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A statistical model for predicting rock avalanche runout using source area width from 63 representative cases

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ABSTRACT

Developing predictive models for rock avalanche runout is crucial for hazard risk mitigation and management, while also deepening the understanding of rock avalanche dynamics. In this study, a database of 63 representative rock avalanches was compiled, and the geometric characteristics of these events were analyzed. Traditional regression methods were compared with neural network regression (NNR) approaches to find the optimal model. Model parameters, loss functions, and evaluation metrics were examined to determine optimal configurations. Based on correlation analyses and model performance, this study recommends the use of source area width as an alternative to failure volume in runout prediction models, effectively addressing the common challenge of estimating avalanche volume. Ultimately, an NNR-based model, utilizing mean squared logarithmic error as the loss function and incorporating source area width and fall height as input parameters, was identified as the optimal approach. This model achieved prediction errors within a −50% to 50% range with 95.2% probability, yielding a mean absolute percentage error of 23.22% and an R^2 of 0.85. These findings enhance rock avalanche prediction methodologies, providing more accurate tools for assessing the potential impact zones of destructive geological events.

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1. Introduction

Rock avalanches (RAs) are catastrophic landslides characterized by large volumes, high velocities, and long runouts (Strom A, 2021; Yin YP et al., 2023). These events pose substantial threats to populations in mountainous and piedmont regions and often lead to the formation of dammed lakes (Chen J et al., 2013; Fan XM et al., 2020). Although numerous hypotheses have been proposed regarding the hypermobility mechanisms of rock avalanches, no single theory has gained broad acceptance (Hungr O, 2006). With the increasing frequency of RAs due to climate warming and seismic activity (Keefer DK, 1984; Qi SW et al., 2011; Coe JA et al., 2018; Bessette-Kirton EK and Coe JA, 2020), accurately predicting RA susceptibility and disaster risks,

particularly runout distances, has become essential for effective disaster preparedness and mitigation.

Recent advances in numerical modeling and laboratory experiments have enhanced the understanding of rock avalanche behavior (Hu W et al., 2020). However, these methods face limitations due to physical constraints (such as mechanical properties) and scaling issues (such as model size), which hinder precise correlations with real landslide processes. Consequently, these models remain limited in their direct applicability to specific landslide events (Iverson RM, 2015). Although statistical approaches may not fully capture the physical principles underlying RAs, they have significantly advanced the predictive capabilities for assessing landslide threats (Strom A et al., 2019).

Historical statistical studies have identified numerous factors influencing rock avalanche formation (Keefer DK, 1984; Hermanns RL and Strecker MR, 1999; Zhang M and Yin YP, 2013), with recent applications increasingly focused on predicting RA mobility. For example, Nicoletti PG and Sorriso-Valvo M (1991) examined 40 cases and identified three types of confinement influencing RA mobility.

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Corominas J (1996) analyzed 204 landslides, demonstrating that the angle of reach (H/L ratio) decreases as volume increases. Legros F (2002) re-examined over 200 cases, analyzing relationships between volume, area, runout, fall height, and H/L ratio, and developing empirical equations for different types. More recent studies include those by Guo DP et al. (2014) and Zhan WW et al. (2017), who developed runout prediction models for RAs triggered by the Wenchuan earthquake. Strom A et al. (2019) compiled a database of about 600 cases from Central Asia, creating an effective area prediction model for different confinement types. Mitchell A et al. (2020) analyzed 49 cases, revealing relationships between runout prediction, volume, fall height, and lateral confinement, as well as correlations between width and volume. Liu H et al. (2021) suggested that runout distance is a better mobility measure than the H/L ratio, based on 36 cases from southwestern China. Dufresne A et al. (2021) compared the characteristics of 594 volcanic debris avalanches with non-volcanic RAs. Yang HL et al. (2022) introduced a model using slope height ratios to predict runouts in deflection-type RAs, and Wen BP and Guan LC (2022) analyzed 98 contemporary RAs, finding that fall height significantly influences mobility across various flow types, paths, and triggers.

Despite these advances, challenges remain in RA statistical studies. Potential errors in geometric parameter estimation, particularly volume, can arise from data quality and measurement limitations, impacting prediction model accuracy (Strom A et al., 2019). Additionally, previous studies have primarily relied on traditional regression (TR) methods. While machine learning has greatly expanded data

analysis tools (Ma ZJ and Mei G, 2021), the application of these techniques to RA runout prediction models remains limited.

