Manuscript number: nhess-2024-90

My co-authors and I would like to express our gratitude to the reviewer for his constructive feedback and suggestions for strengthening our research. The changes we have made to the attached file in response to such feedback and suggestions have been highlighted in blue to facilitate their identification. I would also like to offer my apologies for the length of time it took us to prepare this response. We also record our deep appreciation for the efficient handling of the manuscript.

Response to Editor

Overall Observations: Referees who have reported on your initial submission have evaluated your manuscript again. However, their comments read rather contrasting: While referee #1 recommends publication of the paper as it is, referee #2 still has important concerns regarding the scientific context of your article in accordance to earlier comments mostly considering motivation of your research and discussion of the results including model transferability.

Looking at the current version of your manuscript, I think you thoroughly revised your paper, which is now not far from being publishable in NHESS. However, I agree with referee #2 that the presentation of your research still requires some improvements as detailed in the attached report, but I am not convinced that the paper necessarily needs another round of external peer-review. Based on this, I like to advise you to revise your paper considering the comments made by the referee and resubmit a new version of the article accompanied by a detailed point-per-point reply letter on the comments of the reviewer, and a version in track change mode highlighting the applied changes. After resubmission, the editor will review the article again.

Response: Thank you for your incomparable assistance during the review process of this manuscript. We are grateful for the constructive and insightful comments provided by both reviewers, which have significantly contributed to enhancing the quality and clarity of our work. We sincerely appreciate your recommendation for minor revision and have carefully addressed the comments provided by Reviewer #2, as well as the suggestions from the Editor. These revisions have been incorporated into the revised manuscript.

Response to Reviwer#2

Overall Observations: Thank you for your response, dear authors. I appreciate the revisions made after the previous round of reviews, but I believe the manuscript can still be further improved with additional revisions before it is ready for publication. I have presented my comments and suggestions in this iteration of the review, which I hope the authors will find helpful in enhancing the manuscript further.

Thank you for your valuable suggestions and guidance, which have greatly contributed to improving the earlier version of the manuscript. We acknowledge that the Introduction and Discussion sections required further refinement, and we have carefully revised each part in accordance with your recommendations.

Comment 1A: I will begin the second review and my line of questions starting from the Introduction section. In the last round of review, I raised a general concern about the lack of connection between volume estimation, geomorphological process understanding, and engineering solutions. Unfortunately, I still observe two major issues with the revised version:

It appears that the authors have addressed a wide range of topics, including engineering solutions for mitigation, risk assessment, financial compensation, and related aspects. While these are undoubtedly important, the way they are presented lacks a clear and cohesive narrative, making it difficult for readers to follow. As a reader, it feels like I am encountering a series of disconnected bullet points about various applications of volume information for landslides and their societal or biodiversity impacts, without a clear sense of purpose or direction in the text. Let's take this for example, "Firstly, to manage landslide risk effectively, the quantification of VLDR can be useful for updating hazard maps to reflect the scale of potential landslides in various regions to facilitate the identification of high-risk zones for monitoring and intervention." Now, normally such statements (especially in a review) is followed by a general explanation as to how the volume information can be used directly for the purposes of "updating hazard maps", for instance, by illustrating how these updated maps help prioritize areas for additional ground-based investigations, early warning system placements, or resource allocation for slope stabilization efforts. In other words, the statement should detail the direct linkage between volume quantification and subsequent practical steps that can be taken to mitigate landslide risk, rather than simply asserting that such a connection exists without any further elaboration.

This type of simple assertion is not the best for a reader to gauge what really is going on. Particularly, if there is no direct link between volumes and the respective impact. Other statements have the same 'linking' problem. Moreover, an equally big issue is that the new added paragraphs read the same to me. I do not gain any new information from the new text. The authors mention: "mitigation strategies, effective risk management, emergency response, public awareness on safety measures and preparedness, drainage system to control surface runoff, determining expected number of personnel for 'clean up' and recovery, establishing ecosystem impacts, habitat restoration, protection of crops and farmlands." Frankly, these topics are very diverse and complex, spanning multiple engineering, scientific, and social science disciplines. However, I see no clear connection to the manuscript's main narrative. Are the authors implying that their method can address all of these issues simply because it can accurately predict volumes? Does all of South Korea face these problems (more or less) equally? My point is that I cannot discern a clear, concise rationale or storyline explaining why landslide volume estimation is necessary. I recommend re-writing the two paragraphs related to the volumes and associated topic in the Introduction more carefully. Please keep the linkage direct and to the point, while citing some examples from the literature.

