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My co-authors and I would like to express our gratitude to the reviewer for 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 Reviewer#1

General remarks: I am attaching my full comments in the attached PDF. At the same time, I am summarizing my general comments here for the editor's perusal.

This manuscript presents a valuable reflection of data-driven modelling for robust regional-scale analyses of landslide masses. The authors deserve commendation for their interesting research, which has significant implications for hazard prediction and modelling. However, I have some major comments and concerns. While the study is promising and of great interest to the landslide community, it requires further work. Some aspects of the training and testing regimes are not clear. Furthermore, the choice of certain parameters is not well justified which, in my opinion, must be clarified for readers to understand the logic of choosing said parameters. The English language, particularly in the Introduction, needs improvement. Some sentences read awkwardly and are hard to follow. Improved sentence phrasing is necessary to make the manuscript clearer, especially for non-native English readers. In my opinion, a major revision is required to adapt the manuscript before considering acceptance.

Response: Thank you for your detailed comments and for the recognition of the value of our research. We appreciate your commendation and acknowledge the importance of addressing your highlighted concerns. In the revised manuscript, we have focused on the aspects of the training and testing datasets to enhance understanding, as well as provide a stronger justification regarding the choice of predictor variables to ensure the logic is clear to all readers. Additionally, we revised the language throughout the entire manuscript to enhanced readability.

General comments: The problem of landslide volume estimation has been a focus for the community for quite some time, through methods such as area-volume scaling, geometrical modelling, numerical simulations, and more. This parameter is crucial as it helps gauge the magnitude of landslides, particularly at regional scales. Most highly accurate methods, like numerical simulations, often struggle at the regional scale. This manuscript offers a valuable reflection of data-driven modelling for delivering robust regional-scale analyses of landslide masses. Kudos to the authors for this interesting research, which has significant implications for hazard prediction and modelling. However, there are some major comments and curiosities I have. I believe the study is promising and of great interest to the landslide community, but it requires further work. The English language writing can be improved, especially in the Introduction. Some sentences read awkwardly and are hard to follow. Sentence phrasing must be improved to make the manuscript clearer, particularly for non-native English readers.

Response: We appreciate the thoughtful feedback and for recognizing the value of our research in the context of landslide volume prediction and acknowledgment of the challenges faced by highly accurate methods at regional scales, and we appreciate that our data-driven modeling approach resonates with the landslide community. We took your concerns regarding the clarity of the English language and improved the phrasing and overall readability, particularly in the Introduction, to ensure it is accessible to all readers.

Specific major comments:

Comment 1: The Introduction needs to be revisited for editing in both grammar and phrasing of the language. Moreover, the motivation for the importance of volume quantification appears to be a bit lacklustre. I do not see a geomorphological connection as to why volume estimates are important to understand process mechanism and kinematics. Although, the manuscript does not explore said mechanism and kinematics expressions, however, to build a succinct story, a logical connection between the geomorphology and the surface failure should, in my opinion, be expressed to highlight why volume estimations are important as it directly feeds into the story of hazard prediction moving forward.

Response: Thank you for your insightful comment. We appreciate your suggestion to improve both the grammar and phrasing to enhance clarity. We also acknowledge the need to strengthen the motivation for volume quantification and its geomorphological significance. In the revised manuscript, we emphasized the connection between volume estimates and the understanding of process mechanisms, illustrating their importance in the context of hazard prediction. The revised Introduction is given 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 (Luino et al.,2022; Chen et al., 2021; Chatra et al., 2019; Lacerda et al., 2014; Tsai and Chen, 2010;). 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 (Chen et al., 2017; Bernardie et al., 2014; Chang and Chiang, 2009). 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 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; Islam et al., 2017; Chen et al., 2019).

