Manuscript number: nhess-2023-73

My co-authors and I would like to express our gratitude to the reviewers for their 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#2

General remarks: Landslide volume prediction is the key to Landslide risk analysis and prediction. The topic of this paper is very interesting. However, the paper is poor prepared. The structure of the paper is weakly logical and I cannot follow the paper clearly. My decision of this manuscript is rejection. Please find my comments as following.

We would like to thank the reviewer for her/his insightful comments, which have greatly contributed to improving the text as well as the logical structure of the manuscript. We have responded point by point to all the comments and suggestions raised by Reviwer#2 as follows:

Comment 1: The logic of the paper's structure is unclear. I suggest the authors to organize the paper according to Introduction – study area – Data colleagues and Methods - Results - Discussion - Conclusion.

Response: Thank you for your comment. We understand the reviewer's concern and have accordingly restructured the manuscript as follows: Introduction – Study Area – Data and Methods – Results – Discussion – Conclusion.

Comment 2: The introduction section should rewrite. For example, the author describes the damage caused by the landslide in several places. Line 56 -58: The author talks very abruptly about landslide volumes.

Response: Thank you for your comment. As suggested, the introduction section has been rewritten in the revised manuscript with greater emphasis on landslide volumes as follows:

‘Rainfall-induced landslides (RFIL) frequently occur in the mountainous region of South Korea due to the heavy rainfall during the monsoon season (July to September) (Lee et al., 2013). The RFIL debris occurs when the slope fails due to the saturation of soil after the rainfall exceeds a certain threshold (Au, 1998; Takara et al., 2010; Peruccacci et al., 2017; Segoni et al., 2018; Crawford et al., 2019; Coppola et al., 2022). These RFIL-resulting debris, depending on their volume, cause enormous environmental degradation, infrastructure damage, casualties, and loss of life, which disturb the socio-economic aspect of the community (Li et al., 2012;

Sarkar and Dorji, 2019; Zhao et al., 2019; Taylor et al., 2020; Lacroix et al., 2020; Winter, 2020; Negi et al., 2020; Ju et al., 2020; Van et al., 2021). Park et al. (2013) reported that the annual property damage caused by RFIL in South Korea averaged between US$500M to US$1000M and approximately 36 human deaths per year from 1997 to 2010. Therefore, predicting the volume of debris resulting from RFIL is essential for managing the effect of RFIL debris and planning for post-disaster recovery.

To mitigate and prevent the effect of RFIL in South Korea, different studies have been carried out on landslide susceptibility modeling (Kadavi et al., 2019; Lee and Winter, 2019; Sameen et al., 2020; Panahi et al., 2020; Hakim et al., 2022). Lee et al. (2020) applied the Naïve and Bayesian Networks model for landslide susceptibility mapping in Umyeon Mountain. Lee et al. (2012) used physical slope and probabilistic model, i.e., decision trees and logistic regression for landslide susceptibility mapping in Gangwon-do. Lee et al. (2013) developed the binary logistic regression model for predicting the occurrence of landslides. Woo et al. (2014) constructed a landslide hazard map using binary logistic regression. Park and Kim (2019) compared boosted trees and random forest model's performance in landslide susceptibility mapping for Umyeon Mountain; the same methods were previously applied at Pyeong-Chang by Kim et al. (2018). It was observed that the objectives of previous studies were to predict landslide susceptibility, but they did not specify the size (volume) of the occurring landslides (Lee et al., 2013; Park and Kim, 2019; Lee et al., 2020).

