

Feature Selection for Landslide Forecasting Models in Southern Andes

Labbe et al.,

Reviewer 1

This study presents a machine learning-based approach for landslide forecasting in the Southern Andes, combining feature selection methods (CART and genetic algorithms) with multiple classifiers (SVM, RF, XGB). The research design is sound, the methodology is robust, and the results hold practical significance, particularly in the context of early warning systems for geological hazards. The paper is recommended for publication after addressing the following points.

A: We appreciate the comments of the reviewer. We agree with all the comments, and these were improved in the newer version of the manuscript. Now, we include additional sections and corrections to the information gap and low-quality figures. We would appreciate it if the reviewer could revise the attached document.

Major comments:

1. The introduction currently provides a broad overview of landslide forecasting but could better highlight the specific innovations of this study. For example: (1) The proposed solutions for data scarcity in the Southern Andes (e.g., PU Bagging and buffer control sampling); (2) The unique advantages of the hybrid feature selection approach (GA + CART) in landslide prediction.	Please, see R1 1 response
2. The conclusion should more explicitly summarize the improvements this study offers to existing landslide early warning systems and its practical implications.	Please, revise subsection R1 2 + R1 8 response.

3. The abstract should be refined to convey more insightful information.	Please, see R1_3 response.
4. The paper mentions multiple databases (e.g., ERA5, CLSoilMaps) but lacks details on their temporal coverage, resolution consistency, and handling of missing data. These details should be added.	Please, see R1_4 response
5. The methodology for generating "negative examples" (non-landslide data) via Buffer Control Sampling and PU Bagging requires further justification.	Please, see R1_5 response
6. Tables 4 and 5 present performance metrics for different methods but lack statistical significance tests (e.g., p-values or confidence intervals). Such tests would strengthen the claim that GA-based optimization outperforms other methods.	Please, see R1_6 response
7. The similar performance of GA XGB and GA RF (both with 10.95% error rates) warrants discussion on their trade-offs in real-world applications (e.g., computational efficiency, interpretability).	Please, see R1_7 response
8. The study focuses on two regions in southern Chile (Los Lagos and Los Ríos). The conclusions should clarify whether they are applicable to areas with different geological or climatic conditions.	Please, revise subsection R1_2 + R1_8 response.
9. The discussion should more thoroughly address model limitations.	Please, see R1_9 response
Minor comments:	
1. Labels in Figures 3 and 4 (correlation matrices) are too small and should be enlarged or provided in higher resolution.	Please, see MC_1 response

2. Abbreviated variable names in Tables 1 and 2 (e.g., "AvMoist") should be explained in the main text or footnotes (e.g., "Available Moisture").	Please, see MC 2 response
3. Inconsistent formatting of terms (e.g., "GA XGB" vs. "GA_XGB") should be unified.	Please, see MC 3 response
4. The first paragraph of the conclusion (lines 465–475) could be condensed to avoid redundancy with earlier sections.	Please, see MC 4 response

Reviewer 2

This manuscript provides an interesting study on identifying the primary factors controlling rainfall-induced landslides in four Chilean regions. The framework and methodologies are sound. However, I regret to say that the core innovation of this study has not been sufficiently articulated. As the authors note (line 86-87), the study area is unique and complex in geological and climatological features. Nevertheless, the manuscript does not rigorously discuss which features emerge as the most representative variables for volcanic, sedimentary, and glacial terrains, nor how these features influence susceptibility mapping. Instead, the emphasis is placed on machine learning and feature selection techniques, which are widely used and cannot be highlighted as innovative in comparison with the unique geological setting of the study area. Meanwhile, the writing and structure of the manuscript are not well organised, which makes it difficult for the reader to follow the authors' idea. For these reasons, I do not consider the manuscript is suitable for publication in its current form. Substantial revisions are required to improve its quality. Some detailed comments are as follows.

A: We are grateful to the reviewer for their careful and accurate assessment of our manuscript. We appreciate the positive recognition of the study's sound framework and methodologies and acknowledge the critical feedback regarding the insufficient articulation of the core innovation and the overall structure. The detailed comments have been invaluable in improving the quality and clarity of the revised submission. We fully agree with the reviewer's observation that the original manuscript did not sufficiently articulate the unique contribution in the context of the study area's complex geology. The reviewer correctly identified that the emphasis on well-established machine learning and feature selection techniques (CART and GA) may have obscured the core novelty of our work. Now it was corrected and improved.

We wish to clarify that the primary objective of this study is not the construction of a novel landslide susceptibility map, but rather to systematically identify the most

representative and influential variables that should be prioritised in monitoring networks and future, localised susceptibility models for rainfall-induced landslides in the Southern Andes. Our contribution is focused on filling a critical gap in South American landslide hazard assessment, where monitoring surveys often lack clear, evidence-based prioritisation of variables, especially across diverse, complex geological terrains (volcanic, sedimentary, glacial). In the revised manuscript, we have substantially re-focused the discussion to address the reviewer's point rigorously. Detailing the physical significance of the selected features (e.g., the importance of soil hydraulic properties like bulk density and saturated water content), which reflects the influence of the region's heterogeneous soil and shallow geology on landslide initiation. Moreover, we connected the results directly to practical recommendations for monitoring, thus reinforcing that the predictive power is a means to determine variable importance, not an end in itself for producing a static susceptibility map.

We sincerely apologise for the original writing and structure, which made the manuscript difficult to follow. We recognise that a lack of clear organisation can severely hinder the transmission of the study's ideas. We have performed a comprehensive revision of the entire manuscript's structure and writing to improve coherence and readability. The Introduction has been revised to clearly state the gap (lack of variable prioritisation for monitoring) and the study's specific goal (feature identification for early warning systems). The Methodology section is now more logically organised. The Discussion has been restructured first to present the feature selection results, then provide an in-depth analysis of their physical meaning and implications for regional monitoring/early warning system design, before briefly discussing model performance. We trust that these revisions have significantly enhanced the clarity, quality, and focus of the manuscript, making the unique contribution easily identifiable. We would appreciate it if the reviewer could revise the attached document.