To estimate the volume of the soil mass displaceable subsequent to intensive rainfall, is essential to set appropriate mitigation strategies to reduce environmental degradation, infrastructure damage, casualties, and to establish post-disaster resilience policies to restore the socio-economic aspect of communities (Van et al., 2021; Alcántara-Ayala, 2021). This quantification of the volume of landslides due to rainfall (VLDR) is essential for effective risk management (Tacconi et al., 2020), emergency response, engineering design (Cheung, 2021), economic assessment and environmental protection (Alcántara-Ayala and Sassa, 2023). 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. In addition, to develop mitigation strategies, such as land stabilization measures and land use planning, planners might put in place strict construction regulations in particular regions that are susceptible to landslides (Mateos et al., 2020). The accurate measurements of VLDR can be used to promote public awareness for safety measures and preparedness (Yang and Adler, 2008). Secondly, estimating precise VLDR is crucial for structural engineers to design a structure that can withstand extreme landslide events. Knowing the exact volume of displaceable material, an engineer can set robust stabilization solutions to prevent future occurrences (Dai and Lee, 2001). Moreover, the VLDR can help design the drainage system to manage water flow by controlling groundwater and surface runoff to mitigate landslide risks (Dikshit et al., 2019; Kim et al., 2014). Furthermore, to prepare for emergence responses such as resource allocation, evacuation planning, and search and rescue operations, accurate VLDR estimation is necessary to ensure efficient implementation (Fan et al., 2019). To allocate resources effectively, the volume data is needed to determine the expected number of personnel for evacuation, materials sufficient for cleaning up and recovery (Amatya, 2016; Yang and Adler, 2008; Spiker and Gori, 2003). Further, to establish environmental protection measures such as ecosystem impacts, preservation of soil and water quality, and habitat restoration, the estimates of VLDR are essential (Pradhan et al., 2022; Li et al., 2022a; Barik et al., 2017).

To mitigate the economic impacts of landslides, the values of VLDR can be a basis for estimation of property damages, which is critical for settling insurance claims and assessment of financial impacts on communities and government to facilitate efficient budgeting for repairing damaged infrastructure and restoration of affected parts (Klimeš et al., 2017; Dai et al., 2002). The prediction of the VLDR can assist in long-term economic planning for landslide risk by creating disaster preparedness and recovery funds (Winter and Bromhead, 2012). The accurate estimation of the VLDR is an important key for designing strategies for resilience and planning for the protection of the inhabitants of a particular region with certain landslide risks subjected to a predicted quantity of rainfall (Conte et al., 2022). Consequently, for the safety of communities, the selection of infrastructure construction sites must be done in places with low landslide risks (Fan et al., 2017). Further, for the protection of crops, the farmland location, and other land use activities, accurate landslide prediction taking into account real root causes through the analysis of triggering and influencing factors, is crucial to achieve a durable landslide safety management system (Paudel et al., 2003; Lee, 2009; Fan et al., 2017; Chen et al.,2019; Dai et al., 2019; Alcántara-Ayala, 2021). “

Comment 2: Are the training and testing datasets split randomly with keeping the training data fixed or is the split performed geographically? It would be interesting to see a geographically split dataset to see how well the model(s) perform due to apparent differences in the geological and environmental conditions across the study area.

Response: Thank you for your insightful suggestion, which helped us improve the manuscript. In the present study, we opted to split the training and testing data randomly, implementing a 10-fold cross-validation to obtain an optimal model. This choice was made to balance bias and variance effectively, adhering to a common 70% training and 30% testing split frequently employed in machine learning models (Nguyen et al., 2021), which has been shown to be an optimal data ratio.

While a geographically-based split could offer insight into regional variability, it may introduce challenges for this study, as landslide occurrences in our dataset are unevenly distributed, with about 60% located in the northeast part of the country. Geographically splitting this region as the test set would significantly reduce test data size, which could compromise model reliability and result in a suboptimal training process. To address regional variability without introducing geographic splitting, we incorporated altitude as a predictor variable in the model, recognizing that orographic rainfall in higher-altitude regions impacts soil saturation and may influence landslide susceptibility differently across regions. This approach allows the model to account for environmental differences while maintaining a balanced and representative dataset.

Comment 3: One of my main concerns, or rather my curiosity, is regarding the data set itself. The volume information, along with the inventory, is particularly noteworthy in this case, as most inventories lack volume data. Keeping this in mind, how do the authors think about the application of such methods in other areas? Now, the authors have created a method that works pretty well within the given region. Instead of finding other regions (which might be difficult and time-consuming) could the authors simply use the model and predict volumes on similar nearby regions where the volumes are not calculated? This could serve as a simple prediction example demonstrating the method's application, without requiring extensive investigation. This approach is important as it helps the authors extend beyond a simple ‘exercise’ of the method, since it is currently applied only in the study area. Moreover, this would make the claim in Conclusion, Lines 346-349 more credible.

Response: Thank you for your insightful comment. We agree that extending the applicability of our model to other regions is a valuable goal. While a comprehensive analysis of other regions is beyond the scope of this study, we recognize the potential to apply our model to similar regions with similar geological and environmental conditions.