In this study, a database of 63 global rock avalanche events were compiled. To ensure data quality, this study meticulously redefined the boundaries of each case and remeasured all geometric parameters except volume. Unlike previous studies, this study introduced source area width—defined as the maximum width of the source area (WoS)—as a novel parameter in the prediction model, serving as an alternative to volume for estimating RA runout. Additionally, this study explored multiple modeling approaches, including traditional regression with various loss functions and neural network regression (NNR). This study aims to provide new insights into RA prediction models, thereby supporting the development of early warning systems and disaster preparedness strategies.

2. Database and methodology

2.1. Data collection

High-quality data samples are essential for reliable statistical results. This study initially considered over 200 RA cases, ultimately selecting 63 cases based on data completeness and boundary clarity (Table 1). Notably, some boundaries were delineated through remote sensing imagery, while others were defined using maps from previous studies.

To ensure a consistent analysis of RA behavior, cases involving typical volcanic edifice collapses or events occurring in glacial environments were excluded due to their distinct mechanisms. The resulting database includes both

Table 1. Characteristics and parameters of the 63 rock avalanches in the database.

Confinement condition	Name	$V/10^6 \text{ m}^3$	L/m	H/m	WoS/m	H/L ratio	A/km^2	Year	Reference
Channelized	Nomash River	0.4	2220	460	150	0.21	0.27	1999	(Sivak TJ et al., 2010)
Channelized	Zymoetz River	1.6	4050	1245	300	0.31	0.43	2002	(McDougall S et al., 2006)
Channelized	Guanling	2	1010	420	170	0.42	0.1	2010	(Yin YP et al., 2011)
Channelized	Jiweishan	5	2120	710	265	0.34	0.57	2009	(Zhang M et al., 2019)
Channelized	Touzhaigou	7.2	3270	960	260	0.29	0.41	1991	(Ren Z et al., 2018)
Channelized	McAuley Creek	7.4	1950	500	460	0.26	0.47	2002	(Brideau MA et al., 2012)
Channelized	Niumiangou	7.5	2740	890	328	0.33	0.29	2008	(Zhang M et al., 2011)
Channelized	Acheron	8	3400	693	250	0.20	0.89	1100a BP	(Smith GM et al., 2006)
Channelized	Rubble Creek	25	6120	1060	790	0.17	3.7	1856	(Moore DP and Mathews WH, 1978)
Channelized	Bingham	30	2740	850	540	0.31	1.36	2013	(Hibert C et al., 2014)
Channelized	Baige	31.7	3600	860	480	0.24	1.86	2018	(Li HB et al., 2019)
Channelized	West Salt Creek	43	4620	636	900	0.14	2.43	2014	(Coe JA et al., 2016)
Channelized	Meager Mt	48.5	12200	2183	1070	0.18	8.7	2010	(Guthrie RH et al., 2012)
Channelized	Wenjia Gully	50	4500	1320	803	0.29	2.32	2008	(Zhang M et al., 2016)
Channelized	Falling Mt	55	4290	1070	873	0.25	1.91	1929	(Davies TR and McSaveney MJ, 2002)
Channelized	Khait	75	7660	1421	1000	0.19	5.12	1949	(Evans SG et al., 2009)
Channelized	Tsaoiling	125	5230	524	1250	0.10	4.96	1999	(Yang CM et al., 2014)
Channelized	Luquan	214	8020	1770	1450	0.22	7.52	1965	(Wen BP and Wang F, 2021)
Channelized	Yigong	300	11500	3250	1400	0.28	13.26	2000	(Xu Q et al., 2012)
Nontypical laterally confined	Sutherland	3	1440	270	184	0.19	0.33	2005	(Blais-Stevens A et al., 2007)
Nontypical laterally confined	Ganheba	9.1	4050	1950	425	0.48	1.24	2004	(Chen RC et al., 2023)
Nontypical laterally confined	Walai	52	3300	1110	660	0.34	2.53	40000a BP	(Chen RC et al., 2022)

Table 1. (Continued)

