used in this study was compiled by integrating post-disaster investigations and annual geological hazard potential-site surveys, and these records are relatively more concentrated in areas with human settlements and activities. Under such conditions, randomly generating non-landslide samples across the entire study area may incorrectly treat poorly surveyed or uninhabited regions as true negatives, thereby amplifying the effect of spatial inventory incompleteness and increasing the uncertainty and spatial bias in susceptibility mapping results (Reichenbach et al., 2018). Therefore, we modified the non-landslide sampling strategy by restricting non-landslide sample generation to human presence, as a practical strategy to reduce the uncertainty and spatial bias introduced by inventory incompleteness. The corresponding description has been added to the revised manuscript (Lines 185-192, 428–440).



Response Fig. 5: Relative importance of landslide conditioning factors as determined by the random forest (RF) model. (a) Feature importance derived using non-landslide samples generated in areas with human presence. (b) Feature importance derived using non-landslide samples randomly generated across the whole study area.

We sincerely appreciate your valuable comments once again. If there are any further issues with the revised manuscript or if we have misunderstood any of your points, we would be grateful for your further guidance.

Best wishes!

References

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