In the present investigation, we selected a test set treated as unknown data to the model, where volume predictions were based solely on predictor variables, and actual volume values were used only to evaluate model performance. Our results indicate that the DNN, EGB, GLM, and RF models performed well, achieving an $R^2>0.8$. This level of accuracy suggests that the model could provide reliable volume estimates in adjacent areas with comparable input data. We have clarified this point in the revised manuscript to highlight the model's adaptability.

Comment 4: My biggest concern is related to the soil-depth. Now, it is impossible to imagine the calculation of volumes without the depth of the material that has failed as that is the 3rd volume calculations. It appears that the soil depth was 'removed' after feature importance analysis for the best performing EGB model. Sure, the depth information might not have been that important in this example of model training for this region, but I would argue that in other regions, particularly if the region contains multiple deep-seated landslides and the failure surface runs deep until the bedrock. I am just not convinced that removing soil depth makes sense, as geomorphologically, depth (which also relates to soil composition) is very important for accurate volume estimation and calculation.

Response: Thank you for the fruitful observation. We agree that soil depth is important in the prediction of the volume of landslides due to rainfall. In this study, the average topsoil depth was considered, and during the training process, the contribution was minor in the prediction of volumes and values below 0.01 were not shown even though those features remained in the model. To remove the confusion caused by the absence of those variables with less contribution on the variable importance plot and to acknowledge that those variables may be more significant in other regions, all variables used to train all models were shown in the updated manuscript. The updated figure with its caption in the revised manuscript is depicted below,

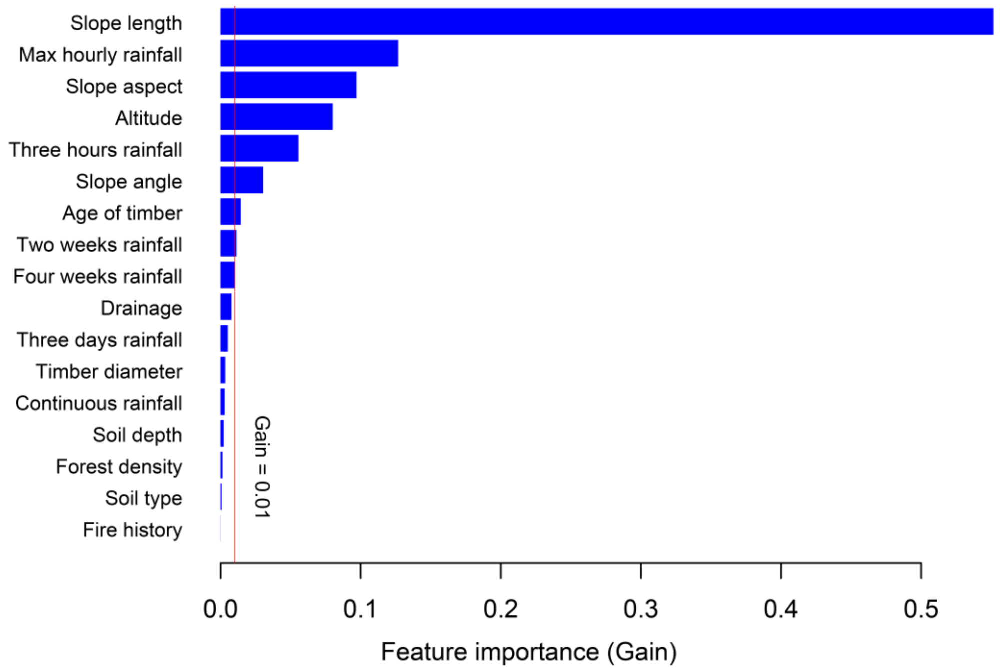

Figure 6. Variable importance for the EGB model.

Comment 5: Another question is pertaining to the type of failure movement. The inventory contains multitude of information but what about the movement types of the landslides? What types of landslides are considered in the inventory? Because clearly shallow and deep landslides would require separate treatments when looking at volume predictions because the material composition, material type, and material depths would be tremendously different. Do the authors combine these landslides together? What is the proportion of these landslide types? Also, are there prevalent debris flows, because volumes of debris flows is another story altogether since entrained volumes due to channelization are different than surface failure volumes. I see that the Discussion can be improved a lot by addressing and discussing these topics and limitations.