Globally, numerous researchers have attempted to predict the landslide magnitude through different statistical approaches (Lombardo et al., 2020). For example, Dai and Lee (2001) analyzed the relationship between landslide volume, cumulative frequency, and the connection between rainfall and landslide occurrence. Malamud et al. (2004) proposed frequency and size distribution for landslides to quantify the magnitude of landslide events. Shirzadi et al. (2017) compared popular statistical and machine-learning methods for simulating the volume of landslides. Lombardo et al. (2018) introduced the concept of estimating landslide intensity to complement susceptibility measures. They used the Poisson distribution for spatial estimates of the landslide intensity within terrain units. Further, Lombardo et al. (2021) explored advanced techniques, leveraging Bayesian versions of a Generalized Additive Model and Log-Gaussian model to estimate landslide susceptibility and intensity. The existing literature lacks a widely applied machine-learning model capable of capturing and predicting landslide sizes (volume). To address this gap and assess the potential of machine learning methods for predicting landslide volume in South Korea, we used the proportional odds logistic regression (POLR), random forest (RF), support vector machine (SVM), and extreme gradient boosting (EGB) methods to evaluate the relationship between various influencing & triggering factors and RFIL debris volume. Consequently, the present study aims to predict the RFIL debris volume based on the triggering and influencing factors. The quantification of debris volume may be useful in land management by highlighting regions prone to higher RFIL debris to know whether economic activities may be carried out in the given region, so that those activities may not be vulnerable to extreme landslide hazards.'

Comment 3: The subject of the paper is very unclear. What is the difference between Rainfall-induced debris and Landslide-induced debris? In my opinion, they are different. The author needs to give a clear definition of the research subject of the paper.

Response: Thank you for your insightful review. We appreciate your insights regarding the clarity of the paper's subject. Your input is valuable in enhancing our research's overall clarity and conciseness.

Rainfall-induced debris and landslide-induced debris are different processes related to the movement of materials on slopes. Rainfall-induced debris occurs when extensive or prolonged rainfall removes loose materials like soil, rocks, and vegetation, leading to erosion and surface runoff. It frequently affects areas with steep slopes and insufficient vegetation cover. On the other hand, landslide-induced debris results from significant slope failures, where a large mass of soil, rock, and debris moves downslope due to triggers like extensive rainfall, earthquakes, or human activities. While both processes involve the movement of debris, rainfall-induced debris mostly involves surface erosion caused by rainfall impact. In contrast, landslide-induced debris stems from more profound slope failures caused by various factors. However, the present study focuses on rainfall-induced landslides (RFIL) debris volume prediction through different machine learning algorithms.

Accordingly, the introduction section has been revised in the manuscript.

Comment 4: Magnitude of landslide-induced debris and debris severity are two totally different probabilities, and the authors confuse them in the introduction. There is a big difference between Landslide and Landslide-induced debris. The author has confused them in the manuscript as well.

Response: Thank you for your comment and valuable insight. We appreciate your observation regarding the distinction between 'Magnitude of landslide-induced debris' and 'debris severity.' We apologize for any confusion caused by our terminology. For clarification, the magnitude of landslide-induced debris refers to the volume and size of materials involved, while debris severity denotes the level of damage caused. These concepts represent distinct probabilities: one quantifies the physical extent, and the other assesses the potential impact and destruction resulting from landslides. Accordingly, we thoroughly revised the introduction section in the revised manuscript.

Comment 5: The authors present a lot of research about landslide susceptibility and hazard mapping in the study area, but this is not necessary. There are some studies about landslide volume prediction, but the author do not presents a review of the topic. This is why the paper's innovation drive is unclear.

Response: Thank you for your insightful comment. In response to your concern and to enhance the clarity of the innovative aspect of our paper, we have included a review of the topic of landslide volume prediction in the revised manuscript as,

