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

Response to Reviewer2 Comments

Reviewer #2: This paper presents a study on the landslide susceptibility evolution influenced by future climate, in China, at the national scale. This subject is of great interest, and the methodology is clearly defined and described. The plan of the paper permits to have an easy lecture, and the paper is well written. However, several points must be deeply described and considered:
Many thanks for your careful review of our manuscript. The comments offered have been immensely helpful. We appreciate your insightful feedback on our paper. We have responded to every question, indicating exactly how we addressed each concern. We sincerely apologize for any issues in our research that may have caused inconvenience during your review process. Thank you for the opportunity to revise this 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. A lot of information is missing, necessary for the understanding and for defining the limits of the approach, especially the limits of the resolution of the different data. In particular, the influencing factors needs to be more detailed, as well as their maps (to put in supplement), their categories, description, accuracy, how they are obtained...

Response:

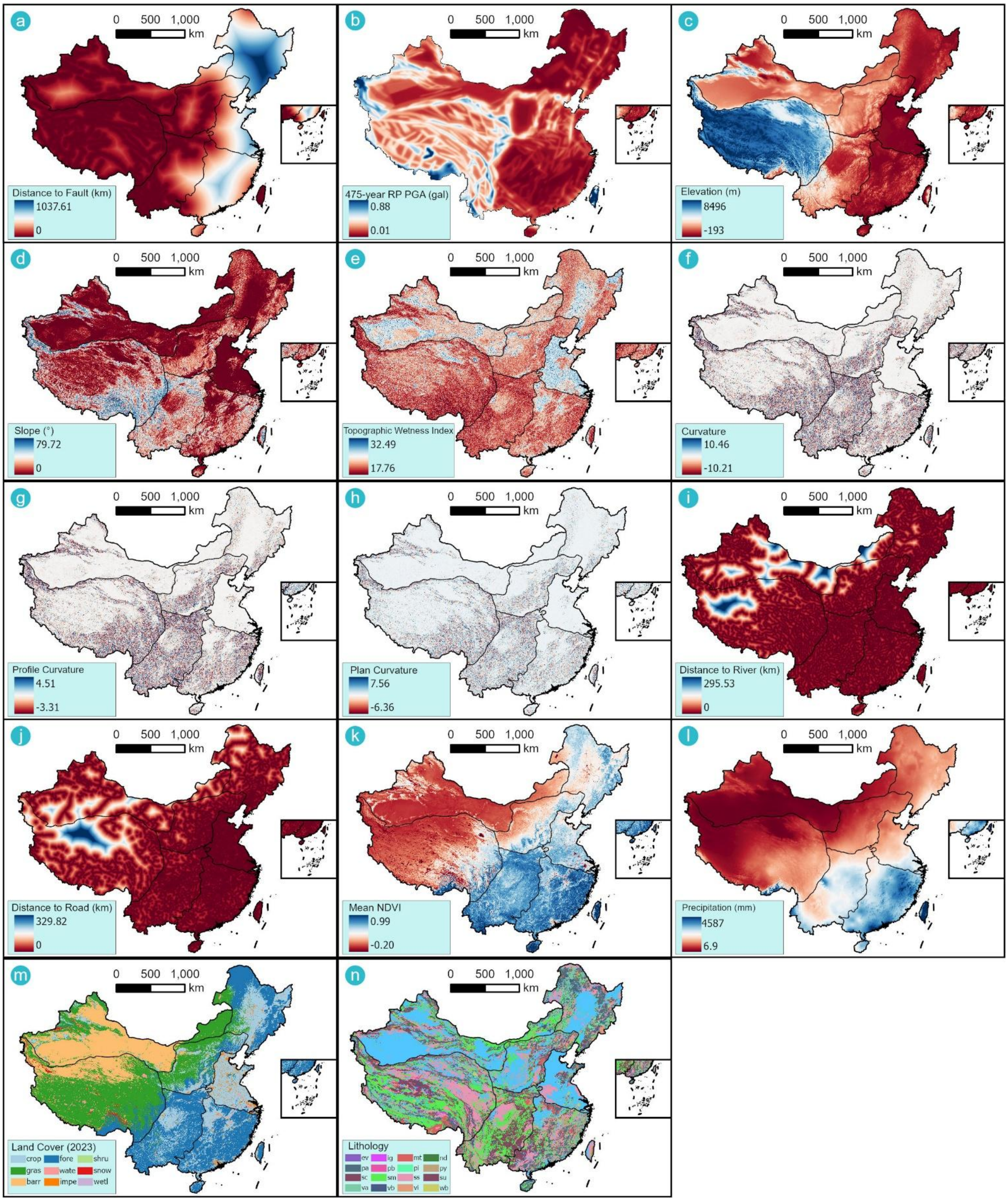
Thank you for your constructive comments on our manuscript. We appreciate your feedback, and we have made revisions to address your concerns. We understand the importance of providing sufficient information to clearly define the limits of our approach, particularly concerning the resolution of the data used in our study. To clarify, the spatial and temporal resolution of the data used in the study is detailed in Table R1, which outlines the datasets and their corresponding spatial and temporal resolutions.