Response: We appreciate the reviewer's insightful comments. We agree that landslide movement types are critical for accurate volume predictions, as they exhibit distinct failure mechanisms, material properties, and depositional patterns. As the reviewer correctly noted, our initial dataset contained a variety of landslide types. Upon further examination, we identified that the majority of landslides in our study area were shallow, translational slope failures. Only one deep-seated landslide, with an approximate volume of 33,000 m^3, was included in the inventory. As observed in prior studies, shallow translational slides are common in granite areas of Korea due to uniform weathering profiles, while metamorphic regions tend to experience larger debris flows due to steeper slopes and irregular weathering profiles (Kim and Chae, 2009). Kim et al. (2001) further noted that in north and northwest part of the country, most landslides are classified as debris flows, though their initiation points often exhibit characteristics of translational slides. Recognizing that shallow and deep-seated landslides exhibit different material properties, failure mechanisms, and volumetric characteristics, we have removed this deep-seated landslide from our analysis to ensure consistency and relevance to our study objectives. We have therefore focused our analysis on this dominant type, as it represents the primary landslide hazard in the region.

This manuscript contains exclusively shallow-seated landslides with volumes below 13,000m^3 with topsoil depth varying between 0.2m and 1m. We have updated the methodology and analysis sections to clarify that our dataset only includes shallow-seated landslides. Additionally, the Discussion section now addresses this limitation, acknowledging that the exclusion of deep-seated landslides and debris flows may affect the generalizability of our findings to other landslide types. This improvement aligns with the study's focus on shallow landslides, allowing for a more accurate assessment of volume predictions within this specific landslide type. We have also noted in the Discussion that future studies would benefit from separate analyses of deep-seated landslides and debris flows, given the unique volumetric and channelization characteristics of debris flows.

Comment 6: The Discussion section is oriented quite too much on the aspects of the different models, conditioning factors, and their roles in the prediction of the volumes. As I mentioned in my previous comment, not much is discussed on the practical questions of scalability, different modes of movements, soil depths, runout volumes of entrained materials etc. These are essential topics as the direct counterpart of statistical models, i.e., numerical models tend to answer these questions. So, a comparison with the literature in that order is missing which I believe would add new levels of arguments to put forward by the authors and cement why their method works well despite lacking/following physical laws.

Response: This study aim was to construct a data-driven algorithm that predicts the volume of landslides due to rainfall. 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%. Further, to understand the applicability of the developed models, the trained model was tested using unknown data, with volume predictions generated solely based on the predictor variables; actual volume values were utilized only for evaluating model performance. We found that the DNN, EGB, GLM, and RF models achieved R^2>0.8, indicating that the model could yield reliable volume estimates in adjacent areas with similar geological and environmental conditions. It was noted that the numerical models and machine learning approach mostly used for the landslide volume estimation depend on landslide geometry (Leong and Cheng, 2022; Do et al., 2017; Shirzadi et al., 2017). As or our knowledge, none of the ML models used to predict volume of landslides using multiple predictors (such as, geological, topographical, geomorphological, soil, vegetation, and rainfall factors) on large scale. Therefore, the 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.

Comment 7: In Table 1, under Geomorphology, the feature "erosion" is presented. Now, erosion itself can be referred to the volume, which is the main variable that the authors are trying to estimate. So, how is this variable used in the training regime?

Or is this erosion feature different than the output of volume? Also, there are summary statistics of the erosion under Table 2. Why is that? My concern is that the authors are not clear as to what ‘erosion’ refers to in the data-driven model construct. If it is in fact similar to volumes, then the predictor variable and output variables are more or less the same. This needs further in-dept clarification.

Response: We appreciate the reviewer comment regarding the confusion originating from the use of ‘erosion’ as a predictor variable. We agreed that the term may have caused confusion.

In the preprint, the feature named 'erosion' was incorporated as a categorical variable with 'Yes' and 'No' values, indicating whether minor erosion events (such as gradual surface degradation due to wind or water) occurred prior to the landslide event. This differs from the volume variable, which is our dependent variable and represents the total mass of displaced material due to a landslide. Importantly, volume was not used as a predictor in the model; rather, it serves solely as the target output. To avoid ambiguity, we have removed the 'erosion' variable from the predictor variable list in Table 1 and accordingly updated Table 2 in the revised manuscript.

Table 2: Summary statistics continuous variables.

