Response letter

Dear Editors and Reviewers:

Re: egusphere-2025-3004

We sincerely thank you and reviewers for providing us with such a valuable revision opportunity. Thus, we can further improve and present our studies. The comments from you and the reviewers were highly insightful and enabled us to greatly improve the quality of our manuscript. We have carefully reviewed the feedback and made corrections that we hope will be met with approval. Revised portions are marked on the revised manuscript. Please note that these resulting revisions did not change the paper's findings.

In the response letter to editor and reviewers, we firstly summarized the major changes in a cover letter to editors, and we then itemized response to editors and reviewers, **in which the blue font indicates the response to each comment and the black font presents the revision from the revised manuscript.**

We hope that the revisions in the revised manuscript and the responses to the comments will suffice to allow our manuscript to be suitable for publication in ***Natural Hazards and Earth System Sciences***.

Sincerely regards,

Songtang He (hest@imde.ac.cn)

Institute of Mountain Hazards and Environment, Chinese Academy of Science

Response to Reviewer #2

[Comment 1] General structure and integration between scales

A central weakness of the paper lies in the lack of clarity regarding how the local-scale analyses are integrated with the regional-scale susceptibility assessment. As currently presented, the local-scale analyses appear disconnected and scientifically irrelevant, adding little to the main argument. If the authors cannot clearly demonstrate the conceptual and methodological linkage between the two scales, I would recommend removing the local-scale component entirely.

Response:

Thank you very much for this valuable comment. We agree that the connection between the major landslide case and the large-scale susceptibility analysis was not clearly presented in the original manuscript. The purpose of introducing this landslide is to use it as a representative case study that links the regional-scale susceptibility assessment with the site-scale mechanisms of slope failure, providing a field-based context for subsequent susceptibility analysis and mechanistic interpretation. The landslide was triggered by the combined effects of prolonged rainfall, anthropogenic loading from waste deposits, and the additional weight of dense vegetation. This event highlights the amplifying effect of the interaction between vegetation and rainfall, indicating that local environmental disturbances can significantly increase landslide risk. In other words, vegetation may enhance slope stability under certain conditions but can also aggravate slope failure due to its additional weight and water-retention capacity. Therefore, this case not only provides empirical validation for the regional analysis results but also reveals the amplification of large-scale controlling factors under local conditions, further supporting the “double-edged sword” role of vegetation identified through the GeoDetector and SEM analyses.

We have revised the manuscript accordingly. Specifically, we have clarified the conceptual linkage between scales at the end of the Introduction, strengthened the role of the case study in the Study Area description, and explicitly integrated the local-scale findings into the Discussion to demonstrate their relevance to the regional susceptibility assessment.

1 Introduction（Revised manuscript line 100）

“*To address these research gaps, this study investigates the dual-edged role of vegetation in landslide susceptibility by integrating watershed-scale statistical analysis with site-specific geomechanical modeling. We selected the Jinkouhe District in Southwest China—a region with high vegetation cover (⩾65.5%) and frequent landslide activity—as our study area. The research aims to (1) Quantify the individual and interactive effects of key environmental factors (rainfall, vegetation, wind speed, slope, lithology, etc.) on landslide susceptibility at the watershed scale using Geodetector and Structural Equation Modeling (SEM). (2) Analyze the mechanical role of vegetation weight and its coupling with rainfall and anthropogenic loading in triggering a typical shallow landslide through slope stability calculations. (3) Integrate findings from both scales to elucidate how vegetation mediates landslide processes under different environmental conditions, thereby providing a multi-scale perspective on its “double-edged sword” function. By bridging macroscopic susceptibility patterns with microscopic failure mechanisms, this study offers novel insights into the complex vegetation–landslide interplay. The results are expected to enhance the accuracy of landslide risk assessments and inform sustainable slope management strategies in densely vegetated mountainous regions.*”

2.1 Study area（Revised manuscript line 142）

“*This study takes the JinKouhe area as the research focus. A major landslide occurred in the study area on June 4, 2023, near the living quarters of a Phosphate Mine (103°2'25.75" E, 29°25'0.6" N), which serves as a representative case providing field evidence for the subsequent discussion of slope-failure mechanisms.*”

4.3 Mechanisms of landslides in areas with high vegetation coverage（Revised manuscript line 544）

“*At the watershed scale, the GeoDetector results indicate that NDVI alone exhibits limited independent explanatory power (q = 0.27, Table 4). However, its* *interaction with rainfall significantly enhances landslide susceptibility (e.g., NDVI × rainfall q = 0.67, Fig. 8), suggesting that vegetation can amplify the destabilizing effects of precipitation under certain conditions. While vegetation intercepts rainfall and promotes evapotranspiration, it can also alter soil moisture distribution via stemflow, root-induced preferential flow, and reduced surface runoff. Under prolonged rainfall, these processes may lead to localized saturation, thereby exacerbating landslide and debris flow risks in vegetated slopes. This aligns with the SEM results, which attribute a total indirect effect of 0.21 to NDVI, mediated largely through soil moisture dynamics and interactions with rainfall and slope (Fig. 9, Table 5). The susceptibility scenario analysis further illustrates this duality: adding vegetation alone (Class II) slightly reduced the extent of very high susceptibility zones, yet when combined with rainfall (Class IV) and wind (Class V), it led to a notable expansion of high-susceptibility areas and an increase in landslide counts (Table 6, Fig. 10). This suggests that vegetation's protective capacity may be offset or reversed under prolonged rainfall, especially on steeper slopes.*

At the site-specific scale, the stability calculations provide direct mechanical insight into how vegetation can transition from a stabilizing to a destabilizing factor. Under natural (unsaturated) conditions, the slope remained stable even with the added weight of vegetation and waste material (Fs = 1.02). However, under saturated conditions, the same additional loads—particularly the self-weight of trees—reduced the stability coefficient to 0.89, triggering failure (Table 3). This demonstrates that the mechanical reinforcement from roots can be outweighed by the gravitational load of vegetation when soil strength is reduced by saturation, a shift that is quantitatively captured by our modeling.

These findings help explain why landslides may occur unexpectedly in densely vegetated areas. Vegetation can create a false sense of stability by masking early signs of movement (e.g., surface cracking, minor slumping) and by being traditionally associated with slope protection. Moreover, the same root networks that enhance soil cohesion also facilitate preferential infiltration, potentially accelerating soil saturation during heavy rainfall—a process reflected in the strong interaction between NDVI and rainfall in our spatial analysis. In terrain with high lateral variability in slope, lithology, or soil depth, vegetation may thus contribute to highly localized and *concealed instability, as exemplified by the 2023 Jinkouhe landslide.*"

[Comment 2] Methodological adequacy – Use of AHP: The use of the Analytic Hierarchy Process (AHP) as the core method for landslide susceptibility mapping raises serious concerns. AHP is highly subjective and largely outdated, having been replaced in the literature by more objective and data-driven approaches (e.g., statistical models, machine learning algorithms, ensemble frameworks). The authors do not provide any convincing justification for this methodological choice. In its current form, this decision undermines the robustness and reproducibility of the results.