In response to your comment on the influencing factors, we have provided more detailed information on the characteristics of these factors, including their spatial distribution and categories. This additional information is included in Table R1 and Response Fig. S1. The accuracy of each influencing factor is assured through the reference to the original articles from which the data were obtained, as indicated in section 2.2 of the manuscript. We have also listed the corresponding download URLs for the data sources.

We believe these revisions provide the necessary clarity regarding the data resolution and influencing factors used in the study. If there are any further issues or areas that require additional clarification, we would be happy to address them.

Table R1: Datasets and their corresponding landslide influencing factors. “-” indicates no time-series information.

Data Type	Dataset	Resolution	Time Period	Influencing Factor
Geological Features	GLiM	1:3750,000	-	Lithology
	GEM GAF-DB	Vectors	-	Distance to fault
	Global Seismic Hazard Map	0.04°	-	475-year return period PGA
Geomorphometric Features	SRTM Digital Elevation Data Version4	90 m	-	Elevation Slope TWI Curvature Plan curvature Profile curvature
Hydrological Features	1-km Monthly Precipitation Dataset for China	1 km	1950-2023	Annual total precipitation
	NEX-GDDP-CMIP6	0.25°	1950-2100	
	Five-level River Dataset of China	1:1,000,000	-	Distance to river
Environmental Features	China's Land-Use/Cover Datasets (CLCD)	30 m	2008-2023	Landcover
	MOD13Q1.006 Terra Vegetation Indices 16-DayGlobal250m	250 m	2008-2023	NDVI
	Open Street Map Global Primary Roads	Vectors	-	Distance to road



Response Figure. 1 | Landslide influencing factors utilised in this study. (a) Distance to fault, (b) PGA with a 475-year return period, (c) Elevation, (d) Slope, (e) Topographic Wetness Index (TWI), (f) Curvature, (g) Profile Curvature, (h) Plan Curvature, (i) Distance to River, (j) Distance to Road, (k) Mean NDVI: Monthly mean NDVI from 2008 to 2023, (l) Precipitation: Annual total precipitation, (m) Lithology. ev: evaporites, sc: carbonate sedimentary rocks, ig: ice and glaciers, sm: mixed sedimentary rocks, mt: metamorphics, ss: siliciclastic sedimentary rocks, nd: no data, su: unconsolidated sediments, pa: acidic plutonic rocks, va: acidic volcanic rocks, pb: basic plutonic rocks, pi: intermediate plutonic rocks, vi:

intermediate volcanic rocks, py: pyroclastics, wb: water bodies., (n) Land cover. crop: Cropland, fore: Forest, shru: Shrub, gras: Grassland, wate: Water, snow: Sonw/Ice, barr: Barren, impe: Impervious, wetl: Wetland.

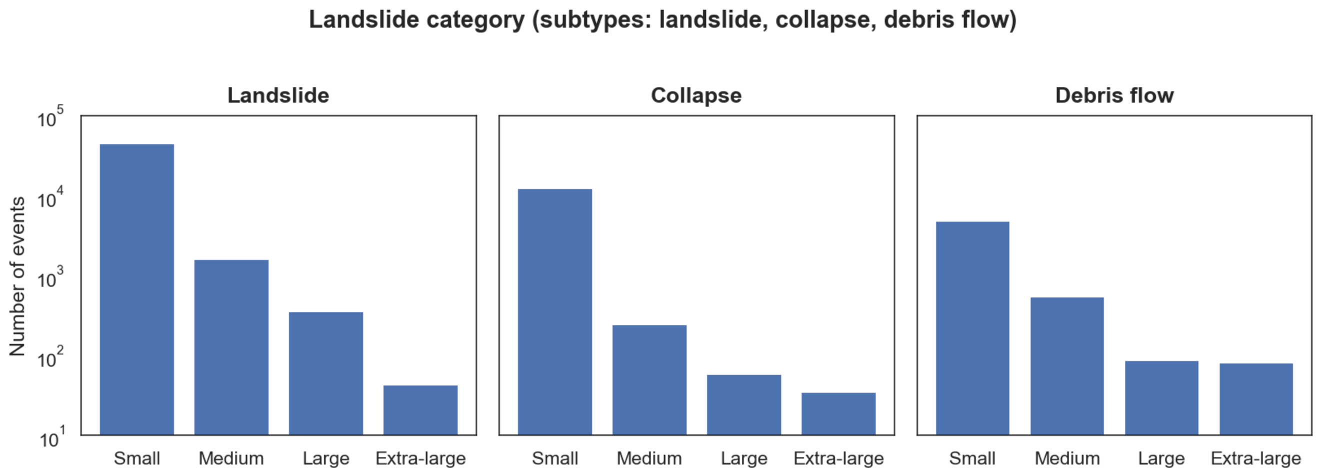
2. Landslide inventory must be more detailed and described; some statistical analyses could be provided (typology, size..); the triggering conditions have to be discussed: as I understand, they are not all triggered by rainfall, but also by earthquake. From a methodological point of view, it is necessary to consider only the ones triggered by rainfall. Moreover, all landslides have been considered here (landslide, collapse, debris flow…), but their predisposing parameters and triggering conditioning are not the same. A separate analysis might be more robust. Finally, it might be useful to provide some statistical analyses on the inventory, related to some predisposing factors (for instance are the landslides localised close to road?)