Confinement condition	Name	$V/10^6 \text{ m}^3$	L/m	H/m	WoS/m	H/L ratio	A/km^2	Year	Reference
Nontypical laterally confined	Linka	310	6080	1488	1380	0.25	6.45	/	(Zeng QL et al., 2021)
Typical frontally confined	Todagin Creek	4	1950	771	467	0.40	0.99	2006	(Sakals ME et al., 2012)
Typical frontally confined	Turnoff Creek	4	1650	554	260	0.34	0.37	1992	(Beguería S et al., 2009)
Typical frontally confined	Mosque Mt	5	1231	420	167	0.34	0.27	Mid 1990s	(Lu ZY et al., 2003)
Typical frontally confined	Val Pola	41	3540	1342	880	0.38	3.21	1987	(Crosta GB et al., 2007)
Typical frontally confined	Hope Slide	47.3	4390	1220	1100	0.28	4.03	1965	(Brideau MA et al., 2005)
Typical frontally confined	Usoi	2200	5770	1800	1500	0.31	12.41	1911	(Ischuk AR, 2011)
Nontypical frontally confined	Xinmo	4.5	2470	1170	385	0.47	1.31	2017	(Fan XM et al., 2017)
Nontypical frontally confined	Jure	5	1880	691	464	0.37	0.88	2014	(Panthee S et al., 2023)
Nontypical frontally confined	Temi	35	1850	591	783	0.32	1.37	2000a BP	(Xia M et al., 2023)
Nontypical frontally confined	Frank	37	3360	800	640	0.24	3.12	1903	(Benko B and Stead D, 1998)
Nontypical frontally confined	Mystery Creek	40	3550	1250	703	0.35	3.33	2000–3600a BP	(Blais-Stevens A et al., 2011)
Nontypical frontally confined	Xuelongnang	62	1970	900	670	0.46	1.05	5300a BP	(Chen J et al., 2018)
Nontypical frontally confined	Hattian	85	2730	750	560	0.28	1.74	2005	(Basharat M et al., 2012)
Nontypical frontally confined	Tschirgant	160	5750	1400	1200	0.24	11.12	2900a BP	(Dufresne A et al., 2016)
Nontypical frontally confined	Yinduba	294	2300	650	1042	0.28	3.48	80000a BP	(Xu H et al., 2023)
Nontypical frontally confined	Kas	300	3580	1080	1250	0.30	6.65	1080a BP	(Ivy-Ochs S et al., 2017)
Nontypical frontally confined	Daguangbao	600	5550	800	1373	0.14	6.8	2008	(Li XP et al., 2021)
Nontypical frontally confined	Cascade	750	5370	620	1200	0.12	10.21	660	(Barth NC, 2014)
Nontypical frontally confined	Bonneville	1000	7240	845	1850	0.12	16.15	1450	(Reynolds ND et al., 2022)
Nontypical frontally confined	Köfels	3100	5900	610	4160	0.10	16.31	9527a BP	(Zangerl C et al., 2021)
Nontypical frontally confined	Flims	12000	16150	2080	2670	0.13	66.38	8500a BP	(Pfiffner OA, 2022)
Typical unconfined	Nayong	0.5	790	270	250	0.34	0.18	2017	(Luo H et al., 2021)
Typical unconfined	Pink Mountain	0.8	1850	450	280	0.24	0.46	2002	(Geertsema M et al., 2006)
Typical unconfined	Chisca	1	1350	330	250	0.24	0.41	1996	(Geertsema M and Cruden DM, 2009)
Typical unconfined	Shuicheng	2	1400	465	182	0.33	0.34	2019	(Zhang YB et al., 2020)
Typical unconfined	Beinn Alligin	3.3	1780	675	165	0.38	0.41	3950a BP	(Ballantyne CK and Stone JO, 2004)
Typical unconfined	Guinsaugon	9.2	4030	810	550	0.20	3.23	2006	(Catane SG et al., 2008)
Typical unconfined	Yadong	11.2	1870	559	600	0.30	1.06	14000a BP	(Peng X et al., 2018)
Typical unconfined	Aishihik	22	2240	527	446	0.24	1.16	Early Holocene	(Brideau MA and Stead D, 2004)
Typical unconfined	Naga	27	1210	210	612	0.17	0.84	2018	(Catane SG et al., 2019)
Typical unconfined	Nyixoi	28	4530	890	474	0.20	4.22	2200a BP	(Wang YF et al., 2019)
Typical unconfined	Dora	34.6	1220	484	893	0.40	0.99	4240a BP	(Wang LY et al., 2021)
Typical unconfined	Luanshibao	43	3870	820	714	0.21	4.29	3500a BP	(Guo CB et al., 2016)
Typical unconfined	Sennwald	92	5060	1148	721	0.23	7.16	4300a BP	(Aksay S et al., 2021)
Typical unconfined	Tagarma	96	5270	1510	764	0.29	4.48	/	(Wang YF et al., 2020)
Typical unconfined	Potrero de Leys	250	4760	830	1735	0.17	10.5	40000a BP	(Penna IM et al., 2017)
Typical unconfined	Blackhawk	283	9960	1100	1548	0.11	16.95	18000a BP	(Friedmann SJ et al., 2003)
Typical unconfined	Iymek	980	16460	2135	2144	0.13	49.23	7100a BP	(Shi AW et al., 2023)
Typical unconfined	Komansu	4000	29660	3000	2981	0.10	142.83	5000–11000a BP	(Robinson TR et al., 2015)
Typical unconfined	Seymareh	44000	19120	1500	8290	0.08	251.83	9800a BP	(Roberts NJ and Evans SG, 2013)