Response:

Thank you for your insightful comment. We fully understand your concern regarding the use of the Analytic Hierarchy Process (AHP). To clarify, AHP is the primary method used in the manuscript for deriving factor weights and producing the susceptibility map. AHP was selected for its transparent and systematic weighting mechanism that facilitates the explicit incorporation of expert judgment, making it well suited for regions characterized by limited or uneven landslide inventory data. We do not claim that AHP is superior to data-driven techniques; rather, in this work AHP serves as the main, interpretable mapping approach appropriate for the study objectives and available data.

Moreover, AHP has continued to be widely applied in recent years for landslide susceptibility mapping due to its interpretability and ease of factor weighting (e.g., Alamrew et al., 2024; Asmare, 2023; Gebrehiwot et al., 2025; Liu et al., 2024; Mustapha et al., 2025). To further address your concern, we conducted a supplementary validation experiment using four interpretable machine learning models—XGBoost, LightGBM, GBDT, and CatBoost—to evaluate the robustness and reproducibility of our AHP-based results. The workflow was as follows: (1) all conditioning factors were extracted and divided into two categories (landslide and non-landslide samples); (2) data were standardized and randomly split into training (70%) and testing (30%) subsets; (3) the Optuna heuristic optimization framework was employed to tune model hyperparameters, replacing the traditional grid search approach; and (4) model performance was compared using ROC curves (Figure R1). The testing AUC values were 0.816 (CatBoost), 0.784 (GBDT), 0.773 (LightGBM), and 0.766 (XGBoost).

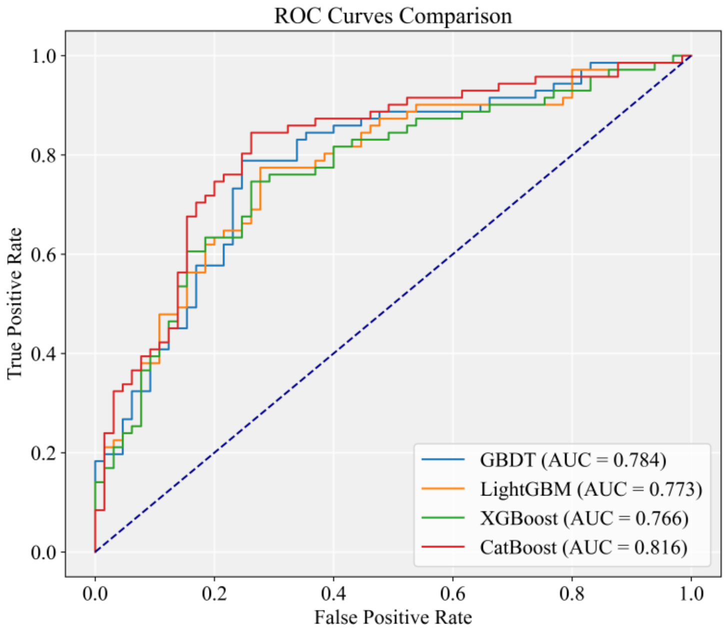

Fig. R1. **ROC curves comparing the four machine learning models**

Furthermore, we applied SHAP analysis to the CatBoost model to interpret feature contributions and found that the main controlling factors identified, such as Elevation, Slope, Distance to fault and Mean annual rainfall, were largely consistent with those derived from the GeoDetector analysis. The slight discrepancies are reasonable since SHAP evaluates the influence of each variable within the model's decision process, while GeoDetector emphasizes spatial heterogeneity.

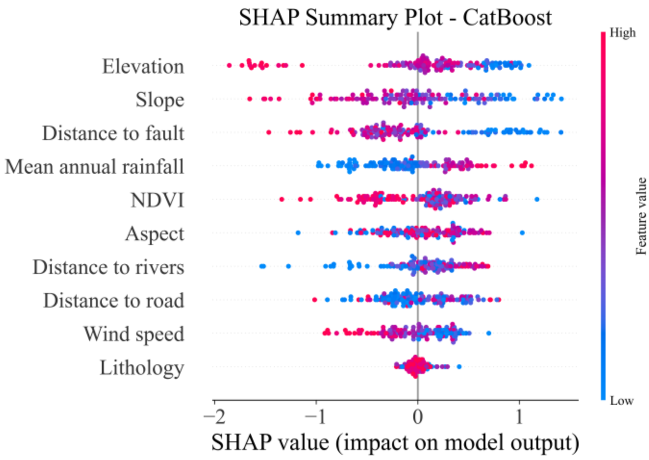

Fig. R2. SHAP summary (swarm) plot for the CatBoost model

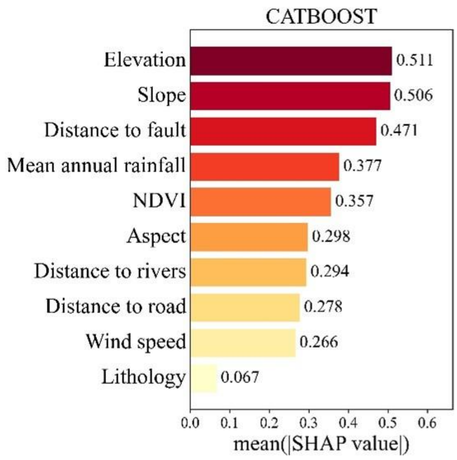

Fig. R3. Mean absolute SHAP values for the CatBoost model

Overall, the AHP model exhibited comparable predictive performance and similar dominant factors to the machine learning models, confirming the robustness and reproducibility of our results. More importantly, the negative samples in this supplementary experiment were generated using the same buffer-based method as in the AHP validation. This ensures the comparability of the results. Although the AUC values of the machine learning models are moderate, their performance could be further enhanced by incorporating more refined sampling strategies, such as factor-based spatial optimization or model-driven negative sample optimization frameworks. These improvements will be considered in our future work to enhance the precision and generalizability of machine learning–based susceptibility models.

References

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Mustapha, A. I. T., Etebaai, I., Taher, M., & Tawfik, A. (2025). Landslide Susceptibility Mapping in the Bokoya Massif, Northern Morocco: A Geospatial and Multi-Factor Analysis Using the Analytic Hierarchy Process (AHP). *Scientific African*, e02980. https://doi.org/10.1016/j.sciaf.2025.e02980

[Comment 3] Landslide inventory and model validation: The description of the landslide inventory is inconsistent and insufficient. The manuscript states that the inventory was downloaded from an online repository and then integrated with 227 manually identified landslides; yet later it is mentioned that the total number of landslides is 227. This discrepancy must be clarified. The authors should:

(i) provide a detailed and transparent description of the inventory, including sources, validation, and completeness; and
(ii) clearly explain the selection criteria for non-landslide points, as this strongly affects the ROC/AUC results.
Without this information, the reported validation accuracy appears potentially overestimated and unreliable.

Response:

We sincerely thank you for the valuable comments regarding the landslide inventory and model validation. The manuscript has been revised to provide a clearer and more detailed description, and we hope these clarifications address your concerns.