Response:

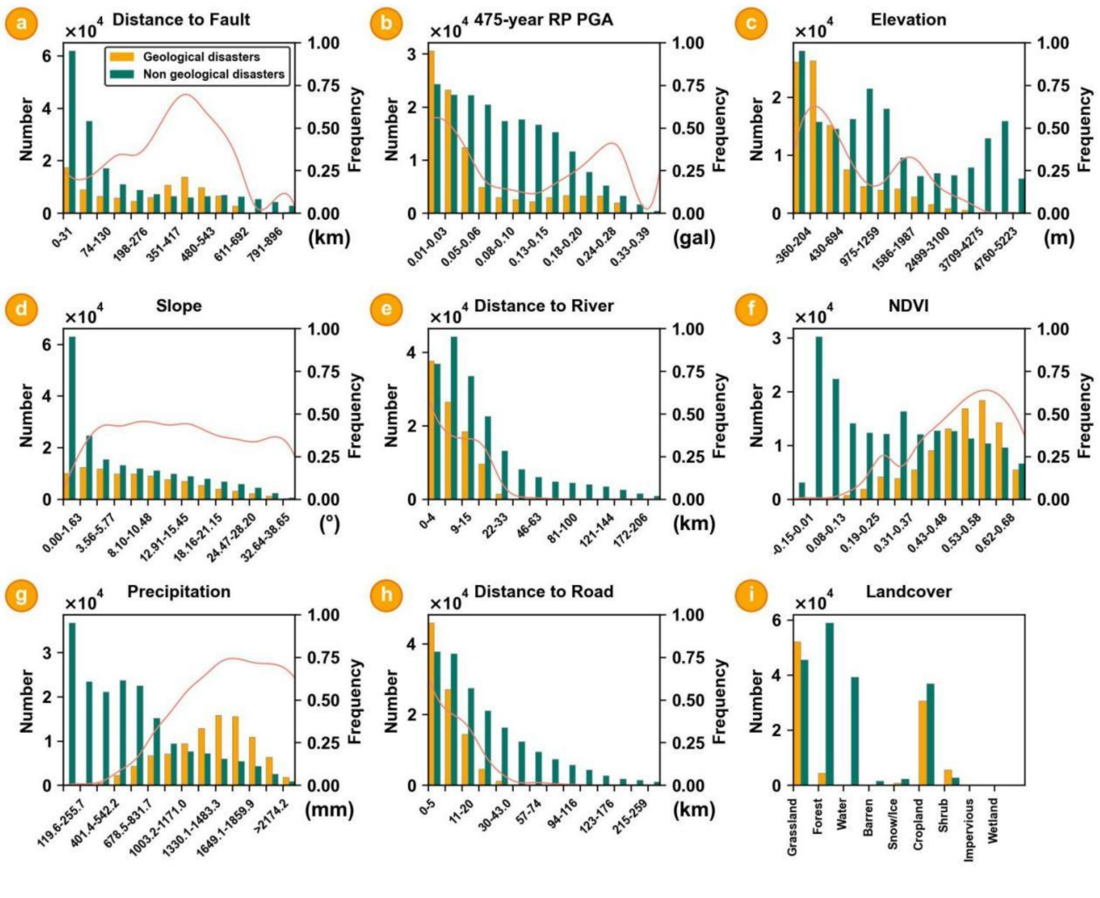
Thank you for your insightful comments on our manuscript. We have carefully considered your suggestions and made revisions accordingly. Below, we address each of your concerns:

We appreciate your suggestion to provide a more detailed description of the landslide inventory. To address this, we have added further information about the inventory, including typology and size distribution. Specifically, the statistics on landslide scale and type are presented in Response Fig. 2. The susceptibility modelling in this study focuses on rainfall-triggered landslides. We have also included an analysis of the spatial distribution and relationship between landslides and influencing factors in Response Fig. 3, with detailed discussions provided in the manuscript text (Lines 393–412). These analyses help to better understand the correlation between landslide occurrences and various predisposing factors, such as distance to road, elevation, and vegetation.