Variable	units	N	Min	Mean	Median	Max	Std dev
Max Hourly rain	mm	455	0	48	48	78	20
Continuous rainfall	mm	455	0	285	327	550	106
Three hours rainfall	mm	455	0	88	80	171	60
Twelve Hours rainfall	mm	455	0	150	99	447	95
One day rainfall	mm	455	0	202	162	538	112
Three days rain	mm	455	0	280	284	550	86
Seven days rain	mm	455	0.5	323	330	634	88
Two weeks rain	mm	455	0.5	385	400	663	90
Three weeks rain	mm	455	86	504	533	914	115
Four weeks rain	mm	455	108	587	561	1135	160
Soil depth	m	455	0.2	0.6	0.75	.75	0.19
Soil type	-	455	1.5	1.6	1.5	1.7	0.087
Timber diameter	m	455	0.15	0.27	0.23	0.35	0.086
Age of tree	Years	455	10	34	35	60	14
Slope length	m	455	1.8	21	13	180	23
Slope angle	Degree (o)	455	10	34	34	65	7.9
Altitude	m	455	9	391	272	1324	273

Comment 8: Table 1: Descriptions should be written properly for each feature/variable. At the moment, the descriptions read more like a summary of the sub-groups, written

altogether. Please provide descriptions individually for each feature properly. For example, Slope angle, slope aspect, and slope length are all written in one statement. Make them three individual statements to make it clearer to understand. Also, the descriptions are not clear enough. For volume landslide due to rainfall". This is not a description. It is a reasoning to justify a claim. Please provide appropriate descriptions.

Response: Thank you for your comment. We have updated Table 1 to enhance clarity by providing separate descriptions for each feature. Each description is now specific to the individual feature, detailing its relevance to landslide volume estimation. While rainfall parameters, such as rainfall on the day of the event and rainfall in prior days were grouped, as they represent related precipitation metrics, all other features have been distinctly separated. The revised version of Table 1, with improved feature descriptions, is shown below.

Table 1. Landslide influencing and triggering factors.

Group	**Features**	**Description**	**Reference**
Vegetation	Fire history	The burning of the vegetation intensifies the mass movement of soil near the uncovered burned stem of trees and free movement on uncovered soil due to post-fire rainfall and storms. The sliding may also be due to loss of vegetation, altered soil property and structure, which lead to soil degradation and infiltration which increase pore pressure, and change in hydrology by concentrating water flow in places that exacerbate landslides.	Highland and Bobrowsky, 2008; Culler et al., 2021; Hyde et al., 2016; Stoof et al., 2012
	Age of tree	Mature forests have more resistance to shallow landslides due to highly developed roots, which improve soil cohesion and leaves that prevent direct contact of raindrops with the soil surface.	Sato et al., 2023; Lann et al., 2024
	Forest density	The presence of forest reduces the likelihood of landslides about three times compared to grassland. Grassland has been revealed to be three times more vulnerable to shallow landslides than broadleaf and, coniferous and in secondary forests.	Lann et al., 2024; Greenwood et al., 2004; Turner et al., 2010; Scheidl et al., 2020; Asada et al., 2023
	Timber	Tree spacing and size had been used to	Cohen and

Group	Features	Description	Reference
	diameter (m)	investigate the effect of root and tree in shallow landslide control. The high root density generally enhances slope stability, and specific tree placement and root sizes between 5 to 20 mm are effective in landslide prevention.	Schwarz., 2017; Wang et al., 2016
Geomorphology	Drainage	The drainage has a significant effect on the slope stability and promotes the efficient control of the influence of rainfall on the ground water fluctuation. The presence of drainage increases the threshold of landslides due to rainfall.	Yan et al., 2019; Sun et al., 2010 ; Wei et al., 2019 ; Korup et al., 2007
	Slope angle (degree)	The steeper slopes have lower presence of landslide due to low transportable materials. Slopes between 20-40 degrees are most vulnerable to greater landslides as rainfall intensity and duration increase. Here, we considered the average angle of the terrain at the landslide location, which provides valuable insight into the region's overall steepness and geomorphic characteristics, which are crucial factors influencing landslide susceptibility and risk modeling.	Duc, 2013 ; Qiu et al., 2016 ; Donnarumma et al., 2013
	Slope aspect	The effect of rainfall on slope differs by slope angle and slope aspect which lead to unevenly distributed occurrence of landslides.	Panday and Dong, 2021; Cellek, 2021
	Slope length (m)	The volume increases as the slope length increases. There exists a complex interplay between rainfall, length of slope and slope angle on the occurrence of landslides.	Turner et al., 2010
	Soil depth (m)	Soil properties, depth, and texture have significant differences in infiltration rates, which have different influences on the occurrence of landslides.	Kitutu et al., 2009; McKenna et al., 2012
	Soil type	Higher rainfall intensity affects the occurrence of landslides differently, particularly in certain soil types that have shorter saturation and failure times.	Liu et al., 2021
Location	Altitude	Regional variability of elevation and mountain steepness affect the quantity of rainfall and associated landslides.	Hyun et al, 2010, Yoon and Bae, 2013; Park,

