Response to Reviewers' Comments on the Manuscript: "Manuscript Number: EGUSPHERE-2025-2298 " (R2)

Dear Editors and Reviewers,

We are grateful for the detailed and constructive feedback provided by you and the reviewers on our manuscript. We have carefully considered all the comments and have made significant revisions to address the points raised. Below, we provide a point-by-point response to each comment. We believe these revisions have substantially strengthened the manuscript, enhancing its scientific rigor, clarity, and potential impact in the field of landslide prediction and management.

Reviewer comments: "The author has significantly improved the manuscript. However, a few minor issues remain and should be addressed. In particular, the author should briefly describe the key results, including relevant numerical values, in the abstract. Furthermore, the author should provide a more detailed description and clear justification for the machine learning models employed. Finally, additional discussion is required to adequately justify and contextualise the reported results."

Response to Issue 1: Abstract Enhancement with Numerical Results

Reviewer's Concern: The abstract should briefly describe key results, including relevant numerical values.

Our Response:

We have substantially revised the abstract to incorporate quantitative findings throughout. The revised abstract now includes:

1. Model Performance Metrics:

- "The Support Vector Machine (SVM) model achieved the best performance using frequency ratio (FR) inputs with a 0.5 km buffer (F1-score: 0.859, AUC: 0.914)"

- "correctly classifying 86.4% of landslides as high or very high susceptibility"

2. Optimal Rainfall Threshold Parameters:

- "The rainfall analysis identified 24-hour intensity combined with 7-day antecedent rainfall as the optimal trigger"

3. Critical Susceptibility Factors:

- "rhyolite and granite slopes and areas near roads emerged as hotspots for failure (distance < 800 m, FR = 1.499 for roads; FR = 1.546 for rhyolite)"

4. Warning System Efficiency:

- "The integrated warning system shows high spatial efficiency, with high-risk areas covering only 34.2% of the study region yet capturing 71.4% of historical landslides"

Response to Issue 2: Detailed Machine Learning Model Description and Justification

Reviewer's Concern: The manuscript should provide a more detailed description and clear justification for the machine learning models employed.

Our Response:

We have comprehensively expanded Section 3.1.1 (renamed "Machine learning models: selection rationale and implementation") to address this concern through three strategic enhancements:

Enhancement 1: Explicit Justification for Model Selection

We added a new opening paragraph that clearly articulates why SVM and LightGBM were selected:

"We selected SVM and LightGBM to address three key challenges in typhoon-specific rainfall-induced landslide prediction: (1) severe class imbalance (landslides <0.5% of study area), (2) complex non-linear interactions between rainfall and terrain factors, and (3) computational efficiency for operational early warning."

This justification is now linked directly to the study's specific challenges rather than presenting models as generic choices.

Enhancement 2: Algorithm-Specific Technical Advantages

For SVM, we expanded the explanation to connect algorithmic properties to typhoon-specific applications:

"SVM excels in binary classification with limited samples through structural risk minimization (Kalantar et al., 2018; Wang et al., 2020), making it suitable for typhoon-triggered landslide mapping. Its margin-maximization approach handles the class imbalance between stable and landslide areas, while the RBF kernel captures localized failure patterns under concentrated typhoon rainfall. The regularization parameter C prevents overfitting to specific typhoon events, ensuring model transferability."

For LightGBM, we clarified its complementary advantages:

"LightGBM complements SVM through gradient boosting with sequential error correction, offering distinct advantages for regional-scale landslide mapping. Its histogram-based algorithm enables efficient processing of large spatial datasets (Sun et al., 2023; Sahin, 2020). Additionally, LightGBM automatically captures complex feature interactions."

Enhancement 3: Comprehensive Hyperparameter Optimization Details

We added detailed implementation specifications that were absent in the original manuscript:

For SVM:

"We optimized the RBF kernel parameters using grid-search with 5-fold cross-validation, where $C \in [0.1, 100]$ and $\gamma \in [0.001, 1]$. Across all configurations (three input methods × five buffer distances), optimal values varied as follows: $C = 5\text{-}15$ and $\gamma = 0.10\text{-}0.25$, with median values of $C = 10$ and $\gamma = 0.15$."

For LightGBM:

"We optimized LightGBM hyperparameters through Bayesian optimization. The optimal hyperparameters ranged as: num_leaves = 25-35, learning_rate = 0.03-0.08, and max_depth = 6-10. Early stopping with a 50-round patience window resulted in model convergence at 120-220 trees across different scenarios."

Response to Issue 3: Enhanced Discussion to Justify and Contextualize Results

Reviewer's Concern: Additional discussion is required to adequately justify and contextualise the reported results.