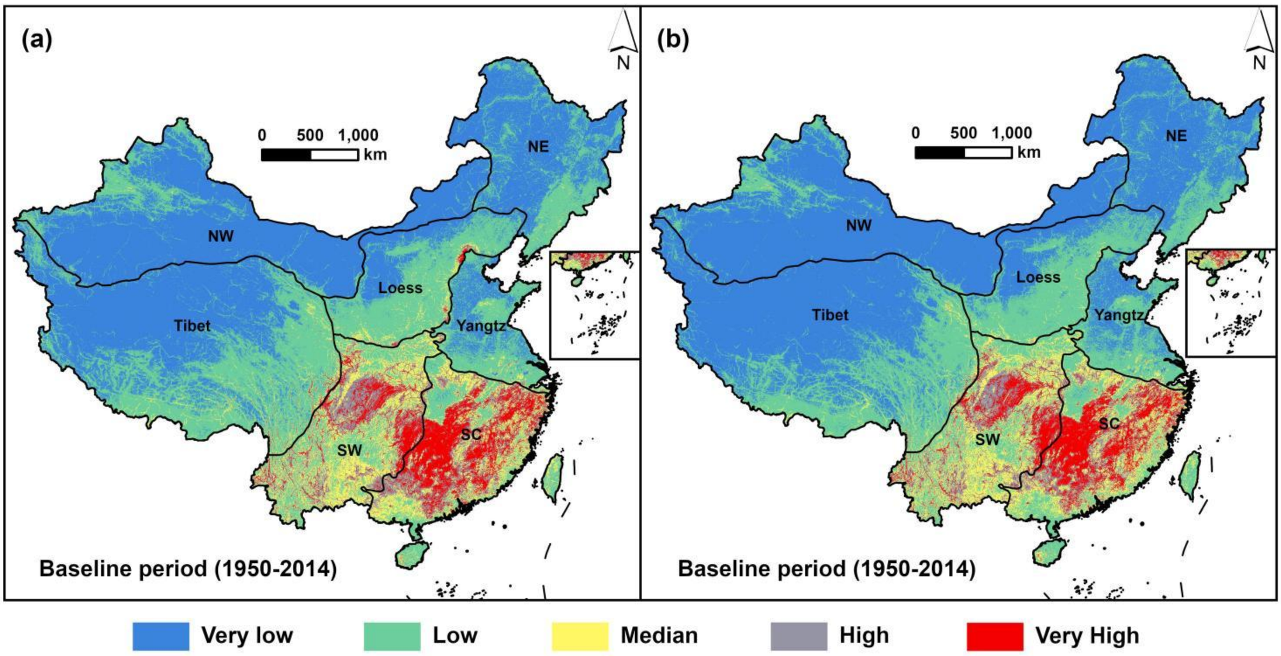
During model development, landslides, rockfalls, and debris flows were collectively treated as a single “landslides” category, following common practice in national-scale landslide inventory studies. To evaluate the potential impact of this merging, we compared susceptibility maps generated using the combined dataset with those derived from a landslide-only dataset. The two sets of results exhibit a high level of agreement (Pearson’s $r = 0.964$; $MSE = 0.12$), suggesting that the merging has a minimal influence on the overall spatial pattern and that the model results are robust (Response Fig. 4). The corresponding analysis and discussion are provided in Lines 421–426 of the manuscript.



Response Figure. 2 | From 2008 to 2023 in China, rainfall-induced landslide-related hazards (here treated as a broad landslide category that includes landslides, collapses, and debris flows) show a clear small-to-medium dominance. Among the three subtypes, landslides are the most frequent, and are overwhelmingly concentrated in the small class. Collapses and debris flows occur less often overall, but they follow the same pattern, with most events falling into the small and medium classes. Event counts decline sharply with increasing scale across all subtypes, and large to extra-large events are comparatively rare. Overall, the 2008 – 2023 record indicates that China's rainfall-induced landslide-related hazards are characterized by high-frequency, smaller-scale events, with extreme large events occurring infrequently.



Response Figure. 3 | The relationship between landslide points and non-landslide points and conditioning factors. (a) Distance to Fault, (b) 475-year return period PGA, (c) Elevation, (d) Slope, (e) Distance to River, (f) NDVI, (g) Precipitation: Annual total precipitation, (h) Lithology, and (i) Landcover. Landslide hazard frequency is defined as the "number of landslide samples/total sample size," where the total sample consists of hazard points and twice the number of non-hazard points.



Response Figure. 4 | Landslide susceptibility mapping in China for the baseline period (1950 – 2014). (a) Combined susceptibility map representing landslides, rockfalls, and debris flows as defined in this study. (b) Susceptibility map for landslides only, excluding rockfalls and debris flows. The correlation coefficient between the two models is 0.964, with a Mean Squared Error (MSE) of 0.12. Both models have an Area Under the Curve (AUC) score of 0.97.

3. The choice of some factors, as well as the data used for characterising these factors, is not justified. For instance, the seismic hazard map might be not adapted to this study as it is focused on landslide triggered by rainfall, and not earthquake. So, I don't have any explanations on the usefulness of this data, nor the mechanical link of this data to landslide occurrence. I am not convinced by the discussion concerning landslide susceptibility distribution related to the 475-year RP PGA data (between lines 327- 333); It is important to only consider landslide triggered by rainfall within the inventory.

Response:

Thank you for raising this point. We agree that our study focuses on rainfall-triggered landslides, and therefore the seismic dataset should not be interpreted as representing seismic triggering. In our framework, the 475-year return-period peak ground acceleration (PGA) is included as a long-term seismotectonic conditioning factor, rather than a triggering variable.

Importantly, previous work has shown that past or persistent seismic activity can weaken slope materials and rock mass structure (e.g., increasing fracture density and damage), thereby predisposing slopes to failure under subsequent rainfall. In this sense, seismicity contributes to rainfall-induced landslide occurrence indirectly by modifying the mechanical and structural conditions of slopes, even when rainfall is the immediate trigger (Leshchinsky et al., 2021). Accordingly, we use PGA to characterize the long-term background susceptibility associated with seismically conditioned terrain, not to model earthquake-triggered landslides.