1. In this study, the landslide inventory was compiled from two sources: the first

source was the landslide inventory of the Jinkouhe area provided by the GeoCloud platform, and the second source consisted of landslides identified through visual interpretation of high-resolution satellite imagery (Sentinel-2) and manual verification. The datasets were integrated, and duplicate or uncertain cases were removed, resulting in a total of 227 landslides, representing the complete landslide distribution within the study area. To address the unclear description in the original manuscript, this has been revised in **# Revised manuscript line 196.** To visually demonstrate the reliability of some landslide points in the study area, Figure R4 shows a subset of landslides identified through visual interpretation, and part of these landslides have been added to Figure 1 in the revised manuscript. And the descriptions are below.

2.2 Data source and preprocessing（Revised manuscript line 197）

"*(8) Landslide hazard point data were obtained from the GeoCloud platform (https://geocloud.cgs.gov.cn/) and through manual interpretation of Sentinel-2 imagery acquired in August 2024. After integrating the sources and removing duplicates and uncertain cases, the final inventory consisted of 227 validated landslides, representing the complete distribution within the study area. Some representative landslides identified through visual interpretation are shown in Figure 1d–h.*"

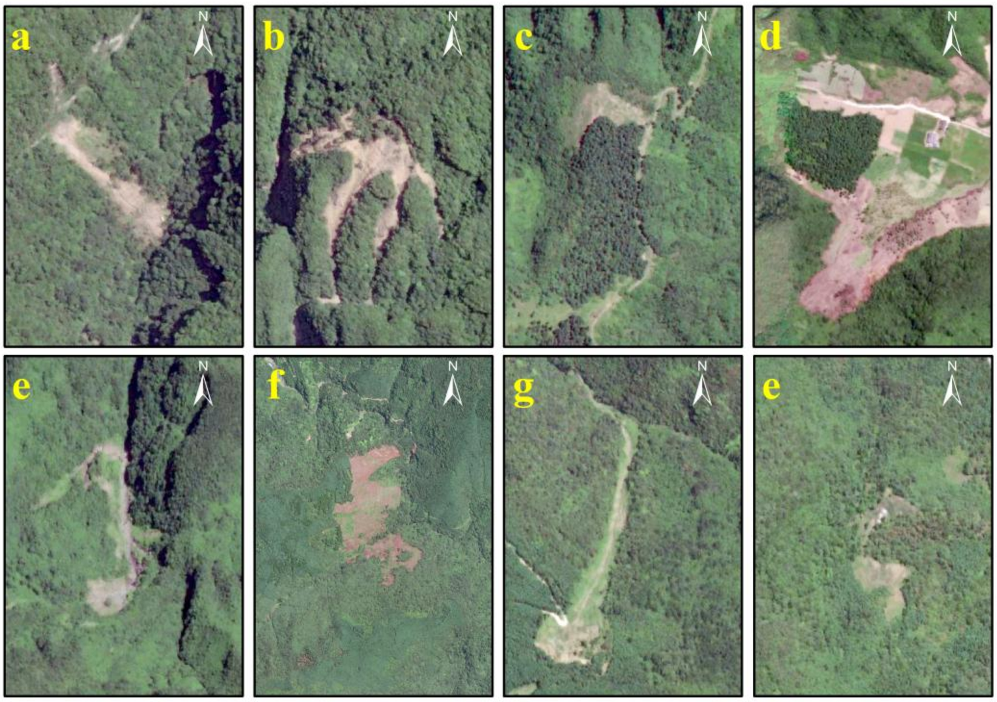

Fig. R4 Visually interpreted subset of landslides

2. To assess the reliability of the dataset and the robustness of the model, a 500 m buffer was generated around the known landslide points, and areas close to water bodies were excluded. Within the remaining regions, non-landslide points (negative samples) were randomly selected while maintaining a balanced ratio between positive and negative samples. Following the repeated random sampling approach commonly used in machine learning studies, 30% of the entire dataset was repeatedly and randomly selected as the testing subset for AUC validation. Multiple repeated validations were performed, and the resulting AUC values showed minimal variation (<0.05), indicating consistent and reliable model performance. These clarifications have been added in the revised manuscript, line 252.

2.3.2 Rationality validation of susceptibility assessment results（Revised manuscript line 252）

"*Based on the susceptibility distribution map and known landslide points, non-landslide points were randomly sampled from areas excluding water bodies and 500 m landslide buffer zones to maintain a balanced ratio between positive and negative samples. Following the repeated random sampling approach commonly used in machine learning studies, 30% of the entire dataset was repeatedly and randomly selected as the testing subset for ROC/AUC evaluation to assess model robustness. The mean AUC values obtained from the five scenarios were 0.774, 0.786, 0.795, 0.810, and 0.801, respectively—all exceeding 0.5. The variation in AUC across repetitions was minimal (<0.05), indicating consistent and reliable landslide susceptibility evaluation (Fig. 4).*"

[Comment 4] Reference to established best practices. The authors should explicitly compare their approach with the guidelines proposed by Reichenbach et al. (2018), who outlined key criteria for producing reliable landslide susceptibility maps. Currently, the manuscript neither demonstrates adherence to these well-established standards nor engages with them critically.

Response:

Thank you for your valuable comment. We carefully reviewed the work of Reichenbach et al. (2018) and compared their guidelines with our modeling approach. First, regarding the selection of conditioning factors, section 3.4.1 in Reichenbach's manuscript (Reichenbach et al. 2018) noted that for each susceptibility model, two to twenty-two thematic variables were typically used, with an average of nine. In our study, we selected ten factors—elevation, slope, aspect, distances to faults, rivers, and roads, lithology, rainfall, NDVI, and wind speed—which are sufficient to construct a robust model. Except for wind speed, all factors are commonly used in landslide susceptibility research. Second, in terms of mapping units, we adopted grid cells (30 × 30 m), which correspond to one of the three basic evaluation units recommended by Reichenbach et al. (2018). Finally, for model validation, we used the Receiver Operating Characteristic (ROC) curve, which is also mentioned as common practice in their work. Taken together, we believe that our methodology follows the best-practice guidelines proposed by Reichenbach et al. (2018). Accordingly, we have revised the manuscript to include the following statement at the beginning of Section 2.3.1.

2.3.1landslide susceptibility based on the analytic hierarchy process （Revised manuscript line 207）

"*Following the best-practice guidelines for landslide susceptibility mapping proposed by Reichenbach et al. (2018).*"

References

Reichenbach, P., Rossi, M., Malamud, B. D., Mihir, M., & Guzzetti, F. (2018). A review of statistically-based landslide susceptibility models. *Earth-science reviews*, *180*, 60-91. https://doi.org/10.1016/j.earscirev.2018.03.001

[Comment 5] Analysis of variables and use of geodetector: The attempt to explore how different variables (and their combinations) influence susceptibility is potentially interesting. However, the application of the GeoDetector method appears methodologically flawed: the authors use the susceptibility map (derived from AHP) as the dependent variable, rather than the landslide inventory itself. Since susceptibility is already a model — and a highly subjective one — this approach introduces a strong bias, making any subsequent inferences about controlling factors or vegetation effects questionable. Such analyses should be based on observed landslide occurrences, not on the output of another model.