Our Response:

We have substantially restructured and expanded the Discussion section (Section 6) with three major revisions that transform it from descriptive observation to analytical contextualization:

Revision 1: New Section 6.1 - "Model Selection Strategy and Optimization of LSP"

We added an entirely new subsection that provides critical interpretation of the comparative model performance:

Algorithmic Performance Interpretation:

"SVM exhibited marked sensitivity to configuration parameters, with F1-scores varying from 0.681 to 0.859 depending on buffer distance and input method. LightGBM maintained more stable performance (F1-scores: 0.838-0.850) across all configurations. These differences reflect fundamental algorithmic characteristics: SVM's kernel-based approach effectively captures localized patterns when properly tuned, while LightGBM's ensemble structure delivers consistent results across varying data conditions."

Justification of Optimal Configuration:

"SVM's superior performance at 0.5-2.0 km buffer distances with FR weighting builds on findings by Kalantar et al. (2018) and Bogaard and Greco (2018). This buffer range appears effective for capturing the spatial patterns of typhoon-induced failures in our study area. FR weighting's effectiveness supports Reichenbach et al. (2018) and Yan et al. (2019), who found that frequency-based methods excel at quantifying terrain-landslide relationships."

Practical Model Selection Guidance:

"These performance patterns justify our dual-model approach. SVM, though requiring careful calibration, enables precise delineation of high-risk zones essential for emergency response, with SVM-FR at 0.5 km achieving peak accuracy (F1=0.859). LightGBM's robustness suits operational contexts requiring consistent predictions under variable conditions. Our results suggest that effective model selection depends on matching algorithmic strengths to specific application requirements rather than identifying a universally superior algorithm."

Revision 2: Substantive Enhancement of Section 6.2 - "Rainfall Threshold Modeling"

We transformed this section from simple result description to mechanistic interpretation:

Quantitative Threshold Interpretation:

"The H24-D7 model achieved 71.8% accuracy, outperforming alternative temporal windows (Table 3). The optimal RC24 value of 0.440 (with inter-fold variation of 0.414-0.472) indicates that landslides typically occur when 24-hour rainfall constitutes approximately 44% of the preceding 7-day accumulation. This pattern is consistent with the multi-temporal triggering framework proposed by Nolasco-Javier and Kumar (2018) for typhoon contexts, where both antecedent saturation and short-term intensity contribute to slope failure."

Critical Limitation Acknowledgment:

"However, the specific hydrological mechanisms underlying this ratio require verification through in-situ soil moisture monitoring."

Spatial Pattern Contextualization:

"Southeastern regions exhibit elevated H24 thresholds exceeding 250 mm (Fig. 7c), while northern areas show reduced thresholds of 100-150 mm. These spatial variations align with findings by Lee et al. (2018) and Cho et al. (2022) regarding topographic controls on typhoon-induced landslides, though the specific mechanisms require further investigation with detailed meteorological analysis."

Revision 3: Critical Refinement of Section 6.3 - "Integration Framework"

We revised this section to adopt appropriately cautious language while maintaining scientific rigor:

Performance Contextualization (Revised):

Original: "Both systems substantially outperform approaches using uniform regional thresholds"

Revised: "These focused distributions contrast with the broader spatial coverage typically required by uniform regional thresholds (Guzzetti et al., 2020), though direct comparative validation would be needed to quantify the performance gain."

Mechanistic Justification:

"The dual-threshold configuration provides complementary perspectives suited to different phases of typhoon evolution, with D7 reflecting cumulative moisture conditions and H24 capturing immediate triggering rainfall. This combination addresses the compound rainfall mechanisms documented in typhoon-affected regions (Gariano et al., 2015; Nolasco-Javier and Kumar, 2018), though the optimal application strategy for operational warning would require integration with real-time meteorological forecasting systems."

Transferability and Limitations:

"The framework advances beyond existing point-based threshold systems (Segoni et al., 2018b; Guzzetti et al., 2020) by providing spatially explicit hazard assessment, though regional adaptation of threshold parameters would be necessary for application in different geological settings."

Summary of Changes

The revisions comprehensively address all three reviewer concerns:

1. Abstract: Now includes 8 specific numerical results (F1-score, AUC, percentage classifications, FR values, efficiency ratios) that immediately communicate study outcomes

2. Methods (Section 3.1.1): Expanded with:

    - Explicit three-point justification for model selection
    - Algorithm-specific technical advantages linked to typhoon contexts
    - Complete hyperparameter optimization specifications for reproducibility

3. Discussion (Section 6): Restructured with:

    - New subsection (6.1) providing comparative model interpretation
    - Enhanced mechanistic explanations in existing subsections (6.2-6.3)
    - Balanced scientific claims with appropriate acknowledgment of limitations
    - Stronger integration with existing literature for contextualization

We thank the reviewers and the editor again for their thoughtful comments and suggestions, which have helped us improve the quality of our manuscript. We hope that the revisions meet your expectations and look forward to your positive response.

Sincerely,

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