The corresponding explanation and clarification are provided in Lines 107–115 of the revised manuscript.

4.In the introduction, the literature analysis related to landslide analysis under climate change is weak, with lack of references. This might be improved.

Response:

Thank you for your valuable comment. We agree that the literature review in the Introduction should provide a more comprehensive overview of advances in landslide susceptibility mapping under climate change. In response, we have expanded the Introduction by adding a dedicated paragraph that systematically reviews studies combining LSM with climate-change scenarios (Lines 46–59 in the revised manuscript).

In recent years, LSM has increasingly been combined with climate-change scenarios. The aim is to assess how the spatial distribution of rainfall-triggered landslide susceptibility may change across future climate scenarios and time periods. Existing work can be broadly grouped into three types. First, physically coupled approaches combine outputs from global climate models (GCMs) or regional climate models (RCMs) with physically based slope-stability models to examine climate-change impacts on landslides (Hürlimann et al., 2022; Peres and Cancelliere, 2018). Typical models and applications include the Fast Shallow Landslide Assessment Model (FSLAM) (Hürlimann et al., 2022), the Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability model (TRIGRS) (Alvioli et al., 2018), and associated landslide warning models (Ciabatta et al., 2016). Second, threshold methods extract rainfall indicators related to triggering from climate scenarios (e.g. daily rainfall and antecedent cumulative rainfall), and then apply historical or scenario-based thresholds to quantify threshold exceedance (e.g. exceedance frequency or counts); these results are used to update landslide susceptibility (Lin et al., 2022; Wang et al., 2021). Third, downscaled climate variables or rainfall-derived indicators are fed into machine-learning frameworks to produce time-slice susceptibility maps (Park and Lee, 2021; Viet Du et al., 2023). Machine learning captures both linear and non-linear relationships and handles high-dimensional data with complex interactions. It also facilitates the integration of multi-source remote-sensing data and large-area samples, making it particularly suitable for regional-to-national scale susceptibility studies.

5. The use of data coming from climate change model is another point: some details must be provided on these models. Is the low resolution of these data adapted for the scientific question of this paper?

Response:

Thank you for this important comment regarding the use of climate change model data. We agree that additional clarification on the selected climate models and their suitability for the objectives of this study is necessary.

In this work, we adopted future climate projections from the NEX-GDDP-CMIP6 dataset, selecting General Circulation Models (GCMs that simultaneously provide simulations for the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios. This selection ensures internal consistency across scenarios and allows a robust comparison of landslide susceptibility changes under contrasting future climate pathways. Detailed information on the selected models, including their performance evaluation and selection criteria, is provided in Table R2 and described in Lines 145–159 of the revised manuscript.

Regarding the suitability of the spatial resolution, it should be noted that this study focuses on national-scale, long-term variations in annual landslide susceptibility, rather than on the detailed representation of individual landslide events or localized extreme rainfall triggering mechanisms. Within this spatial–temporal framework, the primary objective is to identify the relative spatial patterns and long-term evolution of landslide susceptibility under different climate change scenarios. Previous studies have demonstrated that, at large spatial scales and over long-term periods, CMIP6 climate model outputs are appropriate for characterizing overall trends in climate-change-related landslide processes (Duan et al., 2025; Lin et al., 2022).

In this study, we employed the NEX-GDDP-CMIP6 dataset, which preserves long-term climate change signals while providing higher spatial resolution through statistical downscaling. We therefore consider the resolution of these data to be suitable for addressing the scientific questions of this study, namely the assessment of large-scale and long-term trends in rainfall-induced landslide susceptibility under climate change (Lines 145–159, 507–526).

Table R2: Comparison of simulated precipitation and observed precipitation (The root mean square error (RMSE) for different models)

ID	Model	RMSE	Mean RMSE (574.60)
1	IPSL-CM6A-LR	561.81	RMSE ≤ Mean RMSE
2	BCC-CSM2-MR	567.90	
3	MPI-ESM1-2-HR	568.80	
4	INM-CM5-0	568.86	
5	ACCESS-CM2	569.07	
6	NESM3	569.17	
7	CanESM5	569.96	
8	UKESM1-0-LL	570.11	
9	CNRM-ESM2-1	570.14	
10	KIOST-ESM	570.22	
11	EC-Earth3	570.34	
12	HadGEM3-GC31-LL	570.76	
13	EC-Earth3-Veg-LR	570.87	
14	CNRM-CM6-1	571.33	
15	MIROC-ES2L	571.73	
16	FGOALS-g3	571.80	
17	GISS-E2-1-G	572.02	
18	NorESM2-LM	572.61	
19	ACCESS-ESM1-5	573.04	
20	INM-CM4-8	573.18	
21	MRI-ESM2-0	575.14	RMSE ≤ Mean RMSE
22	IITM-ESM	576.75	
23	MPI-ESM1-2-LR	577.33	
24	GFDL-ESM4	577.53	
25	NorESM2-MM	577.96	
26	MIROC6	578.38	
27	CESM2	579.36	
28	CMCC-ESM2	580.93	
29	TaiESM1	581.35	
30	CMCC-CM2-SR5	596.12	
31	KACE-1-0-G	607.04	

Notes:

(1) RMSE is calculated using the formula provided above, which compares simulated and observed annual precipitation totals for each model.