Group	Features	Description	Reference
			2015 Um et al., 2010
	Maximum hourly rainfall	The rainfall infiltrates the slope and increases pore water pressure that reduces soil shear strength, which leads to soil saturation that causes surface failure.	Wieczorek, 1987; Dai and Lee, 2001; Smith et al., 2023
Rainfall	Continuous rainfall	Sudden intense rainfall concentrated in short periods of time is responsible for shallow landslide and debris flow.	Zhang et al., 2019
	Three hours rainfall		
	Three days rainfall	The antecedent rainfalls increase moisture in the soil and weaken soil cohesion.	Ran et al., 2022 Zhang et al., 2019 ; Bernardie et al., 2014; Chen et al., 2015a; Gariano et al., 2017
	Two weeks rainfall		
	Four weeks rainfall		

Comment 9: Lines 311-312: It would be nice explain why the random forest works well with smaller volumes. The connection between the machine learning predictions and the scale of the estimated volumes should be explained more intricately to provide a grounded understanding. Does the EGB model predict larger volumes more accurately than the rest, like Random Forest? If so, then why? Please explain these aspects.

Response: Thank you for your insightful comment. Random Forest tends to perform well with smaller volumes due to its ability to capture complex relationships and interactions in the data without overfitting. RF uses multiple decision trees as base models, builds each tree on a random subset of samples and features, and computes averages as predictions to get the final result (Breiman, 2001). The model's random sampling of both observations and features allows it to build diverse trees; this enhances the generalization capabilities, particularly when the dataset is small. This characteristic helps the RF to maintain accuracy by reducing variance. It was noticed that the difference between of R^2 on training and testing sets was small compared to other models.

In contrast, the EGB model may predict larger volumes more accurately because it employs an iterative process to improve predictions. It uses a decision tree as the base model and builds them sequentially in such a way that each new tree corrects prediction errors made by previous trees using gradient descent, allowing for fine-tuning of predictions over iterations and to minimize loss functions effectively (Chen and Guestrin, 2016). This iterative correction can capture complex patterns in larger datasets that may not be evident in smaller ones. The fact that the RF predictions are averages of multiple decision trees may cause the difference since predicting averages will be less than predictions produced sequentially (Sagi and Rokach, 2018).

Furthermore, as volume size increases, the relationships between features can become more intricate, and EGB's ability to handle these complexities may lead to superior performance in those scenarios. However, Random Forest remains advantageous when data is scarce because it is less prone to overfitting compared to some boosting methods, which may struggle with limited data. A clear understanding of these dynamics provides valuable insights into the varying performance of different models across different volume scales, emphasizing the importance of choosing the right algorithm based on dataset characteristics. This has been highlighted in the discussion section of the revised manuscript.

Minor comments:

Comment 1: Line 31: "high", should be "height".

Response: Thank you for your observation. The identified error has been corrected in the revised manuscript. The entire sentence has been modified as,
"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."

Comment 2: Line 36: "resulting volume of landslides". Change this to "resulting surface failure".

Response: We have made the modification in the revised manuscript, replacing "resulting volume of landslides" with "resulting surface failure" for improved clarity.

Response 3: Line 38: “fragilize”. Not sure if such a word is used commonly to express the weakening of slopes. I'd rather opt for 'weaken'.

Response: Thank you for your suggestion. Accordingly, we have replaced "fragilize" with "weaken" in the revised manuscript.

Comment 4: Similar English issues are found in Section 2 (Study area). Please address the language issues.