Response: Thank you for your insightful observations. We sincerely appreciate your detailed and constructive comments regarding the Introduction section. We agreed with the reviewer's suggestion that the material presented lacked coherence in the Introduction section. Accordingly, we have restructured the Introduction to maintain a clear and direct connection between landslide volume estimation and its engineering and scientific applications. The revised text eliminates broad and generalized statements, focusing instead on specific, practical linkages between volume estimation and its role in hazard assessment, risk mitigation, and resource allocation. The revised Introduction is provided below,

" Landslides due to rainfall are phenomena that dislocate a mass of soil from its natural position and slide downward along a slope due to gravity forces. Intense or long-duration rainfall infiltrates the soil and increases the pore pressure, resulting in soil saturation that leads to slope failure. The saturated soil becomes weak and loses cohesion, and the slope fails when rainfall crosses a certain threshold (Bernardie et al., 2014; Martinović et al., 2018; Lee et al., 2021). The heavy rainfall saturates a slope and triggers a landslide due to the reduction of the soil's shear strength and the increase of pore water pressure (Tsai and Chen, 2010; Lacerda et al., 2014; Chatra et al., 2019; Chen et al., 2021; Luino et al., 2022). For example, steep slopes with loose soils and even moderate rainfall can lead to the displacement of an enormous quantity of soil mass. On the contrary, in slopes with more stable, cohesive soils, the surface failure might be smaller (Tsai and Chen, 2010). The rainfall quantity and duration influence the volume of the landslides; the higher the intensity and the longer the duration of rainfall, the larger the resulting surface failure (Chang and Chiang, 2009; Bernardie et al., 2014; Chen et al., 2017). The landslide occurrences can also be influenced by human activities that weaken the slope, such as excavation at the slope toe and loading caused by construction and land use such as agriculture, mining etc. (Rosi et al., 2016). The rapid urbanization activities in mountainous regions affect the topography through hill cutting, deforestation and water drainage (Rahman et al., 2017); these activities disturb the slope structure and change the water flow, which exacerbates the effect of landslides in regions where human engineering activities are mostly located (Holcombe et al., 2016; Chen et al., 2019). Therefore, to mitigate landslide-induced risks in the runout regions, estimation of the volume of landslides due to rainfall (VLDR) plays a crucial role.

The quantification of the VLDR is essential for effective risk management (Tacconi Stefanelli et al., 2020), emergency response, engineering design (Cheung, 2021), economic assessment and environmental protection (Alcántara-Ayala and Sassa, 2023). With the estimates of VLDR, the morphologist can update hazard maps (Van Westen, 2000) to reflect the scale of potential mass movement in various regions to obtain regions with similar likelihood of landslides of similar soil mass to highlight risk zone levels, i.e., low, moderate and high. These classifications help engineers to apply appropriate slope stabilization techniques depending on the level of risk (Dahal and Dahal, 2017). Additionally, enhancing the precision of VLDR estimations and improving the predictive capabilities is essential for understanding and monitoring landscape evolution. Montgomery (2009) emphasized that the volume of landslides is a key factor in determining the extent of downstream damage, particularly for large debris flows or rock avalanches, which can drastically alter the landscape and affect surrounding ecosystems and infrastructure. Similarly, Korup (2004) further explored the long-term geomorphological effects of large-volume landslides, highlighting their importance in reshaping mountainous terrains and influencing sediment transport, which is critical for understanding both immediate and future landscape changes. However, the existing landslide susceptibility models mostly used for the identification of regions susceptible to landslides (i.e., landslide zonation) (Kim et al., 2014; Gutierrez-Martin, 2020; Chen et al., 2021; Li et al., 2022), which are essential in emergency management because they provide a general overview of zones with a higher probability of landslide occurrence; however, they do not emphasize the determination of the approximate value of the volume of failing mass in relation to excessive rainfall events.