(2) Mean RMSE is 574.60, representing the average RMSE across all models.

6. Is mean annual precipitation adapted to explain the landslide susceptibility? Monthly precipitation might be a proxy of antecedent condition/ soil saturation, but I don't understand why annual precipitation has an influence on landslide susceptibility. As said before, I am not convinced that mean annual precipitation is adapted to explain the landslide susceptibility, as it is not linked with intense rainfall, as suggested in the paper (line 321). At the least, monthly rainfall value before the occurrence of a landslide from the inventory could be a proxy of antecedent rainfall or saturation.

Response:

We thank the reviewer for this insightful comment regarding the suitability of mean annual precipitation in landslide susceptibility modelling. Before addressing the role of precipitation, we clarify how precipitation is used in the modelling framework.

In this study, annual total precipitation is used as a dynamic model input at the annual scale. The random forest model is trained to produce year-specific landslide susceptibility maps, in which each year is associated with its corresponding annual precipitation value. Subsequently, multi-year mean landslide susceptibility maps for different periods and climate scenarios are obtained by averaging the annual susceptibility results, rather than by directly modelling susceptibility using multi-year mean precipitation. Mean annual precipitation is used only for comparing sustained precipitation changes across different periods and scenarios and their corresponding long-term susceptibility variations.

It should be noted that monthly precipitation may better represent antecedent rainfall and soil saturation. However, the objective of this study is to assess spatial patterns and long-term changes in landslide susceptibility at the national scale under climate change scenarios.

In this context, annual total precipitation is adopted as a proxy for the long-term hydroclimatic background, rather than as a direct indicator of intense rainfall events. Annual total precipitation reflects the overall precipitation regime and its interannual variability, which can exert a sustained influence on landslide susceptibility by shaping hydro-environmental conditions such as long-term soil moisture availability, weathering intensity, vegetation growth, and slope material properties. These factors collectively precondition slopes and influence their sensitivity to rainfall-triggered failures at regional to national scales (Lin et al., 2021; Reichenbach et al., 2018).

In addition, the landslide inventory released for this study includes only the year of occurrence; the month and day of occurrence are not available. This limits the ability to establish a temporally consistent linkage with monthly or daily antecedent precipitation indices. Under this constraint, using annual total precipitation ensures temporal compatibility between the precipitation variable and the temporal resolution of the landslide data, while still providing meaningful information on long-term wetness conditions.

Previous national- and regional-scale studies have similarly adopted annual-scale precipitation metrics (e.g., annual total precipitation or mean annual precipitation) as climatic background factors in landslide susceptibility assessments, particularly when investigating long-term or climate-driven changes (Lin et al., 2021; Reichenbach et al., 2018). Besides, the feature importance analysis in our random forest model indicates that annual total precipitation has the highest contribution among all predictors, which further supports— from a data-driven perspective—its relevance in explaining large-scale spatial variability in landslide susceptibility. This issue has been discussed in the revised manuscript (Discussion, Lines 427–440).

7. I don’t understand why the influence of key factors are analyzed on future susceptibility map, and not on current one. I suggest analyzing them on historical landslide susceptibility, and to present this before analyzing future precipitation and future susceptibility.

Response:

Thank you for this valuable suggestion. We agree that analyzing the influence of key conditioning factors based on historical landslide susceptibility provides a clearer and more appropriate baseline for understanding landslide–environment relationships.

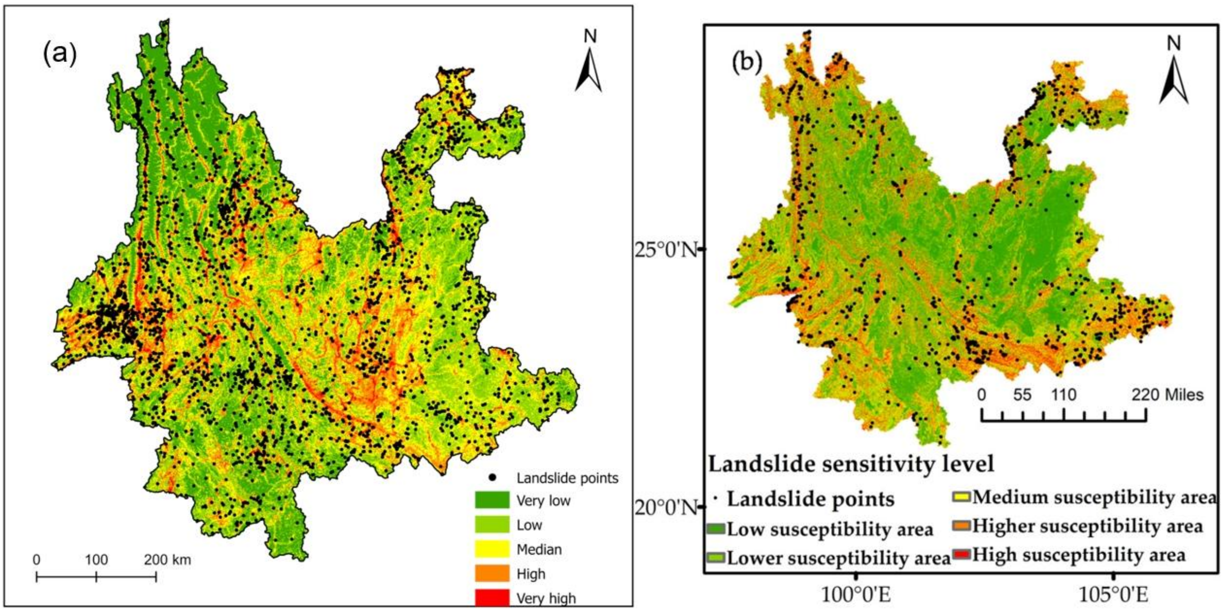
Following your recommendation, we have revised the manuscript so that the analysis of key influencing factors is now conducted using the historical landslide susceptibility map rather than future susceptibility results. This analysis is presented prior to the sections on future precipitation changes and projected future landslide susceptibility. The corresponding analysis is provided in Lines 282–331 of the manuscript.