Response: Thank you for the fruitful suggestion and observations. We have addressed the language issues throughout the entire manuscript, including the Study Area section. The modification made in the study area section is reflected in the text below:

“The region for testing the model is South Korea, characterized by mountainous (63% of total land) relief, especially in the eastern part of the country (Lee et al., 2022). South Korea is located on the southern part of the Korean Peninsula, bordered by the Yellow Sea to the west coast and the East Sea (Sea of Japan) to the East. According to the Korean Meteorological Administration (2020), the country has a temperate climate characterized by four distinct seasons: hot and humid summers, cold winters, and springs and falls with moderate temperatures. The annual rainfall ranges between 1000 mm to 1400mm and 1800mm for the central region and southern region, respectively (Jung et al., 2017; Alcantara and Ahn, 2020). During the summer, heavy rainfall from June to September leads to significant surface runoff, increases landslide risk, and causes approximately 95% of all landslides each year (Lee et al., 2020; Park and Lee, 2021). In addition, the landslides may be aggravated by typhoons, which mostly occur in August and September, and it is anticipated that frequency will increase due to climate change (Kim and Park, 2021). The rainfall trend analysis from 1971 to 2100 predicted the increase in rainfall of 271.23mm, which indicates the growing risk of landslides associated with climate change (Lee, 2016). Temperature variations are influenced by its geographical location, the average summer temperatures range between 25 and 30°C, while winter temperatures can drop to -10°C in some parts of the country (Korea Meteorological Administration, 2020). The South Korean geologically is mainly composed of granitic and metamorphic rocks, such as gneiss, schist, and granite, which influence the stability of the landscape (Jung et al., 2024). The geomorphology is characterized by rugged mountains, river valleys, and coastal plains, with the Taebaek Mountains running along the eastern edge (Kim et al., 2020). In addition, the influence of rainfall, environmental, geomorphology, and geological factors increase the vulnerability to landslides across the country, especially in the northeastern mountainous region, as depicted in Figure 1.

The predominant soil types in South Korea include clay, sandy, and loamy soils, each with different characteristics affecting water infiltration, retention and erosion (Kang et al., 2022; Lee et al., 2023). Clay soils, being more stable, can become highly saturated, increasing landslide risk during heavy rains. On the other hand, sandy soils are more prone to shallow landslides due to fast saturation, leading to instability. Regions with steep topography and poorly consolidated soil (loose) are mostly at risk, especially after prolonged rainfalls (Kim et al., 2015).

Coastal areas are exposed to sea-level rise and coastal erosion, which can further complicate the landscape and increase landslide susceptibility. The combination of heavy summer rainfall, geological composition, and geomorphological factors makes South Korea particularly vulnerable to shallow landslides. Thus, continuous monitoring and research are vital to understand the complex interactions between climate, geology, soil types, and landslide occurrences in this region (Park, 2022). Understanding the combination of environmental, geological stability, and geomorphological features is crucial for developing effective disaster management strategies and enhancing public safety in landslide-prone areas. As climate change continues to impact rainfall patterns, South Korea faces ongoing challenges in mitigating landslide risks and protecting vulnerable communities."

Comment 5: Figure 2. Font size of plot (b) is different than the rest, and also stretched. Please make all font sizes uniform.

Response: Thank you for your suggested improvements. Figure 2 (now Figure 3), titled "Workflow for the Prediction of Volume of Landslide Due to Rainfall," has been revised to ensure uniform font sizes throughout the plot. The updated figure is provided below,