Numerous researchers used landslide inventory, remote sensing data and numerical techniques to establish the relationship between landslide geometry and the influencing factors to determine the landslide volume quantitatively. For example, Saito et al. (2014) studied the relationship between rainfall-triggered landslides to test whether the volume of landslides across Japan that occurred between 2001 and 2011 can be directly predicted from rainfall metrics. The findings revealed that larger landslides occurred when rainfall exceeded certain thresholds, but there were significant discrepancies between peaks of rainfall metrics and maximum landslide volumes, and the total rainfall was the suitable predictor of landslides. Dai and Lee (2001) established the frequency-volume relation for landslides in Hong Kong and noticed that the relation for shallow landslides above $4m^3$ followed the power law. The 12-hour rolling rainfall contributed most to the prediction of the volume of landslides. Jaboyedoff et al. (2012) contributed by demonstrating the value of remote sensing technologies such as Light Detection and Ranging (LiDAR) in conjunction with field data to improve the accuracy of volume estimates and capture the geomorphological changes associated with landslides. Ju et al. (2023) constructed an area-volume power law model for the estimation of the volume of landslides using high-resolution LiDAR data collected between 2010 and 2020 in Hong Kong. The aim was to estimate accurately the volume of landslides on small-scale landslides. The reliance on localized datasets limits the model's applicability in regions with different geological settings, and the model does not consider all variabilities of landslide characteristics. Razakova et al. (2020) calculated landslide volume using remote sensing data to assess the efficiency of aerial photographs in environmental impact assessment and ground-based measurement. The study did not consider the effect of vegetation and topography and only focused on a single landslide case, which may be a source of bias due to differences in soil composition and environmental factors. Hovius et al. (1997) analyzed multiple sets of aerial photos and frequency-magnitude relations for landslides in New Zealand. The finding pinpointed that the landslides frequency-magnitude followed power law and infrequent large magnitude contributed to the landscape change. The study also noticed the importance of soil composition in the size of the landslides. This work had a limitation due to the reliance on aerial photos only, which cannot provide accurate measurement in regions of dense forest, and the climatic conditions, which are landslide triggering factors, were not considered, and this may affect the generality of the findings. Guzzetti et al. (2008) applied statistical methods on regional landslide inventories and antecedent rainfall data ranging between 10 min to 35 days. The findings revealed that the slope angle and soil type significantly influence landslide volume estimates, and the rainfall intensity is more important than duration. Chatra et al. (2019) applied numerical methods to study the effect of rainfall duration and intensity on the generation of pore pressure in the soil; the finding revealed a higher instability in loose soil compared to medium soil slopes. Huang et al. (2020) introduced a hybrid machine-learning model combining support vector regression (SVR) with a genetic algorithm to estimate debris-flow volumes. The model was tested on real-world case studies, showing improved accuracy in volume predictions compared to traditional methods. However, a notable weakness of the study is its reliance on a limited dataset, which may reduce the model's generalizability to environmental contexts. Shirzadi et al. (2017) compared the effectiveness of statistical and machine-learning models in simulating landslide volumes-areal relations, demonstrating that machine-learning techniques outperform traditional statistical methods in terms of accuracy. This method did not consider the climatic and geomorphic factors such as rainfall, vegetation, soil type, etc., triggering and influencing factors for the landslide occurrence. It was noted that existing models only treated the interaction of soil and rainfall without considering the environmental factors, human activity, and non-linear behavior of the triggering and influencing factors.

In the present study, the volume of landslides due to rainfall is predicted using OLS, RF, SVM, EGB, GLM, DT, DNN, KNN and RR algorithms, considering the details of triggering factors (i.e., rainfall) and predisposing factors (i.e., geomorphological, soil and environmental). Here, we aim to construct a data-driven algorithm that combines input parameters for physical-based and empirical models and incorporates more complex non-linear features of input variables to predict the occurrence of associated events more accurately. The main assumption behind the data-driven algorithm is that the considered feature input of the model produces a similar volume of landslides due to rainfall and follows the same pattern at a particular region with the same features under the same quantity of rainfall. Here, we examine different machine learning (ML) algorithms and compare their performance using the coefficient of determinations (R^2), mean square errors (MAE), Root mean square error (RMSE), Mean absolute percentage error (MAPE), and symmetric mean absolute percentage errors (SMAPE) of the predicted volume of landslides. The focus is to optimize the predictions of the volume of landslides due to rainfall, taking into account triggering and influencing factors with higher accuracy."

Comment 1B: Additionally, the authors did not adequately integrate the volume estimations or predictions into a geomorphological context. This aspect is crucial, as it forms the crux for studies linking sediment transport, material mobilization, and sediment influx into river systems for example. Omitting this perspective is problematic since it averts a reader from understanding how the observed volumes relate to underlying geomorphological processes (including hillslope process evolution), ultimately limiting the usefulness and practicality of the study's findings for both scientific insight and practical applications in landscape management and hazard mitigation.