1. L12-13: The abstract ends abruptly without presenting any concrete results. Please expand the abstract to include the key findings and avoid vague statements such as "various predictive models were tested."	Please, see R2 1 response
2. L41-42: Seismic activity is not relevant to this study and should not be included in the introduction.	Please, see R2 2 response

3. L87-88: The diverse geological composition of the study area should be emphasised as one of the most important aspects. Please elaborate on how different soil and lithological types correspond to the selected controlling features.	Please, see R2 3 response
4. L119-121: The phrase “considerable attention” is unclear. Please specify the exact steps taken to ensure data quality.	Please, see R2 4 response
5. L127: The abbreviation “PP” is used without being defined beforehand. Please define it at first mention.	Please, see R2 5 response
6. Figure 7 and 8: These figures are not properly prepared. They contain non-English words, and their captions are incomplete. Please revise accordingly.	Please, see R2 6 response
7. Figure 9: Please add the coordinates to the map.	Please, revise the R2 7 answer.

Response to Reviewers

Reviewer 1

R1_1

“The introduction currently provides a broad overview of landslide forecasting but could better highlight the specific innovations of this study. For example: (1) The proposed solutions for data scarcity in the Southern Andes (e.g., PU Bagging and buffer control sampling); (2) The unique advantages of the hybrid feature selection approach (GA + CART) in landslide prediction.”

ANSWER: We agree with the reviewer's assessment and are grateful for this constructive feedback. We acknowledge the observation regarding the necessary background and have revised the manuscript accordingly to provide a more robust conceptual and contextual foundation for the study. Specifically, we have modified the Introduction to explicitly highlight the novelty, knowledge gap and original contribution of this work, while also emphasising the critical need for this research within the South American context (integrating the relevant point raised by Reviewer 2). Consequently, these revisions have also necessitated modifications to the final two paragraphs of the Introduction section to ensure coherence with the expanded background and justification.

Original version (focused on “The unique advantages of the hybrid feature selection approach (GA + CART) in landslide prediction”):

The drivers and controls of landslide generation exhibit both similarities and differences across various global regions, shaped by a complex interplay of geological, climatic, and anthropogenic factors. At a fundamental level, topography is a significant factor influencing landslide occurrence; however, its importance can vary widely depending on local conditions. For instance, Lin et al. (2016, 2017) note that while topography is often emphasized in landslide susceptibility models, soil moisture emerges as a critical factor on a global scale, particularly in regions prone to rainfall-triggered landslides. Additionally, geological characteristics such as lithology and drainage density are crucial conditioning factors that interact with triggering mechanisms like precipitation and seismic activity (Bisht and Rawat, 2023).

Modified by:

Landslide generation is a complex, multi-variable process driven by a critical interplay of geological, climatic, and anthropogenic factors, exhibiting significant global and regional variability in the key variables (Chen et al., 2024; Fidan et al., 2024). While topography is a fundamental conditioning factor, its relative importance can be overshadowed by local conditions, such as rapid changes in soil moisture at specific depths, particularly for rainfall-triggered landslides (Margaño et al., 2025; Fustos-Toribio et al., 2025). Additional conditioning factors, including lithology and drainage density, interact with triggering mechanisms such as extreme precipitation to initiate landslide events. The assessment of landslide susceptibility is inherently challenging because of the numerous, interrelated variables that complicate the development of accurate predictive models. Therefore, it becomes critical to establish the main variables that could control a landslide to improve landslide susceptibility models (Maragaño et al., 2023; Zighmi et al., 2025). The core difficulty lies in effectively processing this heterogeneous data and identifying the most influential variables. To address this multi-variable complexity and enhance predictive accuracy, advanced methodologies are combined, such as hybrid feature selection approaches that combine optimisation algorithms, like Genetic Algorithms (GA), or feature ranking algorithms, like Classification and Regression Trees (CART), with classification techniques, to refine model inputs and achieve more precise, actionable spatial predictions (Nguyen et al., 2017).

Original version (relevating the innovation and contribution for South America):

In the context of southern Chile, the present work proposes the application of ML methods to analyze a comprehensive database comprising 136 features—ranging from soil properties to climatic conditions, underscoring the importance of regionspecific studies in assessing landslide susceptibility. Classification and Regression Trees (CART) and Genetic Algorithms (GA) were considered for feature selection, facilitating the identification of local critical factors influencing landslide risks (Shirzadi et al., 2018; Miao et al., 2022).

A comprehensive understanding of the complex interplay between rainfall intensity, soil moisture, and geological factors is crucial for developing effective monitoring networks and generating accurate early warning systems for landslides. This manuscript presents an in-depth analysis of the conditioning factors that influence landslide occurrence in a region of the southern Andes (38–42°S) as a pilot case study. It highlights the importance of the critical variables that must be considered in future monitoring approaches based on machine learning.

Modified version:

This manuscript offers a substantial and innovative contribution to understanding the complex, dynamic processes of landslide generation in the Southern Andes (38–42°S) considering for the first time a rigorous, data-driven methodology in this area. We expect to delimitate the main variables that must be considered in Southern Andes to understand the landslide triggering and control conditions using an innovative deployment of Machine Learning (ML) techniques based on Classification and Regression Trees (CART) and Genetic Algorithms (GA) allowing a meticulous feature

selection from climatic variables, soil properties to geological features. This targeted feature selection process is vital for identifying the true local critical factors that govern slope instability in this climatically active and geologically heterogeneous environment, effectively translating complex hydro-geomorphological processes into quantifiable variables. The prioritised factors are then strategically repurposed as high-quality proxies to refine and improve variable mapping, enabling a crucial regional-to-local scale approach that captures the spatial variability of landslide susceptibility. The providing of an in-depth, data-validated analysis of the critical variables that interplay among triggering mechanisms will support the design of next-generation, ML-based monitoring networks and accurate early warning systems (EWS) for this vulnerable mountain range.

R1_2 + R1_8

(R1_2) The conclusion should more explicitly summarize the improvements this study offers to existing landslide early warning systems and its practical implications.

(R1_8) The study focuses on two regions in southern Chile (Los Lagos and Los Ríos). The conclusions should clarify whether they are applicable to areas with different geological or climatic conditions.

ANSWER: Thank you for highlighting this weakness in our contribution. We agree with your assessment and have fully rewritten the conclusion section to clearly improve and elevate the relevance of our scientific contribution within the field.

Original text:

We evaluated the performance of machine learning models—Support Vector Machines (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) to predict landslide susceptibility in the southern Andes (38–42°S). The Southern Andes has a high soil variability that does not allow for deep instrument monitoring. Therefore, we determined the domain-relevant geotechnical, hydrological, and geomorphological variables and applied advanced feature selection techniques, including Genetic Algorithms (GA) and Positive-Unlabeled (PU) Bagging. We were able to systematically identify and optimise the most informative predictors for rainfall-induced landslides.