Response: Thank you for your valuable comment. We fully understand your concern regarding the GeoDetector method and the choice of dependent variable. In most GeoDetector studies, the spatial distribution of landslide occurrences (i.e., the 0–1 variable representing landslide and non-landslide areas) is commonly used as the dependent variable to identify the major conditioning factors strongly associated with landslide occurrence. However, this approach is more suitable for the preliminary stage of factor screening (Liu et al., 2024; Sun et al., 2021; Yang et al., 2019; Zhou et al., 2023), as it can reveal which environmental variables show strong spatial consistency with landslide occurrences, but cannot effectively reflect how multiple factors interact or jointly influence the degree of landslide susceptibility.

The fundamental reason is that the 0–1 variable only represents two discrete states—“occurrence” or “non-occurrence”—and lacks information about continuous variation. It can only capture the spatial consistency between individual factors and landslide occurrence. In other words, when the dependent variable is binary (0–1), GeoDetector can answer the question “Which factors are correlated with landslide occurrence?” but not “How do these factors jointly shape the spatial distribution and intensity of landslide susceptibility?”. Therefore, such analyses reveal the spatial pattern of landslide occurrence rather than the underlying mechanism that controls the spatial heterogeneity of landslide susceptibility.

In this study, we used the landslide susceptibility map derived from the AHP model as the dependent variable, which serves a different purpose from the conventional approach. The susceptibility index is a continuous variable that represents the relative probability of landslide occurrence rather than a simple binary state of “occurred” or “not occurred.” Applying GeoDetector to this continuous susceptibility map allows us to quantitatively evaluate the explanatory power of each factor on spatial variations in susceptibility and further explore how factor interactions jointly influence the susceptibility pattern. This analysis helps clarify which environmental factors and combinations dominate the spatial variation of landslide susceptibility in the study area.

Therefore, this process is not a simple repetition of the AHP model results but rather a mechanism-oriented interpretation and validation from the perspective of spatial heterogeneity. In other words, using the landslide susceptibility map as the dependent variable in GeoDetector is not a methodological error but a deliberate design aimed at shifting the focus from the occurrence of landslide events to understanding the spatial mechanisms that shape landslide susceptibility, thereby giving the AHP results a clearer physical interpretation (Chen et al., 2023). And We fully understand your concern that “the susceptibility map itself is a model output, which may introduce bias.” To verify the rationality and reliability of applying the GeoDetector method based on the susceptibility map, we conducted additional experiments and comparative analyses from two complementary perspectives.

(1) GeoDetector comparison based on binary landslide classification

We re-applied GeoDetector using actual landslide and non-landslide samples (0–1 classification) as the dependent variable with the same set of conditioning factors. The results showed that the major explanatory factors—such as slope, distance to fault, and mean annual rainfall—were largely consistent with those identified by the AHP-GeoDetector analysis (Figure R5), with only minor differences in secondary factors. This demonstrates that the relative importance of conditioning factors remains stable even when the dependent variable differs, confirming the robustness and interpretability of the AHP-GeoDetector results.

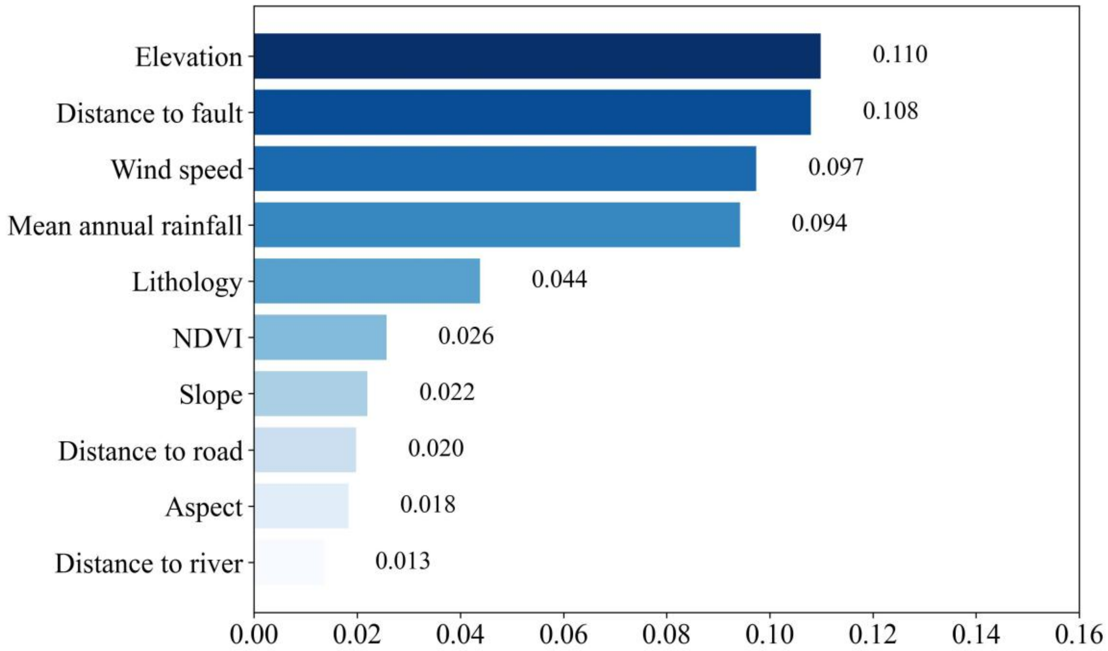

Fig. R5 GeoDetector factor importance using binary (0–1) landslide classification.

(2) Independent validation using a machine learning model

We also performed SHAP-based interpretability analysis using the CatBoost model from our previous supplementary experiments and compared its results with the AHP-GeoDetector analysis (Comment 2, Figure R2&3). The findings showed a high degree of agreement: key controlling factors such as elevation, slope, distance to fault, and mean annual rainfall were consistently identified as dominant contributors. This cross-method consistency indicates that the identification of landslide-driving factors is reproducible and stable across different modeling frameworks, demonstrating that the AHP results were not artifacts of model subjectivity.

In summary, our comparative analyses empirically validate the methodological soundness of applying GeoDetector to the susceptibility map. Although the AHP is an expert-based weighting model, its outputs show strong consistency and spatial explanatory power when verified by multiple independent approaches. Therefore, the GeoDetector analysis in this study did not introduce significant bias, but rather enhanced the understanding of the spatial mechanisms underlying landslide susceptibility formation.

References

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[Comment 6] Structure and clarity of the manuscript: The manuscript is redundant and lacks structural clarity. I recommend:(i) removing repetitive sentences;(ii) improving logical flow and conciseness throughout the text. In particular, several statements about the “ambiguous role” of vegetation are speculative and not sufficiently substantiated by quantitative evidence.

Response:

(1) we have carefully revised the manuscript to remove repetitive sentences and improve logical flow and conciseness. Statements related to the role of vegetation have been consolidated, and the end of the Introduction, the Study Area description, and the Discussion section have been reorganized to better integrate the multi-scale analyses.