'Globally, numerous researchers have attempted to predict the landslide magnitude through different statistical approaches (Lombardo et al., 2020). For example, Dai and Lee (2001) analyzed the relationship between landslide volume, cumulative frequency, and the connection between rainfall and landslide occurrence. Malamud et al. (2004) proposed frequency and size distribution for landslides to quantify the magnitude of landslide events. Shirzadi et al. (2017) compared popular statistical and machine-learning methods for simulating the volume of landslides. Lombardo et al. (2018) introduced the concept of estimating landslide intensity to complement susceptibility measures. They used the Poisson distribution for spatial estimates of the landslide intensity within terrain units. Further, Lombardo et al. (2021) explored advanced techniques, leveraging Bayesian versions of a Generalized Additive Model and Log-Gaussian model to estimate landslide susceptibility and intensity. The existing literature lacks a widely applied machine-learning model capable of capturing and predicting landslide sizes (volume). To address this gap and assess the potential of machine learning methods for predicting landslide volume in South Korea, we used the proportional odds logistic regression (POLR), random forest (RF), support vector machine (SVM), and extreme gradient boosting (EGB) methods to evaluate the relationship between various influencing & triggering factors and RFIL debris volume. Consequently, the present study aims to predict the RFIL debris volume based on the triggering and influencing factors. The quantification of debris volume may be useful in land management by highlighting regions prone to higher RFIL debris to know whether economic activities may be carried out in the given region so that those activities may not be vulnerable to extreme landslide hazards.'

Comment 6: Problem formulation: The authors give a flowchart for the proposed method, but the goal of the prediction is not clearly stated in this section. This subsection should rewrite.

Response: Thank you for your comment. We appreciate your attention to detail and your insights regarding the problem formulation section. The goal of the prediction has been adequately clarified in the revised version of the flowchart. Furthermore, we have thoroughly revised the subsection to ensure that the objective of the prediction is explicitly stated and clearly aligned with the proposed method as follows:

'The present study aims to predict the RFIL debris volume based on the triggering and influencing factors. Predictive models that deal with multi-variate random variables were investigated to predict the volume of the RFIL. In the modeling process, the model choice is based on the distribution of the data and the type of outcome variable. For continuous outcome variables, continuous distributions are adopted after the assumptions constrained on the model are satisfied. The choice of categorical outcome variable depends on the number of categories (levels) and their order. For the case of two categories, the appropriate model is found in binary models, while the multi-level models are adopted when the outcome variable has more than two level categories. Multi-level models are divided into unordered models, which deal with outcome that has no inherent order and ordered models, which deal with data involving multiple ordered outcomes. In the present study, concerning the prediction of the volume of RFIL debris, the outcome variable was ordered; thus, POLR was chosen after verification of proportional odd assumptions (McCullagh, 1980; McNulty, 2021). The POLR has a feature of visualizing the effect of each independent variable in the output. The high prediction accuracy of RF, SVM, and EGB in a classification problem, these last three models were widely used as alternative models for predicting landslide susceptibility (Biau and Scornet, 2016; Lechner and Okasa, 2020; Lee et al., 2017; Noble, 2006; Chang et al., 2018; Georganos et al., 2018). Therefore, the four models were applied to evaluate the relationship between various influencing & triggering factors and RFIL debris volume. Detailed objectives of this study were: 1) to collect data of RFIL inventory, triggering and influencing factors; 2) to conduct exploratory data analysis to understand the relationship between RFIL debris volume and independent variables; 3) to predict the RFIL debris volume based on the triggering and influencing factors using suggested models; and 4) to conduct model effectiveness, model comparison using predictive accuracy and the value of kappa. The overall methodology is depicted in Figure 2.'