Our results demonstrate that models optimised using Genetic Algorithms significantly outperform baseline methods, such as CART with conventional feature selection. Notably, GA RF and GA XGB achieved the lowest classification errors (10.95%). Moreover, compact feature sets highlighted the potential of evolutionary algorithms to enhance both the accuracy and

efficiency of susceptibility assessments. Our models' results consistently identified slope, precipitation, and near-surface soil hydraulic properties—particularly bulk density and saturated water content—as critical factors influencing landslide initiation. Future instrumental developments must consider these variables, monitoring and landslide assessment.

Our findings also underscore the importance of incorporating both shallow and deep soil moisture characteristics, as well as soil retention curve parameters, to better capture the complex subsurface dynamics that precede slope failure. The differences in feature prioritisation between GA RF, GA XGB, and GA SVM reflect distinct modelling philosophies: while RF and XGB emphasised shallow hydraulic traits and retention thresholds, SVM gave greater weight to deeper soil moisture indicators and retention curve shape parameters.

We conclude that integrating data-driven models with physically meaningful features provides a robust framework for enhancing early warning systems and regional risk assessments. The superior performance of GA-optimised ensemble models suggests that future efforts should prioritise hybrid strategies that combine expert knowledge with automated feature selection. These approaches are particularly valuable in data-scarce environments, offering scalable solutions to inform risk management and decision-making in mountainous regions vulnerable to rainfall-triggered landslides.

Modified text:

We evaluated machine learning models (SVM, RF and XGB) to predict landslide susceptibility in the southern Andes (38–42°S), selecting domain-relevant geotechnical, hydrological, and geomorphological variables through feature selection techniques (CART and GA). The GA-optimized models, particularly GA-RF and GA-XGB, significantly outperformed baseline methods, achieving the lowest classification errors (10.95%) with compact feature sets that improved both accuracy and efficiency. Across experiments, slope, precipitation, and near-surface soil hydraulic properties—especially bulk density and saturated water content—emerged as the most critical factors influencing rainfall-induced landslides, underscoring their importance for future monitoring and assessment.

R1_3

The abstract should be refined to convey more insightful information.

ANSWER: Thank you very much for this important suggestion. We improved the abstract by presenting a more concise description of the study, highlighting the main findings, and emphasizing what we consider to be its most important contribution.

Original text:

Abstract. Rainfall-induced landslide (RIL) forecasting is crucial for early warning systems developed to mitigate the devastating impacts of these events on human lives, infrastructure, and the environment. Currently, dense instrumental networks for early warning require large datasets to identify precursor patterns in current machine learning models. Topographic, lithological, vegetation, soil moisture, and climatic characteristics are among the most commonly used variables for training these models. However, there are no universal designs, so it is necessary to adapt the requirements to each context and to the available variables that characterise it. To develop a RIL forecasting model for the Southern Andes, this study gathers data from various local soil and climate databases to identify the most relevant variables. Feature selection is crucial for improving the design of machine learning models, reducing the dimensionality of input data, enhancing computational efficiency, and preventing overfitting. We assessed the impact of various features, both individually and in combination, on the performance of predictive models. Methods such as Classification and Regression Tree and Genetic Algorithms are employed to perform the feature selection. A national landslide database was enriched using techniques such as buffer control sampling, PU Bagging, and clustering methods to incorporate negative examples (non-landslide) data. Various predictive models were tested. The results reveal some consistent variables as the most significant in forecasting landslides in four southern Chilean regions.

Modified Text:

Abstract. Rainfall-induced landslides (RIL) are a major hazard in the Southern Andes, threatening lives, infrastructure, and ecosystems. Early warning systems require accurate predictive models, yet their effectiveness is constrained by heterogeneous data availability and the lack of universal design standards. This study develops a systematic framework for identifying the most influential features controlling landslide generation, integrating local soil, climatic, and topographic datasets. A national landslide inventory was expanded with buffer control sampling and PU Bagging to improve representation of non-landslide cases, yielding a robust database of 3,148 instances with 136 variables. Feature selection was performed using Classification and Regression Trees (CART) and Genetic Algorithms (GA), followed by evaluation with Support Vector Machines, Random Forest, and XGBoost classifiers. Results highlight precipitation, slope, and soil hydraulic properties—particularly bulk density and saturated water content—as recurrent critical predictors. GA-based models significantly outperformed CART, with GA-RF and GA-XGB achieving the lowest error rates (10.95%) using compact feature sets. These findings underscore the potential of evolutionary feature

selection to enhance predictive accuracy while reducing data complexity, and they provide actionable insights into which variables should be prioritized in monitoring networks. By emphasizing both shallow and deep soil moisture dynamics, this work contributes to the design of more reliable and region-specific early warning systems for rainfall-induced landslides in mountainous environments.

R1_4

The paper mentions multiple databases (e.g., ERA5, CLSoilMaps) but lacks details on their temporal coverage, resolution consistency, and handling of missing data. These details should be added.

ANSWER: Thank you for this observation: the following paragraphs show how this information was added to the paper.

Original text:

We considered the soil moisture, precipitation, and slope from the ERA5 database (ERA5, 2023), one of the most widely used climate datasets, with 10km resolution. The slope was obtained combining the ERA5 database with high-resolution digital elevation models. The Chilean soil properties were extracted from the CLSoilMaps database (Dinamarca et al., 2023). The database has soil properties at 100 meters of spatial resolution, being trained using random forest at six standard depths (Table 2), following the GlobalSoilMap standards. For all the characteristics except for the slope, PP and soil moisture values, the measures available were obtained at the six different soil depths (Table 2), totalling 133 soil features in addition to the 3 extracted from ERA5, giving 136 features for each geographical point.