I believe the current structure of the Introduction is not optimal. I encourage the authors to take their time and thoroughly revise this section, especially the two paragraphs related to volumes. I suggest a comprehensive overhaul of the discussion on the importance of volumes, incorporating key works by Montgomery, Jaboyedoff, Korup, and van Westen to strengthen the narrative. Please take this opportunity to carefully revise the text such that the importance of volumes is clear and coherent from an application point of view, ranging from both engineering and geomorphological perspectives.

Response: Thank you for your observations. We understand the importance of incorporating the geomorphological aspect, and some literature was included in the revised manuscript accordingly. We reread the introduction and rewrote it considering your suggestions to improve the technicality, clarity and logical coherence of the section. The revised Introduction provides a clearer and more coherent discussion of the importance of landslide volume estimation from both engineering and geomorphological perspectives. The updated introduction is highlighted in our response to Comment#1A.

Comment 2A. Moving on to the next topic, I want to stress a bit more on the geographical split testing argument and the application of the model to other locations/regions.

Let's start with the geographical split. The authors state that dividing the data by region would compromise model reliability due to the reduced size of the test set. While I partially agree, the authors also mention that they incorporated altitude as a predictor variable to reflect geographical diversity citing the influence of orographic rainfall on higher-altitude areas. This reasoning, however, may be oversimplified. Altitude is only one dimension of regional variability and may not fully capture the complexity of geographic differences in landslide susceptibility (and/or by proxy, volumes). Although incorporating altitude could help the model account for some variations associated with elevation, it cannot completely substitute for explicit geographic variability. Regionally distinct factors—such as geology, lithology, vegetation, land use, and soil types—may not be adequately represented by altitude alone. Relying solely on altitude as a proxy for regional variability implies oversimplifying the spatial heterogeneity inherent in landslide processes.

Please note that, while I do support the approach for splitting the data, I disagree with the notion that altitude alone is sufficient to capture the geographic diversity inherent in South Korea's varied landscapes. In my previous review, my suggestion was to consider performing or evaluating a spatial cross-validation, although a regular 10-fold cross-validation could also suffice (as the authors noted that 60% of the data is concentrated in the northeast), despite the methodological differences between the two approaches. I am interested to hear the authors' thoughts on the use of altitude as a proxy for geographic diversity.

Response: Thank you for your insightful comment. We agree that relying solely on altitude to capture the geographic variability inherent in South Korea's diverse landscapes would be an oversimplification. In the present study, we incorporated additional variables in the modeling process, including soil types, soil depth, slope aspect (versant), drainage, and vegetation-related variables to capture the spatial heterogeneity inherent in landslide processes. Soil types and their coefficients of permeability reflect regional lithological variations; the drainage significantly affects slope stability and promotes efficient control of rainfall's influence on groundwater fluctuation; slope aspect accounts for potential influences of rainfall patterns and wind direction on slope vulnerability, and vegetation-related variables (age of tree, forest density, timber diameter) improve soil cohesion and prevent direct contact of raindrops with the soil surface as highlighted in the feature importance (Fig. 6). These selected variables contribute to capturing regional variability and improving the model's predictive capability. We believe that the selected features provide sufficient insight on the application of suggested methods in the prediction of VLDR.

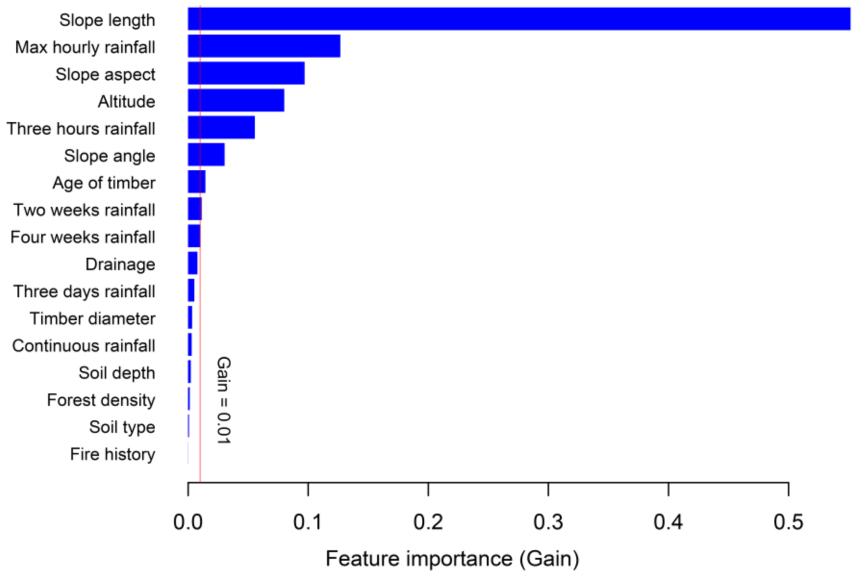

Figure 6. Variable importance for the EGB model.