historical and recent RAs, as the exclusion of glacial-related significantly reduced the sample size of modern RAs. Of the 63 events, 23 occurred after 2000, 13 between 1800 and 1999, and the remainder before 1800.

Seismic or heavy rainfall events can induce numerous RAs in a single region. For example, the 2008 Wenchuan earthquake triggered over 100 large landslides (Li LP et al., 2022). This study selectively included cases from individual events to ensure a broad geographic and geologic diversity. The selected cases are concentrated in geologically active, mountainous regions, such as the eastern and western Himalayan syntaxes, the Alps, the Rocky Mountains, the Andes, and New Zealand's Southern Alps (Fig. 1). This distribution underscores the tendency for RAs to occur in tectonically active zones.

Table 1 provides data on confinement conditions, occurrence ages, and geometric parameters, including failure volume (V), runout distance (L), fall height (H), area (A), and source area width (WoS). Fig. 2 further defines these geometric parameters. Failure volume data were sourced from existing literature. Runout is measured as the maximum horizontal distance along the center line from the headscarp crown to the deposit toe, while fall height is the elevation difference between the headscarp crown and deposit toe. Area (A) covers the entire extent of the RA, including the source, transition, and accumulation zones. The WoS is the maximum width across the source area, measured perpendicular to the central axis. Although most of these parameters are widely used in RA studies (Strom A et al., 2019), source area width is a novel parameter. Note that some geometric parameters in

Table 1 may slightly differ from previous studies due to re-measurement.

2.2. Methodological framework for runout prediction models

Previous research has shown that certain RA parameters often exhibit linear relationships on a logarithmic scale. This relationship can be mathematically represented as $\log L = a + b \log V$ or $\log L = a + b \log V + c \log H$ (Mitchell A et al., 2020). However, most studies lack detail on the regression process, especially regarding the loss function, which is critical for understanding error handling and data variability. This study introduced four distinct loss functions within traditional regression using the hypothesis functions $y = ax^b$ or $z = ax^b y^c$, where x , y and z are variables representing different RA geometric parameters (Table 2). The regression process uses MATLAB's `fminsearch` solver, which is optimized for unconstrained optimization tasks, allowing for the identification of parameter values that minimize the selected loss functions and optimize model fit.

Furthermore, this study employed MATLAB's Neural Net Fitting tool to develop an alternative runout prediction model. Given the limited number of input parameters and small dataset, this study constructed a simple feedforward neural network to reduce model complexity and mitigate overfitting. A systematic grid search was conducted over a range of parameter values, testing neural network performance across various combinations of hidden layers (1–3 layers) and neurons per layer (1–9 neurons). Model performance was evaluated based on monotonicity, mean absolute percentage