Modified Text:

We considered the soil moisture, precipitation, and slope from the ERA5 database (ERA5, 2023), one of the most widely used climate datasets, with 10km resolution. The slope was obtained by combining the ERA5 database with high-resolution digital elevation models. The Chilean soil properties were extracted from the CLSoilMaps database (Dinamarca et al., 2023). The ERA5-Land dataset corresponds to the land

component of the European Centre for Medium-Range Weather Forecasts' (ECMWF) fifth-generation reanalysis, executed under the Copernicus Climate Change Service (C3S) mandate, being generated via offline, high-resolution integrations of the ECMWF land surface model, CHTESSEL. The offline generation approach offers improved temporal consistency in land surface fields, thereby representing global water and energy cycles more accurately (Muñoz-Sabater et al., 2021). The dataset delivers approximately 50 variables essential for describing hydrological and surface energy processes, including soil moisture, runoff, snow cover, skin temperature, evapotranspiration, and land carbon fluxes at high resolution, providing a 9 km global horizontal resolution in comparison to 31 km and 80 km resolutions of ERA5 and ERA-Interim, respectively. The currently accessible public record spans from January 1981 to the present, subject to a typical latency of 2–3 months. To mitigate boundary discontinuities, each stream is preceded by multi-year spin-up periods. However, residual inconsistencies are acknowledged, particularly within variables with long memory, such as deep soil moisture and permanent snow regions. The internal consistency of ERA5-Land is intrinsically tied to its reliance on ERA5 for meteorological forcing, through a 4D-Var data assimilation system. Near-surface air temperature, pressure, and humidity are, however, corrected for elevation discrepancies between the ERA5 and ERA5-Land grids utilising daily lapse rates. Validation against diverse observational datasets, including *in situ* networks, satellite products, and hydrological records, unequivocally demonstrates that ERA5-Land surpasses ERA5 performance in the representation of soil moisture, temperature, runoff, and lake dynamics (Muñoz-Sabater et al., 2021; Bonshoms et al., 2022; Yilmaz et al., 2023). Moreover, we utilised the new CLSoilMaps database, an improvement over global soil databases in Chile. CLSoilMaps provides spatially explicit and high-resolution predictions of critical soil physical and hydraulic properties specifically for continental Chile and its shared transboundary basins with Argentina. The database was rigorously developed using Digital Soil Mapping (DSM) techniques within the SCORPAN framework (McBratney et al., 2003), trained on over 4,000 soil profile observations encompassing diverse and historically underrepresented ecosystems, including the Andes and Patagonia. Modelled soil attributes include clay, sand, and bulk density, with silt content derived indirectly. Hydraulic properties, such as field capacity, permanent wilting point, and available water capacity, were estimated using the well-established Rosetta V3 pedotransfer function (Zhang and Schaap, 2017). The predictions were executed using Random Forest algorithms that incorporated over 200 environmental covariates, spanning climate, topography, and satellite-based reflectance indices, and adhered to the six standardised depth intervals (0–200 cm) stipulated by the GlobalSoilMap project.

R1_5

The methodology for generating "negative examples" (non-landslide data) via Buffer Control Sampling and PU Bagging requires further justification.

ANSWER: We thank the reviewer for this observation. The decision to use PU-Bagging for generating negative cases was motivated to ensure that the additional negative examples are truly representative of the negative class, without introducing contamination from borderline or ambiguous cases. In our setting, many candidate negative samples can exhibit characteristics that are very similar to the positives, and including them could make the decision boundary more difficult to find and the classification unnecessarily more complex.

PUBagging provides a principled way to mitigate this risk by leveraging the positive set and treating the remaining data as unlabeled, iteratively identifying those instances most likely to be reliable negatives. In this way, the method filters out "hard" negatives that resemble positives, while still providing enough negative samples to balance the dataset and improve classifier training. This ensures that the model learns to discriminate between classes more robustly, without being biased by mislabeled or ambiguous data. We included this in the paper.

Original text:

This distance was intentionally chosen given the 10-kilometer resolution of the climatological variables, enabling the capture of spatial variability of the precipitation and soil moisture content, differentiating between landslide and non-landslide conditions. Subsequent refinement of the negative examples was performed via a modified PU Bagging (Positive-Unlabeled Bagging) (Gu et al., 2024), built on the idea of bagging (bootstrap aggregating) by repeatedly sampling subsets of the unlabeled data and combining them with the positive set to train multiple base classifiers. Each subset is treated as if the unlabeled instances were negative (which may introduce noise), and by aggregating the predictions across many such classifiers, PUBagging reduces the bias introduced by this assumption and improves robustness.

Modified text:

This distance was intentionally chosen given the 10-kilometer resolution of the climatological variables, enabling the capture of spatial variability of the precipitation and soil moisture content, differentiating between landslide and non-landslide conditions. Subsequent refinement of the negative examples was performed via a modified PUBagging (Positive-Unlabeled Bagging) (Gu et al., 2024), built on the idea of bagging (bootstrap aggregating) by repeatedly sampling subsets of the unlabeled data and combining them with the positive set to train multiple base classifiers. In our

setting, many candidate negative samples can exhibit characteristics that are very similar to the positives, and including them could make the decision boundary more difficult to find and the classification unnecessarily more complex. PUBagging provides a way to mitigate this risk by leveraging the positive set and treating each subset as if the unlabeled instances were negative (which may introduce noise), and by aggregating the predictions across many such classifiers, PUBagging reduces the bias introduced by this assumption and improves robustness.

R1_6:

Tables 4 and 5 present performance metrics for different methods but lack statistical significance tests (e.g., p-values or confidence intervals). Such tests would strengthen the claim that GA-based optimization outperforms other methods.

ANSWER: We modified the tables and improved the quality. We corrected the text, which previously stated that it referred to the standard deviation, when in fact it was the confidence interval (line 436) indicated for each metric in Tables 4 and 5. In addition, we conducted hypothesis tests to evaluate the statistical significance of the performance differences among the top-ranking models.

Original text:

The features selected by the different methods were used to train and test classifiers implemented with the three models - SVM, RF and XGB - to compare them. The results are presented in Table 5, providing a comprehensive overview of their performance under two distinct conditions: Non PU Bagging and PU Bagging. The evaluation metrics include accuracy and recall, both of which are critical for assessing the effectiveness of these classification models. In the Non PU Bagging category, the classifiers demonstrated notable performance. The SVM achieved an accuracy of 0.735 with a standard deviation of ± 0.029 , and a recall of 0.749 ± 0.041 . The XGB model outperformed the SVM, recording an accuracy of 0.873 ± 0.020 and a recall of 0.885 ± 0.028 , indicating its strong predictive capability. The Random Forest classifier exhibited the highest performance among the three, with an accuracy of 0.879 ± 0.020 and a recall of 0.901 ± 0.027 . These results suggest that all classifiers were effective in identifying instances from the dataset, with Random Forest showing the best overall performance. In the PU Bagging category, the classifiers maintained strong performance, although there were slight variations compared to the Non PU Bagging results. The SVM recorded an accuracy of 0.769 ± 0.0284 and a recall of 0.809 ± 0.0372 , indicating an improvement in its predictive ability with PU Bagging. The XGB model achieved an accuracy of 0.862 ± 0.022 and a recall of 0.889 ± 0.028 , which, while slightly lower than in the Non PU Bagging scenario, still reflects robust performance. The Random Forest classifier, however, showed a decrease in accuracy to 0.856 ± 0.023 and a recall of $0.881 \pm$

0.028, suggesting that while it remained effective, the application of PU Bagging may have introduced some variability in its performance.