(2) We thank you for highlighting the need for stronger quantitative support in Section 4.3 regarding the "ambiguous role" of vegetation. We agree that some statements in this subsection appeared speculative, and we have revised Section 4.3 to better integrate our empirical findings and quantitative results. Detailed explanations and corresponding manuscript revisions are provided in our response to Comment 9 (Response 26).

[Comment 7] Vegetation: The paper focuses on vegetation but does not include an accurate description of the types of vegetation present in the study area. This is a major issue in my opinion.

Response:

Thank you for your valuable comment. As you rightly pointed out, to provide a more accurate description of the vegetation types in the study area, we obtained the vegetation distribution based on the 1:1,000,000 China Vegetation Type Spatial Distribution vector data, as shown in the figure R6. The vegetation in the study area is mainly classified into shrubland, meadow, broadleaf forest, coniferous forest, and cultivated plants. Among them, the shrubland mainly consists of Myrica and Rhododendron; broadleaf forests mainly include Arundinaria-dominated forests, Quercus engleriana forests, and Castanopsis forests; and coniferous forests are primarily composed of Abies forests, Pinus yunnanensis forests, and subalpine Quercus forests. This information has been added to Section 2.1 "Study Area".

2.1 Study Area（Revised manuscript line 134）

"*Vegetation is classified into shrubland, meadow, broadleaf forest, coniferous forest, and cultivated plants. Shrubland is dominated by Myrica and Rhododendron,* *broadleaf forests include Arundinaria-dominated forests, Quercus engleriana forests, and Castanopsis forests, and coniferous forests consist mainly of Abies forests, Pinus yunnanensis forests, and subalpine Quercus forests.*"

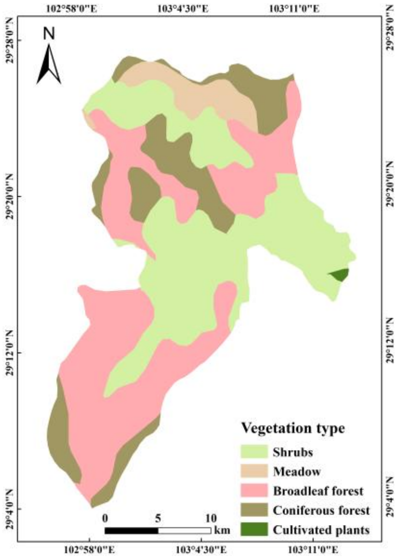

Fig. R6 Vegetation type distribution map

[Comment 8] Specific (but not minor) comments

1. l29: "landslide frequently occur" → How frequently? More than in other soil-cover conditions? I suggest replacing frequently with may.

Response:

Thank you for the suggestion. To improve the academic rigor and structural clarity of the Introduction, we substantially revised this section. During the revision, the original sentence containing the expression "frequently occur" was removed and no longer appears in the revised Introduction.

2. l59: What is meant by "good vegetation"?

Response:

Thank you for your comment. The original text is "...under good vegetation cover conditions...", which refers to areas with dense or well-developed vegetation cover. According to the suggestion on the introduction revision, I have completely rewritten the introduction section, removing the repetition, some ambiguous words, and logical errors. Please check the introduction section in the manuscript, lines 55-116, pages 4-6.

3. l60: change to: “mitigation also depends on…”

Response:

Thank you for your suggestion. We appreciate your attention to phrasing. To improve the academic rigor and structural clarity of the Introduction, we substantially revised this section. During the revision, the original sentence containing the expression “mitigation also depends on” was removed and no longer appears in the revised Introduction.

4. l73: What do you mean by “susceptibility to external disturbances”? I believe susceptibility refers specifically to landslides in this paper.

Response:

Thank you for your comment. In this context, “susceptibility to external disturbances” refers to the slope’s sensitivity to external triggering factors such as rainfall, seismic activity, or human disturbance. This phrasing was used to emphasize that root wedging can increase the likelihood of slope instability when exposed to such external factors. In this study, landslide susceptibility is specifically quantified using the Landslide Susceptibility Index (LSI)

5. l75: You probably mean apparent cohesion, since cohesion itself is not reduced by rainfall.

Response:

Thank you for this insightful comment. After further verification and consultation with domain experts, we confirm that soil cohesion is a standard technical term widely used in geotechnical literature to represent the cohesive component of soil shear strength in slope stability analyses. In this context, the original expression is scientifically appropriate and has therefore been retained in the revised manuscript.

6. l76: “downslope forces generated by gravitational water distribution” — please clarify.

Response:

Thank you for your comment. Here, “downslope forces generated by gravitational water distribution” refers to the component of the slope weight acting along the slope surface, which contributes to driving forces for slope failure. As rainfall infiltrates the soil, the overall weight of the slope increases due to added water content, leading to a larger downslope force component and thus an increased potential for slope instability.

7. l89: What are the “geoscience factor weights”? In any case, multiple techniques for landslide susceptibility exist, and the references at the end of the sentence are insufficient.

Response:

Thank you for your comment. The term “geoscience factor weights” refers to methods that assign weights to geological and environmental factors (e.g., slope, lithology, land use) to quantify their relative contribution to landslide occurrence. Such weighting approaches are commonly based on expert judgment or methods like Analytic Hierarchy Process (AHP). We acknowledge that multiple techniques exist for landslide susceptibility assessment, including statistical models, machine learning methods, and multi-criteria evaluation. To address your concern, we have expanded the references to include representative studies covering various approaches. The revised sentence now reads:

Introduction (Revised manuscript, line 82)

“*Substantial efforts have been made to assess landslide susceptibility using various methodologies, including geoscience factor weighting, statistical models, machine learning, and Geographic Information Systems (GIS)-based spatial analysis (Abay et al., 2019; Gebrehiwot et al., 2025; Guo et al., 2023; Pham et al., 2018; Sun et al., 2024; Wang et al., 2024).*”

References

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Wang, Y., Ling, Y., Chan, T. O., & Awange, J. (2024). High-resolution earthquake-induced landslide hazard assessment in Southwest China through frequency ratio analysis and LightGBM. *International Journal of Applied Earth Observation and Geoinformation*, 131, 103947. https://doi.org/10.1016/j.jag.2024.103947

8. l93: “few studies” → please cite them.

Response:

Thank you for your comment. Due to substantial revisions of the Introduction to improve clarity and structure, the original sentence has been modified. It now reads: "*Many studies provide qualitative descriptions of factor influences but lack quantitative analysis of spatial correlations and interactive effects among multiple driving factors (Shu et al., 2025; Triplett et al., 2025).*" Corresponding references have been added to support this statement.

References

Shu, H., Qi, S., Liu, X., Shao, X., Wang, X., Sun, D., ... & He, J. (2025). Relationship between continuous or discontinuous of controlling factors and landslide susceptibility in the high-cold mountainous areas, China. *Ecological Indicators*, *172*, 113313. https://doi.org/10.1016/j.ecolind.2025.113313

Triplett, L.D., Hammer, M.N., DeLong, S.B. *et al.* Factors influencing landslide occurrence in low-relief formerly glaciated landscapes: landslide inventory and susceptibility analysis in Minnesota, USA. *Nat Hazards* **121**, 11799–11827 (2025). https://doi.org/10.1007/s11069-025-07262-8

9. l110: "frequent" again — misleading: it suggests landslides mostly occur in vegetated areas.