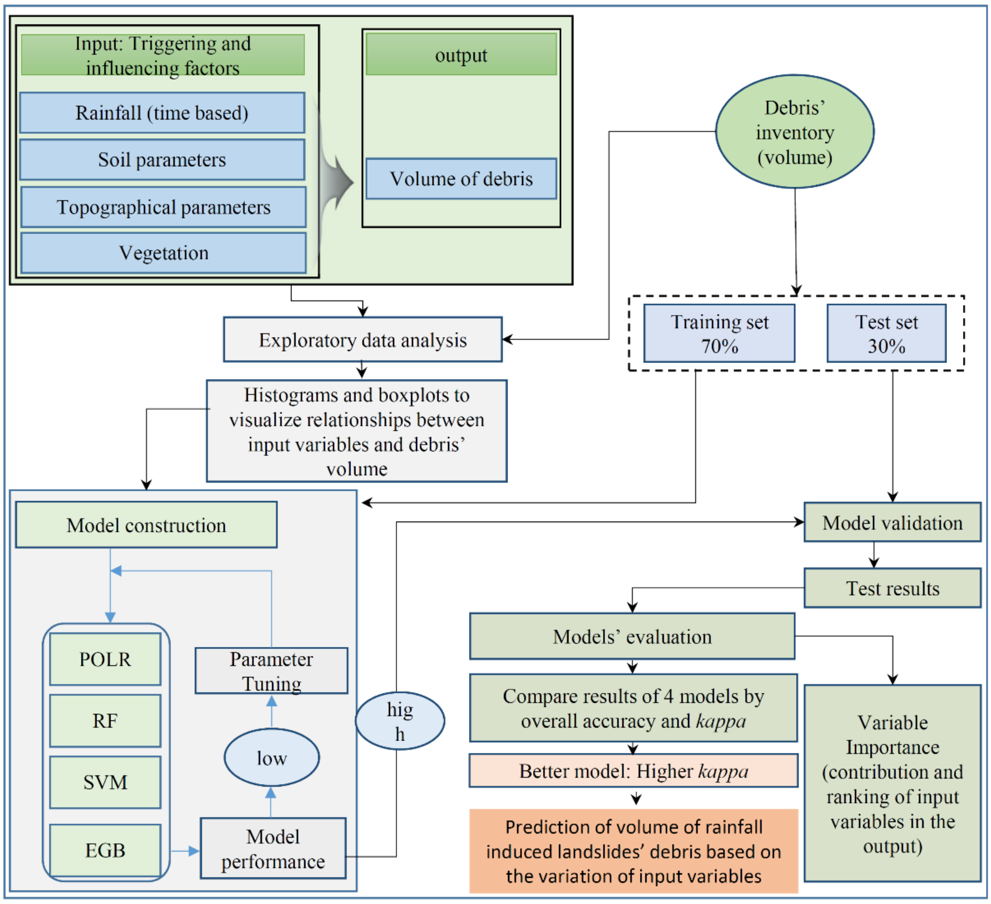

Figure 2. Modeling workflow process for the prediction of RFIL debris volume.

Comment 7: Table 1: The failure mechanism of each landslide/rackfall type is different. It is not reasonable to conduct the volume prediction for these different types without distinction.

Response: Thank you for your insightful comment. The different types of landslides mentioned in Table 1 are not all technically distinct landslide types but rather variations in erosion processes or morphological features. The landslide classes mentioned in Table 1 (preprint version) describe different geomorphological processes that lead to various landslide forms. For instance, valley erosion occurs when material moves due to a valley's erosion, and falling rocks describe the tumbling of loose rocks down slopes (Causes, 2001). While mixed or complex landslides involve multiple processes, slope failures result from a slope's collapse (Wang et al., 2016). Landslides from scour result from erosion, while curved wedge-shaped slides display a distinctly curved structure (Ritchie, 1958). Circular arc-shaped landslides take on a semi-circular shape, and plane-shaped ones occur on inclined planes (Causes, 2001). Each type emerges from specific geological actions, defining distinct characteristics and appearances.

However, in the present study, we considered 455 landslide inventory data based on the magnitude of the landslides: below 500m³, between 500-2000m³, 2000-5000m³, and above 5000m³ (Fig. 1b). Consequently, we analyzed the relationship between independent variables and debris size. As a result, Table 1 has been updated in the revised manuscript to provide a detailed summary of data features rather than focusing solely on different geomorphological processes. Additionally, a summary of continuous variables is provided in Table 2, including minimum, mean, median, maximum, standard deviation, and associated units for each considered feature.