The RandomForest discriminator results indicate that all classifiers performed well in both scenarios, with Random Forest consistently demonstrating the highest accuracy and recall. The application of PU Bagging appears to have had a mixed impact on classifier performance, enhancing some models while slightly reducing the effectiveness of others. These findings highlight the importance of evaluating different modeling strategies and their configurations to optimize predictive performance in classification tasks. Future research should explore the underlying factors contributing to these performance variations and consider additional techniques for further enhancing model accuracy and recall.

The model performance shows good agreement. Our results showed that the best-performing model is the XGB classifier utilizing GA optimization under the "PU Bagging" approach, achieving an accuracy of 0.896 ± 0.019 and a recall of 0.886 ± 0.026 . Conversely, the worst-performing model is the Support Vector Machine (SVM) classifier with GA optimization and "No PU Bagging," which recorded an accuracy of 0.735 ± 0.029 and a recall of 0.749 ± 0.041 .

Modified text:

The features selected by the different methods were used to train and test classifiers implemented with the three models - SVM, RF and XGB - to compare them. The results are presented in Table 5, providing a comprehensive overview of their performance under two distinct conditions: Non PU Bagging and PU Bagging. The evaluation metrics include accuracy and recall with their respective confidence intervals, both of which are critical for assessing the effectiveness of these classification models. In the Non PU Bagging category, the classifiers demonstrated notable performance. Table 5 shows that the best-performing models were those obtained using the features selected through GA-RF. The SVM achieved an accuracy of 0.735 with a confidence interval of ± 0.029 , and a recall of 0.749 ± 0.041 . The XGB model outperformed the SVM, recording an accuracy of 0.873 ± 0.020 and a recall of 0.885 ± 0.028 , indicating its strong predictive capability.

The Random Forest classifier exhibited the highest performance among the three models, achieving an accuracy of 0.879 ± 0.020 and a recall of 0.901 ± 0.027 . However, a Wilcoxon signed-rank test showed that the difference between RF and SVM—both with and without PU-Bagging—is statistically significant ($p\text{-value} = 1.23 \times 10^{-27}$). In contrast, no significant difference was observed between RF and XGB under either sampling strategy ($p\text{-value} > 0.56$). These findings indicate that all classifiers were effective in identifying landslide and non-landslide instances, with Random Forest and XGBoost consistently demonstrating the strongest overall performance. Moreover, the comparison between PU-Bagging and Non-PU-Bagging strategies revealed no statistically significant differences, suggesting that PU-Bagging did not substantially alter the classifiers' general predictive ability.

The superior performance of XGB further highlights its effectiveness in capturing complex, nonlinear relationships within the dataset. Although the GA optimization improved all models, the SVM appears less capable of fully exploiting hyperparameter tuning when compared to the more flexible and expressive structure of XGB. Prior studies also show that SVMs can perform competitively on simpler datasets but tend to lose effectiveness in more heterogeneous or high-dimensional contexts unless subjected to extensive parameter optimization. The recall results reinforce this interpretation: XGB achieves a higher recall than SVM, indicating a stronger ability to minimize false negatives. This characteristic is particularly crucial in applications where the identification of true positive cases—such as potential rainfall-induced landslides—is a priority for early warning and risk mitigation.

R1_7:

The similar performance of GA XGB and GA RF (both with 10.95% error rates) warrants discussion on their trade-offs in real-world applications (e.g., computational efficiency, interpretability).

ANSWER: We appreciate the reviewer's suggestion to discuss the trade-offs between GA-XGB and GA-RF, given that both achieved the same error rate (10.95%). Although their predictive accuracy was similar, the models differ in aspects that are relevant for real-world applications. We added this text in the fourth paragraph of the 6.2 section of the discussion.

Original text:

-

Added text:

Although the similar performance of GA-RF and GA-XGB, they differ in practical trade-offs. GA-RF is computationally lighter and easier to interpret, favoring operational applications, while GA-XGB is less interpretable but more robust in heterogeneous environments, as it may capture more complex interactions. This complementary perspective may underscore the importance of applying ensemble classifiers for operational landslide forecasting.

R1_8

Please, revise subsection R1_2 + R1_8 response.

R1_9

The discussion should more thoroughly address model limitations.

ANSWER: Thank you again for this suggestion. We added these lines to the 2nd paragraph of the 6.3 section of the discussion.

Original text:

The development of automated systems that utilize continuous monitoring of critical parameters can enhance the reliability of landslide predictions, as demonstrated by recent studies that have successfully employed deep-learning techniques to forecast landslide occurrences based on rainfall and soil conditions (Abraham et al., 2019; Qiao et al., 2020). Additionally, establishing a network of monitoring stations across diverse geomorphological environments can provide valuable insights into the varying responses of slopes to rainfall, thereby improving the generalizability of predictive models (Kuradusenge et al., 2020; Bortolozo 450 et al., 2024).

Modified text:

However, while the proposed classifiers showed strong performance (Abraham et al., 2019; Qiao et al., 2020), their effectiveness is constrained by the quality of the database, which in this domain is challenged by data scarcity, sparsity, and features availability. Another limitation is that the models may not readily generalize to other regions, or even fully capture the evolving dynamics within the study area. Finally, their limited transparency underscores the need for further validation and for integration with physically based models to enhance interpretability and reliability. Thus, future work should focus on validating these models across diverse regions and integrating them with physically based approaches to enhance both their robustness and interpretability. Additionally, establishing a network of monitoring stations across diverse geomorphological environments can provide valuable insights into the varying responses of slopes to rainfall, thereby improving the generalizability of predictive models (Kuradusenge et al., 2020; Bortolozo 450 et al., 2024).

Minor comments (MC)

MC_1

Labels in Figures 3 and 4 (correlation matrices) are too small and should be enlarged or provided in higher resolution.

ANSWER: Thank you for this observation. We removed the text from the figures and instead referenced the tables listing the correlated variables. Additionally, we enlarged the figures to improve readability.