Comment 2B: For the application of the model, the authors mention using an unknown dataset—presumably the independent test set—where the model achieved an R^2 value above 0.8, which is quite good. My previous recommendation was to see if the authors could apply the model elsewhere, ideally in a nearby area (still in the South Korean Peninsula) with new (or even old) landslides for which no volume information is currently available. While ML/DL models often perform well on familiar data, they may produce unpredictable, random or less meaningful results when applied in a 'new' region or context. This way, the authors might see how the model behaves under different conditions, while providing insights into its generalizability and practical applicability to scenarios beyond the training environment. Of course, the authors will not be able to validate these results (for N number of landslides) since no ground truth exist, but it will give a good idea if the predicted volume prediction numbers are off the charts (e.g., extremely large or very small). This is important to investigate how random the model(s)' predictions can be and, beyond that, provides additional motivation for the authors' work, moving it beyond merely a 'modelling exercise'.

Response: Thank you for your suggestion. We acknowledge the importance of testing the model in diverse conditions to evaluate its robustness and behavior under different environmental and geological contexts. In the present study, to understand the applicability of the developed models, the trained model was tested using unknown data (test data), with volume predictions generated solely based on the predictor variables; actual volume values were utilized only for evaluating model prediction accuracy. The outcome exhibited that the difference in R^2 on the training and holdout set of 7.72% for the optimal model (i.e., EGB) highlights that the model can be applied to another region of a similar setting. It was noted that without proper model calibration with the independent data set, it's difficult to determine whether these discrepancies in performance are due to model limitations or data differences in different regions (Huang et al., 2020). Therefore, in future work, we plan to develop an independent database based on collecting the extensive recent landslide geometry at different parts of the Korean Peninsula to improve the models further by calibrating region-specific parameters to ensure the transferability of the model to other regions.

Comment 3: Regarding the Discussion, the authors stated in their response: "direct comparison with result of existing numerical and statistical models that solely depend on geometrical features of landslide (such as, surface area or runout length) is out of the scope of this investigation". It seems that the authors may have misinterpreted my suggestions. The recommendation was not to perform a numerical comparison with other methods, such as statistical or numerical models, but rather to review the literature on such methods and highlight why the authors' approach is reliable.

This suggestion is particularly important because, as the authors themselves mentioned, no previous study has used such a multivariate predictor approach for volume predictions. Therefore, it is important to discuss and review this aspect as a huge chunk of the literature rely on, for instance, numerical and geometrical methods for volume estimations. Additionally, it is crucial to discuss and review related topics in common geomorphological research—such as sediment transport, landscape evolution, and material mobilization—since these processes rely heavily on volume data for quantification. This connects back to the Introduction section, which I previously noted requires an overhaul. Elements introduced in that section can be further expanded upon in the Discussion to emphasize potential applications of the proposed approach. While volume information is undeniably important, simply focusing on the influence of ML/DL on model performance significantly underestimates the broader implications that the Discussion section could address given the scope and nature of the study.

Response: Thank you for your insightful comment. Regarding the improvement in the Introduction and Discussion, the suggested modifications have been incorporated in the updated version of the discussion section as follows,

Line Nos 457- 480:

Numerical models have traditionally been employed due to their foundation in physical principles such as slope stability and hydrological dynamics (Glade et al., 2005). These models are valuable for understanding the underlying mechanisms of landslide processes but often face limitations when applied to regions with complex or heterogeneous terrain, as they require detailed, high-quality input data that may not always be available (Caine, 1980). In the same way, statistical models, which use historical rainfall and landslide data to establish correlations, can offer useful predictions of VLDR in regions with extensive historical records (Chung and Fabbri, 2003). However, these models may struggle to account for local variations in topography or rapidly changing weather patterns, limiting their general applicability. Additionally, ML techniques have shown significant promise in improving predictive accuracy at the regional level due to the capability of processing large, diverse datasets and capturing complex, non-linear relationships that traditional models might fail to capture (Pourghasemi and Rahmati, 2018). Further, ML models can adapt to regional variations and continuously improve as new data is introduced, offering a more flexible and dynamic approach to predict VLDR on a regional scale (Liu et al., 2021). Subsequently, the aim of this study was to construct a data-driven algorithm that accurately predicts the VLDR. The result of nine different tested algorithms revealed a tremendous difference between classical regression models (OLS, RR, and GLM) and other data-driven machine learning models. In this study, apart from SVM regression, DT and KNN, other machine learning models (DNN, DT, RF, and EGB) exhibited high prediction capability with R^2 above 50% (Fig. 5). The DNN, EGB, and RF models achieved R^2>0.8 on both training and test set with accuracy reduced R^2 by 1.75, 7.72, and 12.17% for RF, EGB and DNN respectively, on the holdout set, indicating that the model could yield reliable volume estimates in adjacent areas with similar geological and environmental conditions. The random forest model performed well in predicting smaller volume; however, as the volume increased, the model underpredicted volume values.