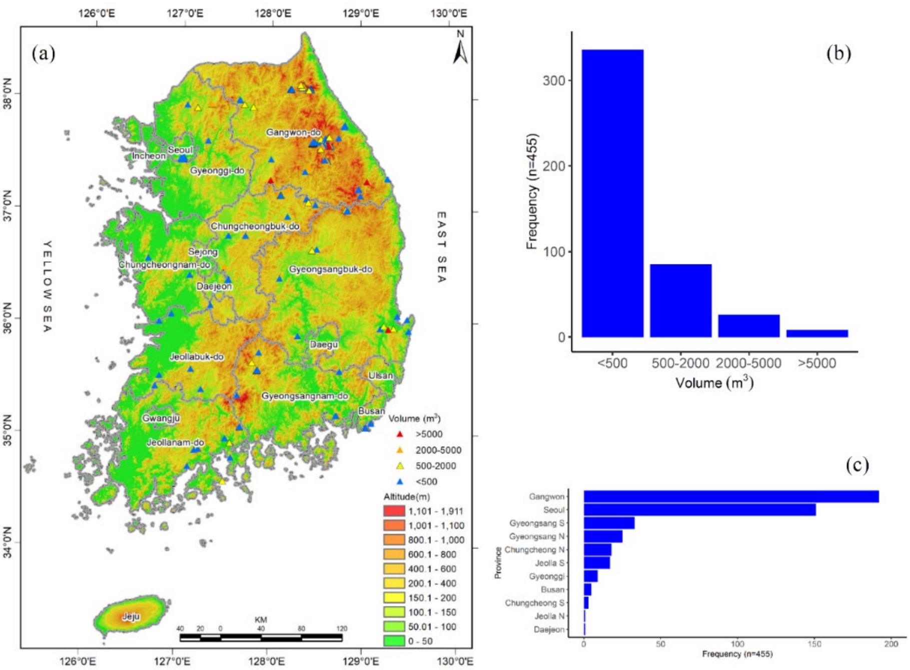

Figure 1. (a) The distribution of RFIL in South Korea, (b) Histogram of RFIL debris volume, and (c) Province-wise RFIL debris frequency distribution (Data source: elevation data acquired from NGII, 2018).

Table 1: The detailed description of continuous and categorical variables.

Causative factors	**Variables**	**Type**	**Importance**
Rainfall	Continuous hourly rainfall	Continuous	Triggering factor and effect on soil moisture (Ngo et al., 2021)
	Three hours rainfall		
	Six hours rainfall		
	Nine hours rain		
	Twelve hours rain		
	One day rain		
	Three days rain		
	Seven days rain		
	Two weeks rain		
	Three weeks rain		
	Four weeks rain		
Soil	Soil depth (cm)	Categorical 1) <20, 2) 20-50, 3) 50-100	Permeability, infiltration, surface runoff, and soil strength affect slope stability (Meena et al., 2022)
	Soil type	Categorical 1) Sandy loam, 2) Silt loam, 3) Lithosol, 4) Clay	
Forest features	Leafage	Categorical 1) Broad-leaved, 2) Mixed, 3) Pines	Effect on slope stability i.e., vegetation roots cause more stability (Ngo et al., 2021)
	Size of wood	Categorical 1) No tree, 2) Small, 3) Average, 4) Large	
	Age of tree	Categorical 1) No tree, 2) 1-5, 3) 5-15, 4) 15-25, 5) 25-35, 6) 35-45, 7) 45-60, 8) >60	
	Forest density	Categorical 1) No tree, 2) Low, 3) Medium, 4) High	It reflects the inhibitory effect of landslide occurrence (Huang et al., 2020)
	Forest Fire history	Categorical 1) No, 2) Yes	Effect on soil erosion
Topographical and geomorphological parameters	Slope (degree)	Continuous	Effect on infiltration process, shear stress, and gravity. Landforms with a steep slope and high slope length are usually more susceptible to collapse (Pham et al., 2018)
	Slope length (m)	Continuous	
	Slope aspect	Categorical (8 directions) North, Northeast, south, East,	Effect on rainfall, soil moisture, and vegetation cover (Dahal et al., 2008)

Causative factors	Variables	Type	Importance
		Southeast, South, Southwest, West, Northwest	
	Altitude (m)	Continuous	Effect on rainfall, vegetation cover, and soil depth (Raja et al., 2017)
	Drainage	Categorical 1) Bad, 2) Good, 3) Very good	Effect on water flow, saturation, soil moisture, and valley landslides (Shahabi and Hashim, 2015)

Table 2. Summary statistics of continuous variables.