MC_2

Abbreviated variable names in Tables 1 and 2 (e.g., "AvMoist") should be explained in the main text or footnotes (e.g., "Available Moisture").

ANSWER: Thank you for this observation. We have defined all abbreviated variable names in the footnotes of Tables 1 and 2

MC_3

Inconsistent formatting of terms (e.g., "GA XGB" vs. "GA_XGB") should be unified.

ANSWER: Thank you for pointing out this error in the text. We have corrected it, carefully reviewing the entire document, tables and figures

MC_4

The first paragraph of the conclusion (lines 465–475) could be condensed to avoid redundancy with earlier sections.

ANSWER: Thank you for highlighting this. We agree with your assessment and performed the changes, condensing the first two paragraphs of the conclusion in one paragraph.

Original text:

We evaluated the performance of machine learning models—Support Vector Machines (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) to predict landslide susceptibility in the southern Andes (38–42°S). The Southern Andes has a

high soil variability that does not allow for deep instrument monitoring. Therefore, we determined the domain-relevant geotechnical, hydrological, and geomorphological variables and applied advanced feature selection techniques, including Genetic Algorithms (GA) and Positive-Unlabeled (PU) Bagging. We were able to systematically identify and optimise the most informative predictors for rainfall-induced landslides.

Our results demonstrate that models optimised using Genetic Algorithms significantly outperform baseline methods, such as CART with conventional feature selection. Notably, GA RF and GA XGB achieved the lowest classification errors (10.95%). Moreover, compact feature sets highlighted the potential of evolutionary algorithms to enhance both the accuracy and efficiency of susceptibility assessments. Our models' results consistently identified slope, precipitation, and near-surface soil hydraulic properties—particularly bulk density and saturated water content—as critical factors influencing landslide initiation. Future instrumental developments must consider these variables, monitoring and landslide assessment.

Modified text:

We evaluated machine learning models (SVM, RF and XGB) to predict landslide susceptibility in the southern Andes (38–42°S), selecting domain-relevant geotechnical, hydrological, and geomorphological variables through feature selection techniques (CART and GA). The GA-optimized models, particularly GA-RF and GA-XGB, significantly outperformed baseline methods, achieving the lowest classification errors (10.95%) with compact feature sets that improved both accuracy and efficiency. Across experiments, slope, precipitation, and near-surface soil hydraulic properties—especially bulk density and saturated water content—emerged as the most critical factors influencing rainfall-induced landslides, underscoring their importance for future monitoring and assessment.

Reviewer 2

R2_1

L12-13: The abstract ends abruptly without presenting any concrete results. Please expand the abstract to include the key findings and avoid vague statements such as “various predictive models were tested.”

ANSWER: Thanks for this observation. We agree with your suggestion and incorporated the recommended changes into the new version of the abstract that we present in R1_3.

R2_2

L41-42: Seismic activity is not relevant to this study and should not be included in the introduction.

ANSWER: We are grateful for your valuable feedback on this point. We agree with your comment and have now revised the text to ensure it is more consistent with our overall scientific contribution and methodological approach.

Original text:

- Additionally, geological characteristics such as lithology and drainage density are crucial conditioning factors that interact with triggering mechanisms like precipitation and seismic activity (Bisht and Rawat, 2023).
- Conversely, in areas like the Southern Andes, seismic activity plays a more pronounced role, with earthquakes serving as significant triggers for landslides (Marc et al., 2016; Fan et al., 2021).
- Studies indicate that the presence of certain rock types and the geomorphological features of the terrain can predispose areas to landslides, particularly during seismic events (Pánek et al., 2022; Serey et al., 2019). Seismic activity is a critical trigger for landslides in this region, as evidenced by the correlation between earthquake occurrences and landslide events (Serey et al., 2019, 2020). The 2010 Maule earthquake, for instance, led to numerous landslides, underscoring the impact of seismic forces on slope stability.

Modified text:

- Additionally, geological characteristics such as lithology and drainage density are crucial conditioning factors that interact with triggering mechanisms like extreme precipitation events (Bisht and Rawat, 2023).
- Sentence removed

- Studies indicate that the presence of weak lithology along the margin and the geomorphological features could predispose areas to landslides, particularly during extreme precipitation events (Maragano-Carmona et al., 2025).

R2_3

L87-88: The diverse geological composition of the study area should be emphasized as one of the most important aspects. Please elaborate on how different soil and lithological types correspond to the selected controlling features.

ANSWER: We greatly appreciate this comment from the reviewer. We agree that further clarification is needed, and we have now incorporated additional information related to the geological composition of the study area to provide a more complete context.

Original text:

The area presents a unique and complex geological and climatological landscape that significantly influences soil moisture dynamics and mass wasting processes. This region is characterized by a diverse geological composition, including volcanic rocks, sedimentary formations, and glacial deposits, contributing to various soil types and structures. The interplay of these geological features with climatic conditions creates a dynamic environment that is crucial for understanding hydrological processes.

The geological framework of the Southern Andes is predominantly shaped by tectonic activity, resulting in a range of rock types, including andesites, basalts, and sedimentary rocks. The presence of glacial deposits from the last glacial maximum has resulted in the formation of heterogeneous soil profiles, which vary in texture and composition throughout the region. These geological characteristics influence water retention and drainage properties, thereby affecting soil moisture levels and slope susceptibility to mass wasting events. Understanding the geological context is essential for assessing the stability of slopes and predicting potential landslide occurrences. Moreover, the climate of the Southern Andes shows a high variability, influenced by altitude, latitude, and prevailing weather patterns. The region experiences a range of climatic conditions, from arid to humid, with significant precipitation occurring primarily in the winter months. This variability leads to distinct wet and dry seasons, profoundly affecting soil moisture dynamics at different depths with unknown control. Moreover, climate change poses additional challenges, as shifts in precipitation patterns and increased frequency of extreme weather events may exacerbate soil erosion and landslide risks.

The area is highly influenced by volcanic eruptions of different style, ranging from plinian to strombolian. These eruptions generate different volcanic soils derived from the tephra degradation during the holocene. Soil variability in the Southern Andes is characterized by differences in texture, moisture retention capacity, and organic matter content. The region hosts a range of soil types, including Andosols, which are rich in volcanic ash and exhibit high moisture retention, and more sandy or gravelly soils that drain quickly. This variability complicates the prediction of soil moisture levels and their influence on slope stability. Current knowledge gaps exist about the specific relationships between soil texture, moisture dynamics, and susceptibility to mass loss.