Response: Thank you for your comment. The original sentence containing "frequent" has been replaced with another expression in the revised Introduction. In addition, all other similar instances in the manuscript have been revised to use "may occur" to accurately reflect the possibility of landslides in areas with high vegetation cover

10. l113: GeoDetector and structural equation modeling require references.

Response: Thank you for your comment. To improve the clarity, scientific rigor, structure, and overall quality of the Introduction, we have substantially revised this section. In the revised Introduction, the original sentence has been removed, but references supporting the application of GeoDetector and structural equation modeling (SEM) have been added to the Research Methods section to ensure the rigor of the methodology. *(e.g.,Lu et al., 2024; Fan et al., 2016; Wang et al., 2010).”*

References

Lu, F., Zhang, G., Wang, T., Ye, Y., Zhen, J., & Tu, W. (2024). Analyzing spatial non-stationarity effects of driving factors on landslides: a multiscale geographically weighted regression approach based on slope units. Bulletin of Engineering Geology and the Environment, 83(10), 394. http://doi.org/10.1007/s10064-024-03879-4

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11. l127: Forest is 65%. Which type of forest? And what about the remaining 35%?

Response:

Thank you for your comment. The 65.55% forest coverage refers to the overall forested area in the study region. The remaining area consists of non-forested land, including cropland, grassland, and other land uses. We made minor modifications to line 138 of the original manuscript.

2.1 Study area (Revised manuscript line 133)

“*Forest covers 65.55% of the area, while the remaining land consists of non-forested terrain. Vegetation is classified into shrubland, meadow, broadleaf forest, coniferous forest, and cultivated plants. Shrubland is dominated by Myrica and Rhododendron, broadleaf forests include Arundinaria-dominated forests, Quercus* *engleriana forests, and Castanopsis forests, and coniferous forests consist mainly of Abies forests, Pinus yunnanensis forests, and subalpine Quercus forests.*"

12. l127: "terrain slopes from southwest to northeast" — what do you mean? This sounds strange.

Response:

Thank you for pointing this out. The original phrase "terrain slopes from southwest to northeast" was intended to indicate the overall elevation trend in the study area, with lower elevations in the southwest and higher elevations in the northeast. To avoid potential misunderstanding, we have removed this phrase. The elevation range and vertical drop are retained, providing clear information about topography: elevations range from 530 to 3,321 m, with a vertical drop of 2,700 m.

13. l137: It is unclear why you introduce this major landslide and how it connects to the large-scale analysis. This point is crucial.

Response:

Thank you very much for your insightful comment. We agree that the connection between the described major landslide and the large-scale susceptibility analysis needs to be clarified. The inclusion of this landslide aims to serve as a representative case study that bridges our regional-scale susceptibility assessment with the mechanistic understanding at the site scale. Specifically, this event occurred within an area classified as a moderate-susceptibility *zone* in our AHP-based regional evaluation. Although it was not located in a high-susceptibility area, the landslide was triggered by the combined effects of prolonged rainfall, anthropogenic loading from waste deposition, and the additional weight of dense vegetation. These local conditions significantly increased slope instability, leading to failure even in a zone that was only moderately susceptible at the regional scale. This observation highlights the amplifying influence of vegetation and rainfall interactions, which supports the "double-edged sword" role of vegetation revealed by our watershed-scale GeoDetector and SEM analyses. By presenting this case, we aim to demonstrate how local environmental disturbances can alter slope stability beyond regional susceptibility levels, thus linking large-scale statistical results to field-scale mechanisms. Manuscript content modifications regarding the major landslide and its relation to the large-scale analysis have been provided in Comment 1.

14. l174: SoilGrids (Hengl et al., 2017) describes soils, not lithology. How did you derive lithology from those data?

Response:

Thank you for pointing this out. The citation was incorrect in the previous version. The lithology data used in this study were actually derived from the Global Lithological Map (GLiM), which provides global-scale information on rock types and lithological properties. The correct reference is as follows:

" *Hartmann, J., & Moosdorf, N. (2012). The new global lithological map database GLiM: A representation of rock properties at the Earth surface. Geochemistry, Geophysics, Geosystems, 13(12), Q12004.* https://doi.org/10.1029/2012GC004370"

15. l178: Why "maximum"? Please clarify.

Response:

Thank you for your comment. The maximum NDVI raster was used to represent the densest or most developed vegetation in each pixel. In our study area, which generally exhibits high vegetation coverage, the maximum NDVI effectively captures the characteristic high vegetation conditions, while reducing the influence of temporary vegetation loss or seasonal variations. This provides a consistent and representative indicator of vegetation cover for landslide susceptibility modeling. It is worth noting that the maximum NDVI usually occurs in summer, when vegetation reaches its peak biomass and self-weight. This condition corresponds to the period when vegetation exerts the greatest mechanical influence on slopes, providing a solid basis for investigating its role in enhancing or reducing slope stability in well-vegetated areas.

16. l189: "Landslide hazard point data were obtained from the GeoCloud platform..." — this sentence is poor. The GeoCloud data are never mentioned again. No description is provided for the method or imagery used to prepare the inventory. Were these recent landslides? Is it a geomorphological inventory? What imagery and what dates were used? Without this, the inventory's quality cannot be assessed — a major issue.

Response:

Thank you for your valuable comment. In this study, the landslide inventory was compiled from two sources. The first source was the officially released landslide inventory of the Jinkouhe area provided by the GeoCloud platform, which mainly includes historical landslides with detailed attribute information such as geographic coordinates, township location, landslide scale, hazard level, occurrence time, and associated losses. The second source consisted of landslides identified through visual interpretation of high-resolution Sentinel-2 imagery acquired in August 2024 and subsequent manual verification. The datasets from both sources were integrated, and duplicate or uncertain cases were removed, resulting in a total of 227 landslides, representing the complete landslide distribution within the study area. We have revised the manuscript to provide a clearer and more detailed description of the landslide inventory and its preparation process. To address the unclear description in the original manuscript, this has been revised in # Revised manuscript line 196. Specific revisions related to this issue are detailed in our response to Comment 3.

17. l196: "Landslide susceptibility analysis was conducted by overlaying landslide sites with…" → You only overlaid the landslide points?

Response:

Thank you for your comment. We believe this issue may stem from a misunderstanding of the methodological description. The phrase "overlaying landslide sites with conditioning factors" does not simply refer to a basic overlay of landslide point data, but rather to a multi-factor spatial analysis conducted within the framework of the Analytic Hierarchy Process (AHP). Specifically, each conditioning factor (elevation, slope, aspect, distance to faults, rivers, and roads, lithology, rainfall, NDVI, and wind speed) was classified, and buffer and statistical analyses were performed to determine the number of landslides occurring within each category. These results served as one of the important bases for determining the weights of the factors. Subsequently, all factor layers were weighted and overlaid according to the AHP-derived weights, and consistency tests were performed to ensure reliability. Finally, a landslide susceptibility distribution map was generated. The detailed procedure has been described in the main text, and the classification criteria and statistical results for each factor are provided in Appendix Text S1. To avoid ambiguity, we have revised the corresponding description in the revised manuscript at line 206.