8. The importance of some parameters is surprising; indeed, the lithological map at 1:3 750 000 is a tricky issue because of the low resolution. That might explain why these data have low relative importance within predisposing factors in RF analysis. Indeed, it is questionable that lithology is not within the most important feature. This point has to be largely discussed; if no more accurate data exist, one solution might be to compare the susceptibility map to other ones at regional scale, or to compare lithology at national and regional scale and discuss the differences.

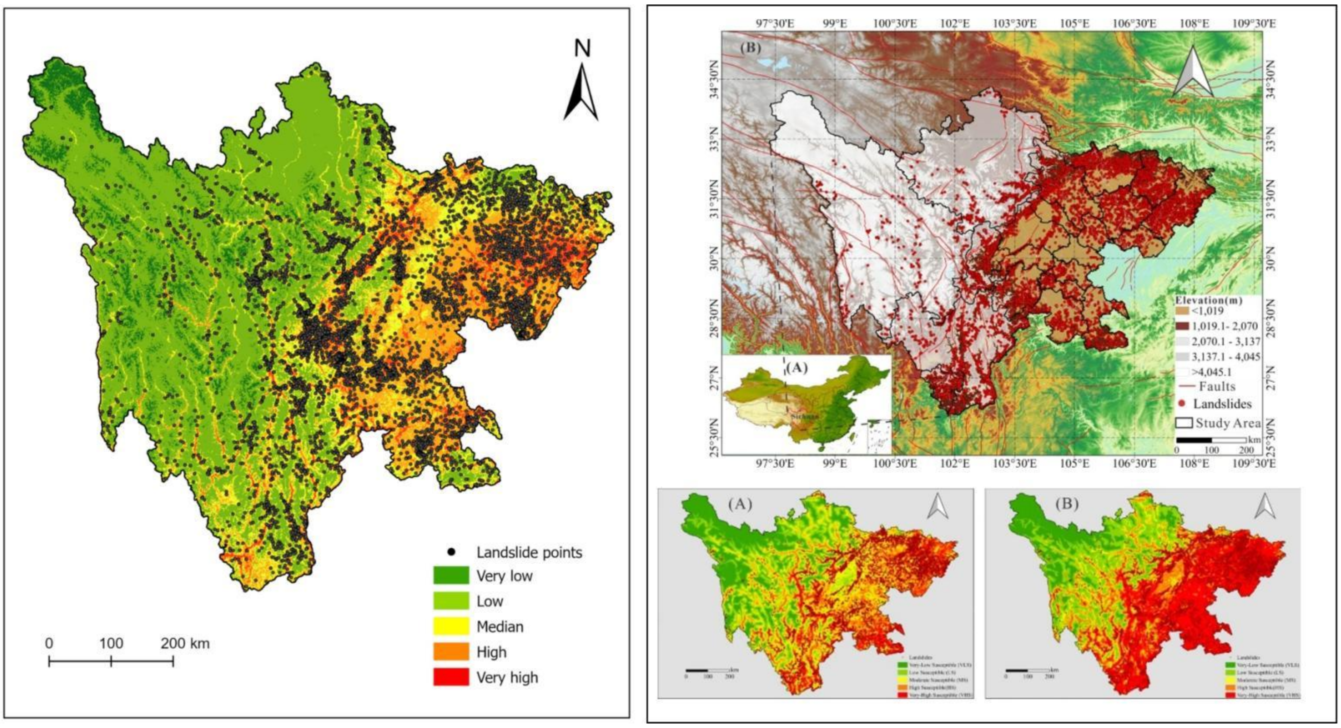
Response:

We thank the reviewer for raising this important point regarding the relatively low importance of lithology in the RF analysis and the potential influence of lithological data resolution.