Despite the wealth of geological and climatological data available, significant gaps remain in our understanding of soil moisture dynamics and their parametric controls, that could control mass wasting. Specifically, there is a need for comprehensive studies that integrate geological, climatic, and soil data to develop a holistic understanding of how these factors interact to influence soil moisture levels and slope stability. Additionally, the impact of invasive species on soil moisture and erosion processes has not been extensively studied, presenting an opportunity for future research to explore these interactions.

Modified text:

The area presents a unique and complex geological and climatological landscape that significantly influences soil moisture dynamics and mass wasting processes. The diverse geological composition of the study area yields a complex landscape, formed by numerous relief changes related to volcanic and glacial processes during the Holocene and more recently, influenced by different-scale mass wasting processes (Maragaño et al., 2025; Fustos-Toribio et al., 2022, 2025). From a geological perspective, the area has a wide range of lithological units, encompassing volcanic rocks (andesites, basalts), metamorphic rocks (Horton et al., 2018), sedimentary formations, and glacial deposits (Rabassa and Clapperton, 1990; Cuzzzone et al., 2024). This variability introduces potential soil sources from weathered rocks and sediment sources that will send their material to sedimentary environments in the central valley. However, the amount of the source is still poorly quantified. The geological framework of the Southern Andes is predominantly shaped by tectonic activity, resulting in a range of rock types, including andesites, basalts, and sedimentary rocks. Stand out the volcanic activity, where this area contributed to volcanic eruptions, ranging from plinian to strombolian, which formed tephra deposits with different mineralogies (Moreno-Yaeger et al., 2024). The tephra degradation during the Holocene triggered high soil variability, characterised by different textures and water retention capacities, which could control the landslide triggering processes. Moreover, the different soil textures generated from lithological and tephra deposits control the water storage and the following organic matter content.

The area was covered by two pulses of glacial periods (Cuzzzone et al., 2024), which modified the relief and eroded previous deposits. Therefore, early-stage soils are available on the eastern side. Meanwhile, ancient soils are present in the western area, creating a good contrast between soil ages. The presence of glacial deposits from the last glacial maximum has resulted in the formation of heterogeneous soil profiles, which vary in texture and composition throughout the region (Vasquez-Antipan et al., 2025). These features influence the water retention and drainage properties, thereby affecting soil moisture levels and slope susceptibility to mass wasting events. Understanding the main control of the soil features becomes essential for assessing the stability of slopes and predicting potential landslide occurrences. In addition to the wide range of lithological and soil properties and features existing in the area, the climate of the Southern Andes exhibits an extreme range of climates, from arid to humid, influenced by altitude, latitude, and patterns of western winds and atmospheric rivers (Tetzner et al., 2025). The main precipitation amount occurs primarily in the austral winter months (May-September), reaching over 4,000 mm/year. The summer dry seasons modify soil moisture dynamics at different depths, with an unknown impact on landslides. Recently, climate change has posed additional challenges, as shifts in precipitation patterns and increased frequency of extreme weather events may exacerbate soil erosion and landslide risks.

Nowadays, accurately assessing landslide risk in this region presents significant challenges. The high variability in multiple variables introduces a complex dynamic that acts as a primary control on slope stability, which is currently poorly understood. The interplay of these varying variables creates a highly dynamic environment where the key relationships governing stability can change dramatically over short distances. The study area has been affected by large-scale mass wasting events (Fustos-Toribio et al., 2021; Ochoa-Cornejo et al., 2024; Maragano et al., 2025; Vasquez-Antipan et al., 2025), underscoring the need to develop a robust early warning system and enhance assessment accuracy. This requires comprehensive, integrated studies to create models that fully incorporate geological, climatic, and soil data, including the often-overlooked parametric controls, enabling a reliable landslide early warning system. A network of advanced sensors is needed to monitor real-time changes in all the variables across the varying lithological units. However, it needs to focus on the main variables, which have not yet been established.

R2_4

L119-121: The phrase “considerable attention” is unclear. Please specify the exact steps taken to ensure data quality.

ANSWER: We agree. Now, we modify the text:

Original text:

In constructing the database, considerable attention was paid to data quality, temporal resolution, and spatial consistency, which are critical for capturing the transient nature of the environmental processes leading to landslides in the Southern Andes.

Modified text:

The construction of the database was guided by constraining the data to high quality, considering the exact emplacement of the landslide and the date it occurred. This constrains the compiled dataset to ensure an extensive temporal distribution and high spatial consistency across the full spectrum of lithological and climatic features within the study area. This deliberate selection, by encompassing wide environmental variability, allows capturing the range of soil and lithologic features under different hydrometeorological and climatic conditions in the Southern Andes. The selected data provided a robust framework for analysing the dynamic relationships between hydrological, geological, and climatic controls in landslide generation.

R2_5

L127: The abbreviation “PP” is used without being defined beforehand. Please define it at first mention.

ANSWER: Now, we state the variable PP in the caption of the table 1.

Original caption:

Table 1. List of Variables available in the databases

Modified caption:

Table 1. List of Variables available in the databases. AvMoist: Available moisture = $\theta_{\{FC\}} - \theta_{\{PWP\}}$ ($\text{cm}^3 \text{ cm}^{-3}$); AWC: Available water capacity (mm); Bulk: bulk density of the fine fraction (g cm^{-3}); Clay/Silt/Sand: textural fractions (%); FC: field capacity at 330 kPa ($\text{cm}^3 \text{ cm}^{-3}$); PWP: permanent wilting point at 1500 Kpa ($\text{cm}^3 \text{ cm}^{-3}$); θ_s : saturated water content ($\text{cm}^3 \text{ cm}^{-3}$); θ_r : residual water content ($\text{cm}^3 \text{ cm}^{-3}$); ksat: saturated hydraulic conductivity (cm day^{-1}); n, α : van Genuchten shape parameters ($-, \text{cm}^{-1}$); Vmoist: volumetric soil moisture ($\text{cm}^3 \text{ cm}^{-3}$); PP: precipitation (mm); slope: terrain slope (degrees); Tex_Class: soil textural class (%); PIRange_X: prediction-interval range for property X ($_Bulk: \text{g/cm}^{-3}$; $_Clay: \%$; $_Sand: \%$); Total_AWC: depth-integrated AWC (mm).

R2_6

Figure 7 and 8: These figures are not properly prepared. They contain non-English words, and their captions are incomplete. Please revise accordingly.