2.3.1 landslide susceptibility based on the analytic hierarchy process（Revised manuscript line 207）

“*Following the best-practice guidelines for landslide susceptibility mapping proposed by Reichenbach et al. (2018), landslide susceptibility analysis was conducted using a multi-factor spatial evaluation approach within the framework of the AHP. The analysis considered the following conditioning factors: elevation, slope, aspect, distances to faults, rivers, and roads, lithology, rainfall, NDVI, and wind speed. All factors passed the multicollinearity test with variance inflation factor (VIF) values below 10 (Arabameri et al., 2019; Chen et al., 2018). Range normalization was applied to standardize all indicators (He et al., 2024). Each factor was then classified, and to quantify its influence, buffer and statistical analyses were performed to calculate the number of landslides occurring within different classified zones, serving as one of the key bases for determining the factor weights (Table S1). The factors were subsequently weighted through AHP and validated using consistency tests. Finally, the overlay analysis produced a landslide susceptibility distribution map of the study area (Ahmad et al., 2023; Asmare, 2023), with susceptibility categorized into five levels: very low, low, medium, high, and very high, based on existing standards.*”

References

Ahmad, M. S., MonaLisa, & Khan, S. (2023). Comparative analysis of analytical hierarchy process (AHP) and frequency ratio (FR) models for landslide susceptibility mapping in Reshun, NW Pakistan. *Kuwait Journal of Science*, 50(3), 387-398. https://doi.org/10.1016/j.kjs.2023.01.004

Arabameri, A., Pradhan, B., Rezaei, K., Sohrabi, M., & Kalantari, Z. (2019). GIS-based landslide susceptibility mapping using numerical risk factor bivariate model and its ensemble with linear multivariate regression and boosted regression tree algorithms. *Journal of Mountain Science*, 16(3), 595-618. http://doi.org/10.1007/s11629-018-5168-y

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Reichenbach, P., Rossi, M., Malamud, B. D., Mihir, M., & Guzzetti, F. (2018). A review of statistically-based landslide susceptibility models. Earth-science reviews, 180, 60-91. https://doi.org/10.1016/j.earscirev.2018.03.001

18. l238: “An equal number of non-landslide points were created” — how?

Response: Thank you for your insightful comment. To assess the reliability of the dataset and the robustness of the model, a 500 m buffer was generated around the known landslide points, and areas close to water bodies were excluded. Within the remaining regions, non-landslide points (negative samples) were randomly selected while maintaining a balanced ratio between positive and negative samples.

2.3.2 Rationality validation of susceptibility assessment result（Revised manuscript line 252）

"*Based on the susceptibility distribution map and known landslide points, non-landslide points were randomly sampled from areas excluding water bodies and 500 m landslide buffer zones to maintain a balanced ratio between positive and negative samples. Following the repeated random sampling approach commonly used in machine learning studies, 30% of the entire dataset was repeatedly and randomly selected as the testing subset for ROC/AUC evaluation to assess model robustness.*"

19. l253: The GeoDetector method should be applied with a large number of landslides; are 227 sufficient?

Response:

Thank you for raising this important question. According to previous studies, the Geodetector method requires an adequate sample size to ensure the reliability of variance decomposition. However, GeoDetector does not rely on a large number of samples; instead, it emphasizes the spatial consistency between the dependent variable and explanatory factors (Wang et al., 2010). Based on the recommendations of Wang and Xu (2017) and subsequent research (Zhou et al., 2021), a sample size ranging from 100 to 500 points is generally sufficient to ensure stable q-statistic estimation. In this study, a total of 227 landslide samples were used, which falls within the recommended range and meets the statistical assumptions of the Geodetector. In addition, the grid-based sampling design ensured a sufficient number of spatial strata for factor detection, thereby enhancing the robustness of the analysis. Therefore, we consider that the sample size is adequate for applying the GeoDetector approach in this study.

References

Wang, J., Li, X., Christakos, G., Liao, Y., Zhang, T., Gu, X., & Zheng, X. (2010). Geographical Detectors-Based Health Risk Assessment and its Application in the Neural Tube Defects Study of the Heshun Region, China. *International Journal of Geographical Information Science*, *24*(1), 107–127. https://doi.org/10.1080/13658810802443457

Wang, J., & Xu, C. (2017). Geodetector: Principle and prospect. *Acta Geographica Sinica*, 72(1), 116–134. https://doi.org/10.11821/dlxb201701010

Zhou, X., Wen, H., Zhang, Y., Xu, J., & Zhang, W. (2021). Landslide susceptibility mapping using hybrid random forest with GeoDetector and RFE for factor optimization. *Geoscience Frontiers*, *12*(5), 101211. https://doi.org/10.1016/j.gsf.2021.101211

20. l258: Why did you use landslide susceptibility as the dependent variable? It is already a model. Why not use the landslide inventory?

Response:

Thank you for your insightful comment. In conventional GeoDetector applications, the landslide inventory is usually used as the dependent variable to identify the main conditioning factors influencing landslide occurrence. However, treating landslide and non-landslide samples as a binary (0–1) dependent variable is more suitable for factor screening and cannot effectively explain how conditioning factors interact to influence landslide susceptibility (Liu et al., 2024; Sun et al., 2021; Yang et al., 2019; Zhou et al., 2023;). Consequently, most previous studies using this approach have focused on identifying dominant factors rather than revealing the underlying mechanisms. In contrast, the present study employed the GeoDetector for a different purpose—to quantify the explanatory power of each conditioning factor on the *modeled landslide susceptibility* derived from the AHP framework and, more importantly, to reveal how factor interactions contribute to susceptibility patterns. This design enhances the interpretability and physical consistency of the susceptibility model (Chen et al., 2023).

References

Chen, Z., Song, D. & Dong, L. An innovative method for landslide susceptibility mapping supported by fractal theory, GeoDetector, and random forest: a case study in Sichuan Province, SW China. Nat Hazards 118, 2543–2568 (2023). https://doi.org/10.1007/s11069-023-06104-9

Liu, X., Shao, S., & Shao, S. (2024). Landslide susceptibility prediction and mapping in Loess Plateau based on different machine learning algorithms by hybrid factors screening: Case study of Xunyi County, Shaanxi Province, China. Advances in Space Research, 74(1), 192-210. https://doi.org/10.1016/j.asr.2024.03.074

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21. l259: what’s “geological hazard risk” — a scientific paper should use terms accurately.

Response:

Thank you for your comment. We agree that the term should be more precise. The term “geological hazard risk” in this part has been revised to “*landslide hazard risk*” to ensure terminology accuracy.

22. l324: “84 landslides covering 53.77% of the total area” — you said landslides are points: how can they cover an area? In pixels?