It should be noted that, at the national scale of landslide susceptibility mapping, lithological information is often affected by data resolution. Its influence may be partly weakened in machine-learning models. To evaluate the applicability of the lithological data used in this study at the national scale and its potential impact on the results, we compared our susceptibility maps with those from regional-scale studies based on higher-resolution lithological data (Response Fig. 5–6). In Yunnan Province, the overall spatial patterns are consistent (Response Fig. 5). However, in central-eastern Yunnan, our predicted susceptibility is generally higher and more widespread. This discrepancy may be due to a lack of representative landslide samples in the comparison study, which can lead to an underestimation of locally susceptibility areas (Liu et al., 2023). In Sichuan Province, both our results and the regional study exhibit a clear “higher susceptibility in the east and lower susceptibility in the west” pattern (Response Fig. 6). The regional study predicts higher susceptibility in eastern Sichuan (Zhao et al., 2025), while differences in susceptibility levels and spatial extent between the two studies may be related to differences in variable construction, training sample size, and model structure. It may also reflect uncertainty from model choice. Different models can respond differently to the same conditions. They can assign different weights to controlling factors. This can change both susceptibility level and spatial extent. Overall, despite the relatively low feature importance of lithology in the RF analysis, the national-scale landslide susceptibility patterns obtained in this study show good spatial stability. Future availability of more detailed lithological data is expected to further reduce uncertainty in landslide susceptibility mapping (Henriques et al., 2015). This issue has been discussed in the revised manuscript (Discussion, Lines 457–470).



Response Figure. 5: Comparison of landslide susceptibility maps in Yunnan Province derived from lithological data with different spatial resolutions. (a) Landslide susceptibility map produced in this study; (b) landslide susceptibility map obtained from a published study employing higher-resolution lithological data(Liu et al., 2023). Black dots indicate landslide locations. For comparison, the susceptibility classes in panel (a) were reclassified using the classification scheme applied in panel (b).



Response Figure. 6: Comparison of landslide susceptibility maps in Sichuan Province derived from lithological data with different spatial resolutions. (a) Landslide susceptibility map produced in this study; (b) landslide susceptibility map obtained from a published study employing higher-resolution lithological data (Zhao et al., 2025). Black dots indicate landslide locations. For comparison, the susceptibility classes in panel (a) were reclassified using the classification scheme applied in panel (b).

9. Moreover, it might also be surprising that geomorphological parameters (e.g. slope, curvature…) are not so important. At the contrary, NDVI, Elevation and Mean annual precipitation are the most important factors; this result is also quite surprising and must be discussed. NDVI reflects the vegetation density, but the effect of vegetation on landslide stability is not easy as several features can explain it : as explained in the paper the vegetation areas may imply more infiltration compared to urban areas ; but it is also important to consider the land use with different typology of vegetation; for instance some trees permit to stabilise the soil due to reinforcement of the roots ; some species also capture the rainfall , leading to the reduction of infiltration within the soil. All these aspects might be analysed and discussed.

Response:

We thank the reviewer for this valuable comment regarding the relative importance of geomorphological parameters and the dominant role of NDVI, elevation, and mean annual precipitation in the model.

As shown in Response Fig. 4, landslides are mainly concentrated in areas characterized by low elevation and high NDVI. This spatial pattern is closely related to the regional topographic setting and the spatial clustering of human activities. Low-elevation areas often correspond to river valleys, piedmont plains, and transportation corridors, where population density and engineering activities are more intensive. Such activities may disturb natural slopes through excavation, loading, and drainage modification, thereby weakening slope stability and increasing the likelihood of landslide occurrence (Brenning et al., 2015). High NDVI does not necessarily imply greater slope stability. Instead, at the national scale, it often reflects hilly and mountainous environments under relatively humid climatic conditions, where vegetation growth is vigorous. Under such humid background conditions, increased soil moisture content, elevated pore-water pressure, and enhanced convergence of surface runoff may collectively promote landslide initiation, despite the presence of vegetation (Li and Duan, 2024). Therefore, the positive association between NDVI and landslide susceptibility observed in this study should be interpreted as an indicator of humid environmental settings rather than as a direct stabilizing or destabilizing effect of vegetation itself.

In contrast, slope, plan curvature, and profile curvature show relatively low feature importance. It should be noted that, at the national scale of landslide susceptibility mapping, geomorphological characteristics are represented by a set of highly interrelated variables. Among these, elevation plays a dominant role in capturing large-scale topographic gradients. Because DEM-derived morphometric variables such as slope and curvature are partially correlated with elevation, their explanatory information may be jointly integrated within the model and partly captured by elevation itself (Saleem et al., 2019). Therefore, the relatively low importance of these factors can, to some extent, be interpreted in the context of the overall contribution of geomorphological characteristics, rather than being judged solely on individual factor results. Overall, geomorphological features exhibit high explanatory power, accounting for more than 30% of the total contribution.

As explained in our response to Comment 6, annual total precipitation is the annual-scale dynamic predictor used for year-specific susceptibility mapping, whereas mean annual precipitation is used only for inter-period and inter-scenario comparisons of sustained precipitation change and associated long-term susceptibility variations. These issues have been discussed in the revised manuscript (Discussion, Lines 427–456).

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