ANSWER: We improved the quality of the figures in the manuscript, and completed the captions. We suggest to eliminate figure 8, because it does not retrieve more information than explained in the text.

Original figures:

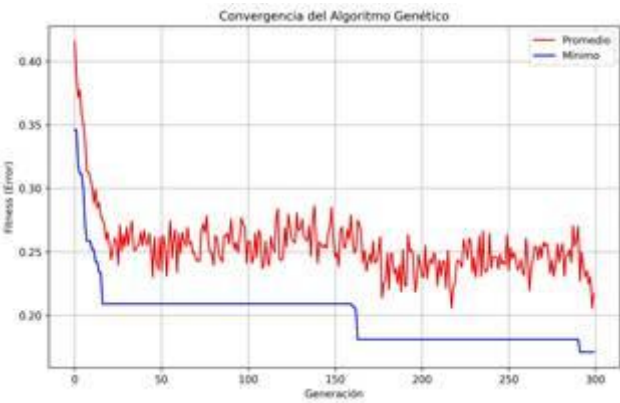


Figure 7. Genetic Algorithm Convergence

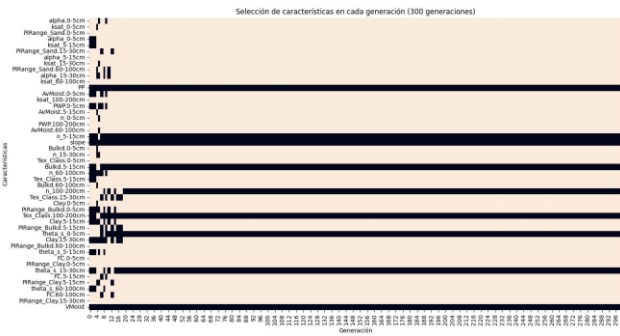


Figure 8. Evolution

Modified figures:

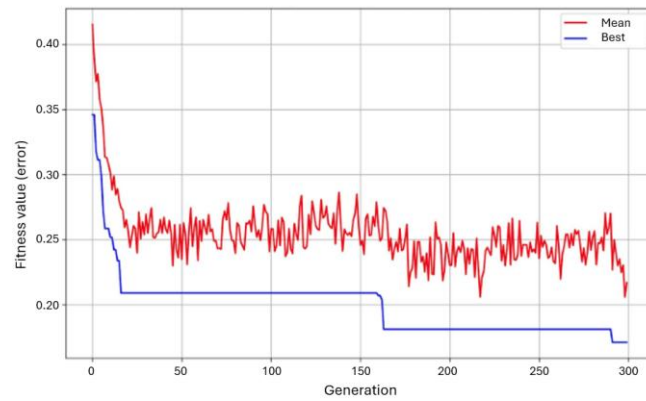


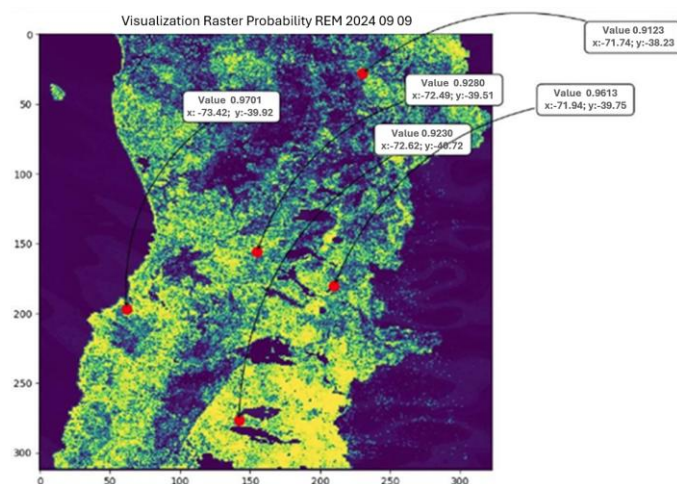
Figure 7. Genetic Algorithm Convergence: the curves show the population's average performance (Mean) and the best individual's performance (Best) across an evolution of 300 generations.

R2_7

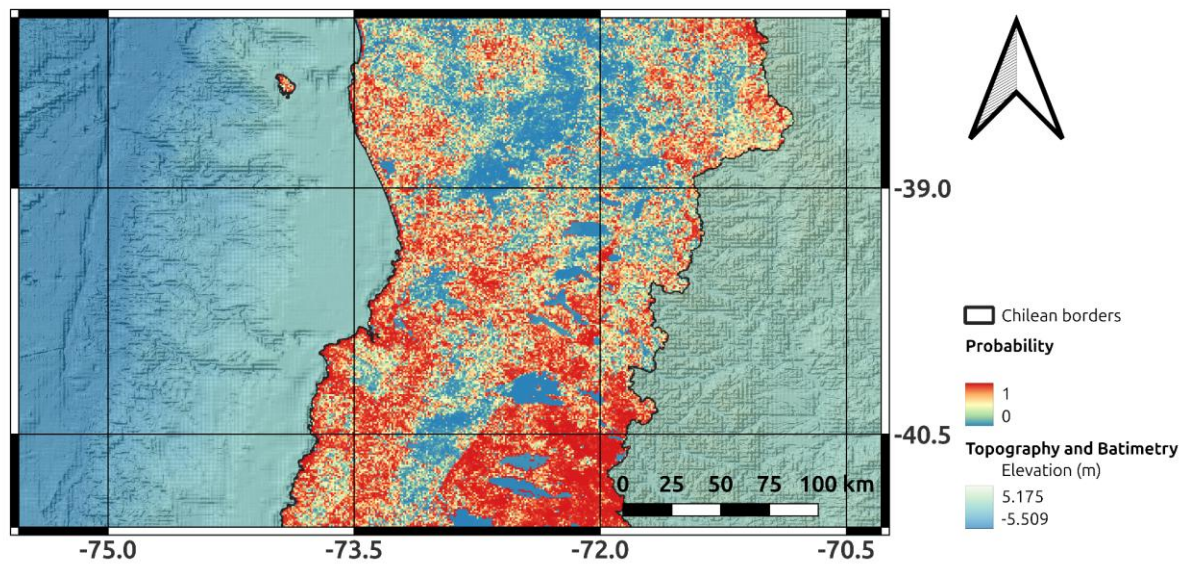
Figure 9: Please add the coordinates to the map.

ANSWER: Thanks for your observation. Now, we replaced the original figure with a new one. The final version will appear in the resubmitted version of the manuscript.

Original Figure:



Modified figure 9



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