Response:

Thank you for your comment. We acknowledge the potential confusion. The percentages reported (e.g., 53.77% of the total area) refer to the proportion of the study area classified as moderate landslide susceptibility, not the area physically covered by the landslide points themselves. The numbers of landslides indicate how many inventory points fall within each susceptibility class, while the percentages describe the corresponding area of each class. We have revised the text to clarify this distinction.

3.1 Landslide susceptibility mapping and distribution characteristics （Revised manuscript line 364）

“*Most of the study area shows moderate landslide susceptibility, occupying 53.77% of the total area and containing 84 landslide points.*”

23. l336: This section pops up quite suddenly and without any clear justification, in my opinion.

Response:

Thank you for this comment. We agree that the purpose of this section was not sufficiently clarified in the original manuscript. The H/L ratio is introduced to provide a quantitative characterization of landslide mobility and runout behavior, which helps place the representative landslide case in the context of landslide magnitude and potential hazard. In the revised manuscript, we have added a brief justification at the beginning of Section 3.2 to clarify its relevance and to explain how this analysis supports the interpretation of landslide dynamics discussed later in the paper.

3.2 Relationship between H/L and area of a typical landslide （Revised manuscript line 378）

"*To quantitatively characterize the mobility and runout behavior of the representative landslide, the relationship between landslide height (H), travel distance (L), and affected area was analyzed.*"

24. l400: "faults occur where the structural stability of the slopes is poor" — this is scientifically incorrect; the causal direction is reversed.

Response:

Thank you for your careful review. We agree with your comment. The original sentence reversing the causal relationship has been deleted. The revised text now reads:

 # Revised manuscript line 442

"*This is because faults zones can cause localized stress and weaken the structural integrity of slopes, especially in the study area, which lies at the intersection of the Longquanshan Fault Zone and the Ebian-Mabian Seismic Belt located in the central segment of China's north–south seismic belt.*"

25. l462: "public factors" — what do you mean by this?

Response: Thank you for pointing out this inconsistency. This was an oversight on our part. The term "public factors" on line 462 was used in error. Our intended term, as defined in the Methods section (Line 231), is "common factors", which refers to [elevation, slope, aspect, lithology, and distances to faults, rivers, and roads.] the factors that are shared across different factor combinations in our analysis. We have corrected "public factors" to "common factors" on line 504 in the revised manuscript to maintain terminological consistency throughout the paper.

26. l500: The statements throughout this section are not supported by data analysis, in my opinion.

Response:

We thank you for highlighting the need for stronger quantitative support in Section

4.3 regarding the "ambiguous role" of vegetation. We agree that some statements in this subsection were more speculative and have now revised this section 4.3 better integrate our empirical findings and quantitative results. Specifically, we have:

1.Explicitly linked the discussion to our quantitative results from GeoDetector and SEM (e.g., NDVI's interaction effects, total effect coefficients), as well as slope stability calculations under saturated vs. natural conditions.

2.Replaced speculative statements with evidence-based interpretations, using data from our susceptibility scenarios (Categories I–V) and stability factor (Fs) values to explain how vegetation's role shifts with rainfall and slope conditions.

3.Clarified that the "ambiguity" is not merely hypothetical, but is demonstrated through: The bifactor enhancement between NDVI and rainfall (Fig. 8), showing that vegetation can amplify rainfall's impact in certain contexts; The decrease in slope stability (Fs) from 1.13 to 0.89 under saturated conditions when vegetation weight is considered (Table 3), providing direct mechanical evidence of its potential destabilizing effect; The shifts in susceptibility zoning when vegetation is added to the model (Table 6), illustrating its spatially varying influence.

We believe these revisions strengthen the subsection by grounding the discussion in our own analytical results, thereby providing a more substantiated explanation of vegetation's dual role.

 # 4.3 Mechanisms of landslides in areas with high vegetation coverage （Revised manuscript line 543）

"*The mechanisms underlying landslide initiation in densely vegetated areas are complex and context-dependent, as evidenced by the contrasting effects of vegetation revealed in our multi-scale analysis. Our findings demonstrate that vegetation does not act uniformly as a stabilizer; rather, its role is modulated by hydrological conditions, slope gradient, and external loading.*

At the watershed scale, the GeoDetector results indicate that NDVI alone exhibits limited independent explanatory power (q = 0.27, Table 4). However, its interaction with rainfall significantly enhances landslide susceptibility (e.g., NDVI × rainfall q =

0.67, Fig. 8), suggesting that vegetation can amplify the destabilizing effects of precipitation under certain conditions. While vegetation intercepts rainfall and promotes evapotranspiration, it can also alter soil moisture distribution via stemflow, root-induced preferential flow, and reduced surface runoff. Under prolonged rainfall, these processes may lead to localized saturation, thereby exacerbating landslide and debris flow risks in vegetated slopes. This aligns with the SEM results, which attribute a total indirect effect of 0.21 to NDVI, mediated largely through soil moisture dynamics and interactions with rainfall and slope (Fig. 9, Table 5). The susceptibility scenario analysis further illustrates this duality: adding vegetation alone (Class II) slightly reduced the extent of very high susceptibility zones, yet when combined with rainfall (Class IV) and wind (Class V), it led to a notable expansion of high-susceptibility areas and an increase in landslide counts (Table 6, Fig. 10). This suggests that vegetation's protective capacity may be offset or reversed under prolonged rainfall, especially on steeper slopes.

At the site-specific scale, the stability calculations provide direct mechanical insight into how vegetation can transition from a stabilizing to a destabilizing factor. Under natural (unsaturated) conditions, the slope remained stable even with the added weight of vegetation and waste material (Fs = 1.02). However, under saturated conditions, the same additional loads—particularly the self-weight of trees—reduced the stability coefficient to 0.89, triggering failure (Table 3). This demonstrates that the mechanical reinforcement from roots can be outweighed by the gravitational load of vegetation when soil strength is reduced by saturation, a shift that is quantitatively captured by our modeling.

These findings help explain why landslides may occur unexpectedly in densely vegetated areas. Vegetation can create a false sense of stability by masking early signs of movement (e.g., surface cracking, minor slumping) and by being traditionally associated with slope protection. Moreover, the same root networks that enhance soil cohesion also facilitate preferential infiltration, potentially accelerating soil saturation during heavy rainfall—a process reflected in the strong interaction between NDVI and rainfall in our spatial analysis. In terrain with high lateral variability in slope, lithology, or soil depth, vegetation may thus contribute to highly localized and concealed instability, as exemplified by the 2023 Jinkouhe landslide.

In summary, our integrated analysis provides quantitative evidence that *vegetation's role is not merely "ambiguous" in a speculative sense, but is quantifiably dual: it stabilizes slopes through root reinforcement under moderate conditions, yet can promote instability through added weight, enhanced infiltration, and synergistic interactions with rainfall when critical thresholds are exceeded. This duality underscores the importance of considering vegetation not as a static stabilizing factor, but as a dynamic component of the hillslope system in landslide susceptibility assessments.*"

We sincerely appreciate your constructive feedback. We hope the revisions and responses provided will ensure our manuscript meets the standards for publication in ***Natural Hazards and Earth System Sciences***.