Variables	Observation	Min	Mean	Median	Max	SD	unit
Maximum hourly rainfall	455	0	48.2	48	78.5	20.262	mm
Continuous hourly rainfall	455	0	285.341	327	549.5	106.279	
Three hours rainfall	455	0	87.716	79.5	171	60.166	
Six hours rainfall	455	0	114.381	89	240.5	79.493	
Nine hours rainfall	455	0	136.317	95	284.5	85.988	
Twelve hours rainfall	455	0	150.161	99	447	95.431	
One-day rainfall	455	0	201.598	162	538.5	111.62	
Three-days rainfall	455	0	279.6	283.5	549.5	85.875	
Seven-days rainfall	455	0.5	323.16	330	633.5	87.895	
Two-weeks rainfall	455	0.5	385.033	399.5	663	89.754	
Three-weeks rainfall	455	85.5	503.989	533	914.4	114.888	
Four-weeks rainfall	455	108	586.585	561	1135	159.945	
Slope	455	10	34.004	34.004	65	7.938	Degree
Slope length	455	1.8	21313	13	180	22.623	m
Altitude	455	9	390.789	272	1324	273.069	m

Comment 8: Why these four machine learning methods were chosen. These methods have become very common. Please simplify the principle of the methods. Model inputs and parameters need to be given.

Response: Thank you for your comment. The rationale behind selecting POLR, RF, SVM, and EGB for predicting landslide-induced debris is rooted in their widespread adoption and demonstrated success in predictive modeling tasks, including those involving complex relationships in data. Their common use in the landslide susceptibility modeling adds credibility to our approach. To simplify the principles of these methods, we have thoroughly revised section 3 in the revised manuscript as follows:

'In the modeling process, the model choice is based on the distribution of the data and the type of outcome variable. For continuous outcome variables, continuous distributions are adopted after the assumptions constrained on the model are satisfied. The choice of categorical outcome variable depends on the number of categories (levels) and their order. For the case of two categories, the appropriate model is found in binary models, while the multi-level models are adopted when the outcome variable has more than two level categories. Multi-level models are divided into unordered models, which deal with outcome that has no inherent order and ordered models, which deal with data involving multiple ordered outcomes. In the present study, concerning the prediction of the volume of RFIL debris, the outcome variable was ordered; thus, POLR was chosen after verification of proportional odd assumptions (McCullagh 1980; McNulty 2021). The POLR has a feature of visualizing the effect of each independent variable in the output. The high prediction accuracy of RF, SVM, and EGB in a classification problem, these last three models were widely used as alternative models for predicting landslide susceptibility (Biau and Scornet, 2016; Lechner and Okasa, 2020; Lee et al., 2017; Noble, 2006; Chang et al., 2018; Georganos et al., 2018). Therefore, the four models were applied to evaluate the relationship between various influencing & triggering factors and RFIL debris volume. Detailed objectives of this study were: 1) to collect data of RFIL inventory, triggering and influencing factors; 2) to conduct exploratory data analysis to understand the relationship between RFIL debris volume and independent variables; 3) to predict the RFIL debris volume based on the triggering and influencing factors using suggested models; and 4) to conduct model effectiveness, model comparison using predictive accuracy and the value of kappa. The overall methodology is depicted in Figure 2'

Additionally, model input and parameters are now incorporated into Tables 1 and 2 in the revised manuscript.

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