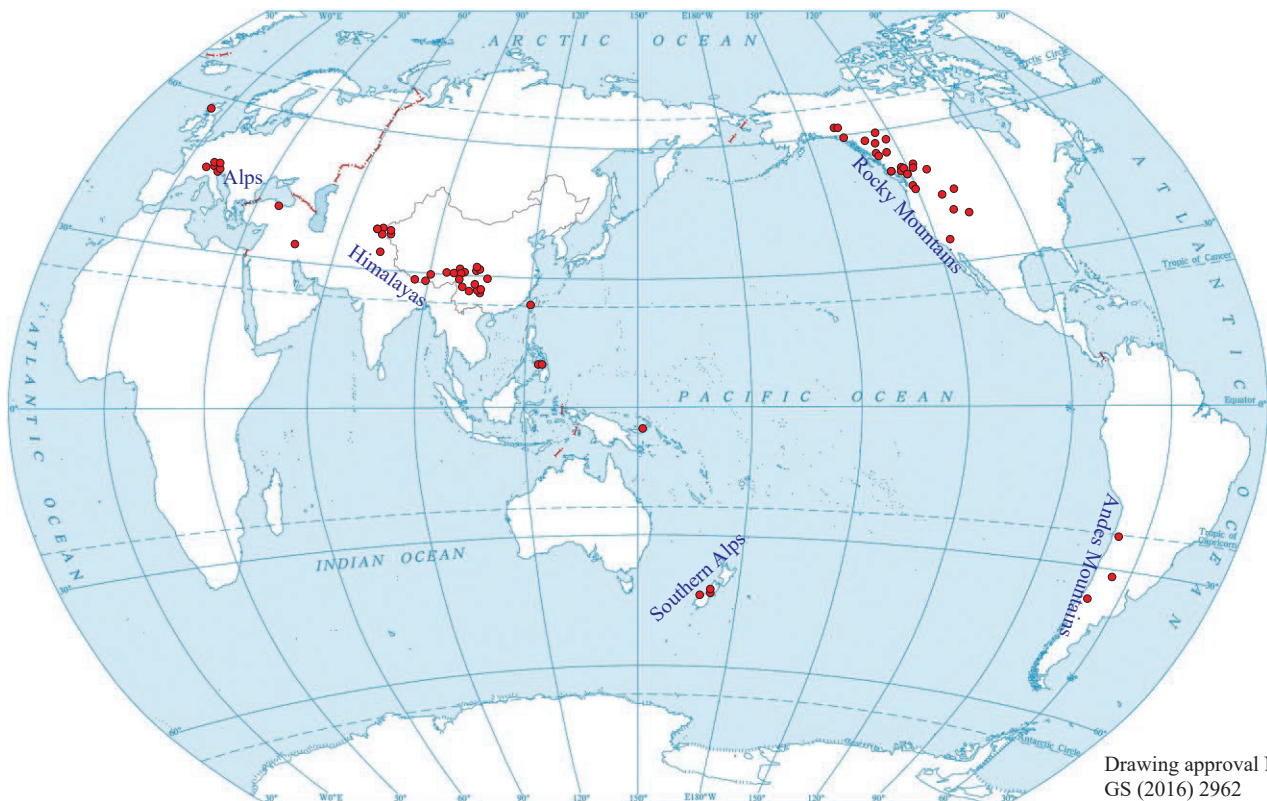


Fig. 1. Spatial distribution of the 63 rock avalanche cases.