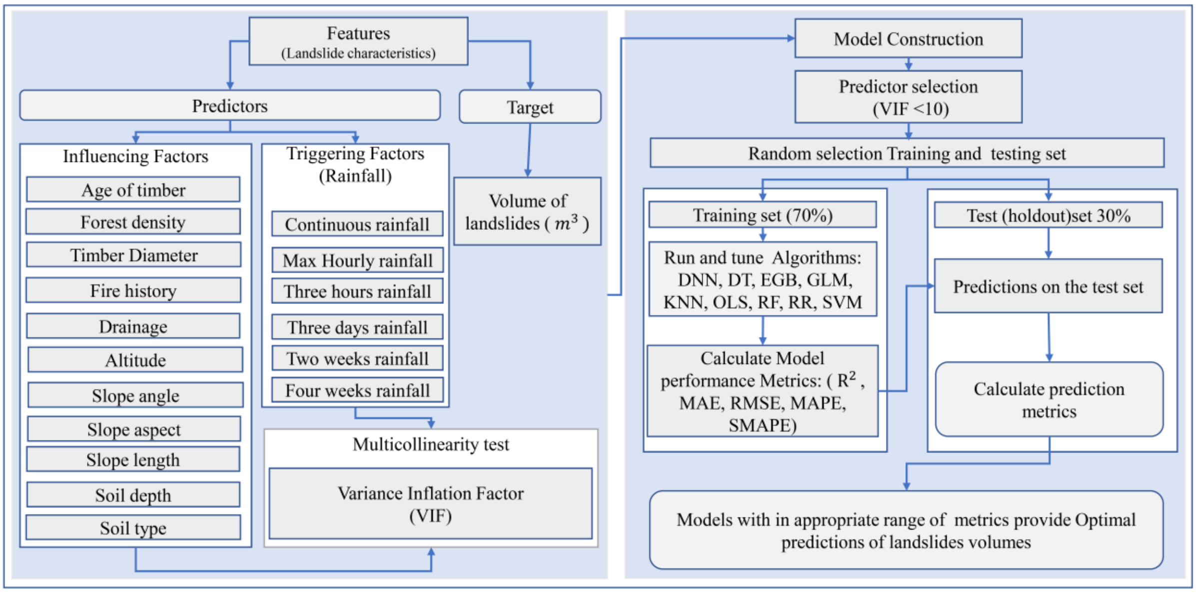

Figure 3. Workflow for the prediction of the volume of landslides due to rainfall.

Comment 6: Line 111: Replace ‘joined’ with ‘combined’.

Response: Thank you for your comment. As suggested, the term "joined" has been replaced with "combined" in the revised manuscript.

Comment 7: Line 128: “flown away”? I am not sure if using this term is accurate. Generally, we refer to them as “removed material” from the surface. Can you please double-check this?

Response: Thank you for your valuable comment. The suggested modifications were incorporated in the revised manuscript as,

“The estimation of the volume of removed material by landslides is important as it helps to assess risks the estimated damage can cause down at the toe of the failed slope, such as blocking transportation network, burying crops or farmland, the damage-built environment near landslide risks area, and post-disaster recovery planning (Evans et al., 2007; Rotaru et al., 2007; Intrieri et al., 2019).”

Comment 8: Is the slope angle the average angle of the terrain where the landslide was located or is the angle of reach? In my opinion, the angle of reach would make more sense as landslides that are closer to each other will exhibit different angles of reach but the same adjacent landslides would bear the same average slope angle as you are averaging based on the terrain. Please make it clear as to which one you have considered and why.

Response: Thank you for your comment. The slope angle referenced in the manuscript pertains to the average angle of the terrain at the landslide location. This measurement provides valuable insight into the overall steepness and geomorphic characteristics of the area, which are crucial factors influencing landslide susceptibility and risk modeling (Donnarumma et al., 2013). On the other hand, the angle of reach refers to the angle at which a landslide material travels after detaching from the slope, which is important for assessing mobility and potential impact (Corominas, 1996). However, this is a different metric and not the focus of our analysis. While the angle of reach considers the mobility of landslides, the average slope angle is critical for assessing the risk of landslide occurrence. We acknowledge your point regarding the differences in angle of reach among closely situated landslides, but in our study, the average slope angle is more relevant for evaluating landslide volume. We have clarified this distinction in the revised manuscript (Table 1) to ensure a better understanding.

Comment 9: Line 136: What do you mean by ‘composing material’? This is not clear.

Response: Thank you for your insightful comment. The term "composing material" refers to soil composition properties, which significantly impact slope stability. These properties, including soil permeability indices, influence water infiltration and saturation levels, both of which are critical factors in landslide susceptibility (Chen et al., 2015a). The revised sentence is as follows,

“The slope stability depends on soil composition properties, including soil permeability indices that affect water infiltration and saturation level (Chen et al., 2015a).”

Comment 10: Lines 140-142: Please check the English grammar here. The sentence can be improved a lot.

Response: Thank you for your comment. We revised the sentence in the updated manuscript. Additionally, we conducted a thorough review of the manuscript to identify and correct similar issues throughout.

Comment 11: Line 341: Change to “Among the tested models,” Response: Thank you for your comment. The sentence has been modified in the revised manuscript as,

"Among the tested models, extreme gradient boosting (EGB) produced the most accurate prediction."

Comment 12: Conclusion- Line 349: Change from "can be a better tool" to "can be a good tool".

Response: Thank you for your comment. As suggested, the sentence has been revised in the updated manuscript as,

"Therefore, this model can be a good tool for planning for resilience and infrastructure pre-construction risk assessment to ensure the new infrastructure is placed in stable regions free from severe landslides."

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