Line Nos. 514-525:

“To understand the applicability of the developed models, the trained model was tested using unknown data (test data), with volume predictions generated solely based on the predictor variables; actual volume values were utilized only for evaluating model prediction accuracy. The outcome exhibited that the difference in R^2 on the training and holdout set of 7.72% for the optimal model (i.e., EGB) highlights that the model can be applied to another region of a similar setting. It was noted that without proper model calibration with the independent data set, it's difficult to determine whether these discrepancies in performance are due to model limitations or data differences in different regions (Huang et al., 2020). Therefore, in future work, we plan to develop an independent database based on collecting the extensive recent landslide geometry at different parts of the Korean Peninsula to improve the models further by calibrating region-specific parameters to ensure the transferability of the model to other regions.”

Comment 4: Table 1 column ‘Descriptions’ seem misleading. Descriptions should also include the definition of the variables, not just the ‘influence’ of the variable. For example, for Slope angle, there’s no definition as to what it means, but rather a statement which explains the influence of the slope angle (e.g., slope at 20-30 degrees more vulnerable to landslides due to rainfall). This is not really a ‘description’. I suggest either changing the column name or adding a definition first for each variable and then explaining their influence on landslides.

Also, based on line 287, it seems that there are only three types of soil, sandy loam, loam, and silt loam. Please add them in the table for soil types as well.

Response: Thank you for your observations, and we agree with your suggestion. Accordingly, the word ‘description’ was replaced by ‘feature relevance’ in the revised manuscript. Additionally, the feature relevance of three types of soil has been incorporated in Table 1. The revised text incorporated in Table 1 is given below.

‘Soil types, namely, Sandy loam, silt loam and loam, with their coefficient of permeability 1.7, 1.65 and 1.5, respectively, retain water differently, leading to different saturation times. The soil with higher permeability tends to drain water more efficiently, making it less prone to saturation. In contrast, the soil with lower permeability, the pore pressure rapidly increases, which leads to shallow landslide initiation during intense rainfall events.’

Comment 5. The authors have provided a clear explanation of the feature importance for soil depth, and I appreciate their decision to retain it, as it is crucial for volume estimations. The authors noted that soil depth could play a more significant role in different regional settings with varying behaviors or responses, and I agree with this perspective. I have no further comments on this matter.

Response: Thank you for your insightful comment. We appreciate your earlier suggestions, which helped us refine and clearly articulate the rationale for including soil depth as a critical predictor variable in the model.

Comment 6: I appreciate the response and explanation regarding the differences between the Random Forest and EGB models in predicting smaller and larger volumes, respectively. Indeed, an iterative process like EGB, guided by gradient descent, is likely to capture the more intricate patterns associated with landslides generating large volumes. Similarly, the 'average' behaviour of the ensemble approach in Random Forest effectively accounts for the prediction of smaller volumes on average. I have no further comments on this matter.

Response: Thank you for the comment, which helped us to improve the interpretation regarding the differences in the predictions of different models.

Comment 7: The authors have also explained the landslide movement query very well, and I have no further questions in that regard.

Response: Thank you for your feedback. We appreciate your observations, which have greatly improved the clarity and quality of the manuscript. We are pleased that the explanation regarding the landslide movement met your expectations.

Comment 8: In conclusion, my impression of the technical aspects of the work is positive since much of the authors' clarifications addressed my concerns. However, the justification for the importance of volume information, its applications, and the future scope remains limited, which undersells the contribution of this study. I believe that an additional round of revisions would further enhance the manuscript, making it more accessible and impactful for a broader audience. I wish the authors good luck with their revisions.

Response: Thank you for the positive response regarding the technical aspect of the manuscript. The suggested improvements were incorporated into the revised manuscript.

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