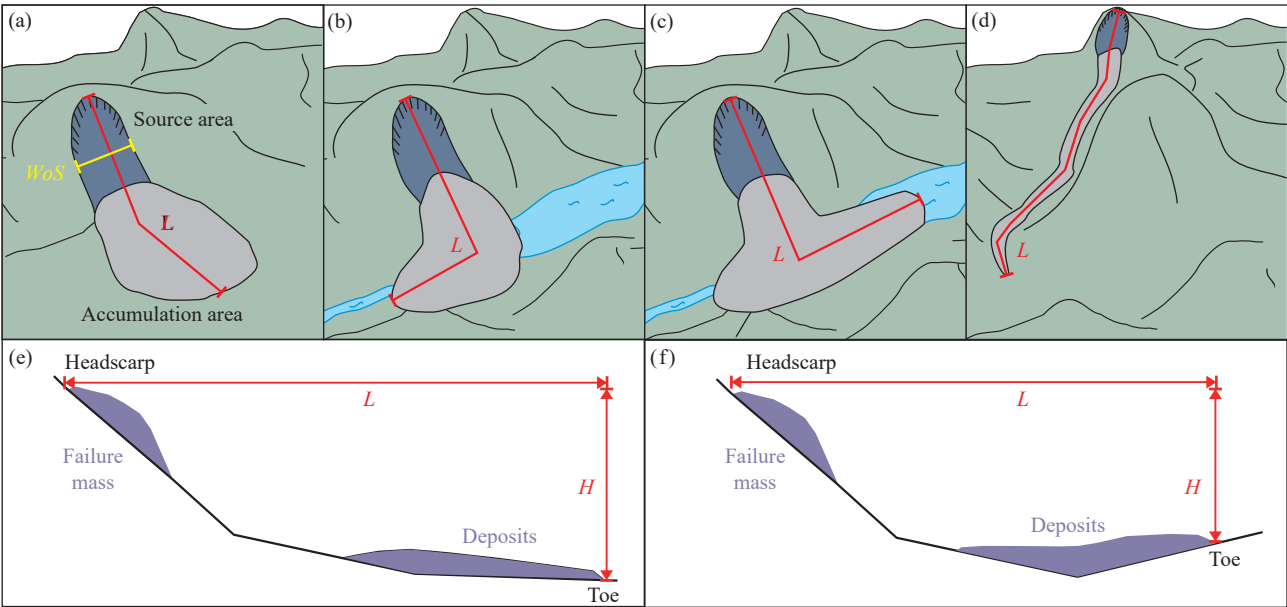


Fig. 2. Schematic diagram illustrating the methodology for measuring geometric parameters of the rock avalanche. *WoS*–Source area width; *L*–runout; *H*–fall height. a–Measurement for unconfined RA; b–measurement for frontally obstructed RA with deflection; c–scenario of lateral spreading under topographic control, where the longer path is selected for measurement; d–measurement for channelized RA; e, f–runout and fall height are measured from the headscarp to the deposit toe across all scenarios.

Table 2. Loss functions used in traditional regression modeling in this study.

Name	Loss function
Mean squared error (MSE)	$\frac{1}{n} \sum (y - \hat{y})^2$
Mean squared logarithmic error (MSLE)	$\frac{1}{n} \sum (\log_e((\hat{y} + 1)/(y + 1)))^2$
Mean absolute percentage error (MAPE)	$\frac{1}{n} \sum (y - \hat{y})/y $
Customized mean absolute percentage error (cMAPE)	$\frac{1}{n} \sum (y - \hat{y})/\hat{y} $

error (MAPE), goodness-of-fit (R^2), and the probability that prediction errors $((y - \hat{y})/y)$, where y is the observed value and $\hat{y}$ is the predicted value) fall within the range of -25% to 25% . The optimal neural network regression model was selected according to these criteria.

3. Categories and geometric characteristics of the cases

3.1. Confinement categories of the 63 rock avalanche cases

Previous studies indicate that RA geometry is linked to confinement categories, triggering mechanisms, and path materials (Wen BP and Guan LC, 2022). However, identifying the triggering mechanisms and the path material of these historical landslides presents a significant challenge. The confinement classification system was adopted in this study, but it was found that the practical classification is more complex than anticipated. Usually, rock avalanches are divided into three categories: Laterally confined, frontally confined, and unconfined (Nicoletti PG and Sorriso-Valvo M, 1991; Strom A et al., 2019).

Unconfined RAs, which spread over open piedmont plains, are widely accepted and noncontroversial (Fig. 3a).

Channelized RAs, typically developing within gullies (Fig. 3b), are often grouped with laterally confined RAs. However, they exhibit distinct morphological differences compared to other laterally confined RAs (Fig. 3c). Additionally, some frontally confined RAs transform into a channelized form within valleys (Figs. 3d–f), while others do not significantly impact the opposing terrain (Figs. 3g, h). To address these ambiguities, this study proposes a refined classification system with five categories: Typical frontally confined, nontypical frontally confined, channelized, nontypical laterally confined, and typical unconfined RAs. Under this system, the types of certain cases were redefined. For instance, the McAuley Creek RA, Falling Mountain RA, Baige RA, and Tsaoling RA are now considered channelized RAs due to their unique depositional morphology (Figs. 3d–f), distinguishing them from typical frontally confined RAs like Hope RA and Val Pola RA (Fig. 3h).

In this classification, 19 RAs were identified as channelized, 19 as typical unconfined, and 6 as typical frontally confined. The remaining cases were categorized as nontypical laterally confined (4 cases) and nontypical frontally confined (15 cases). Due to the limited number of samples in each confinement category, separate runout prediction models were not developed for each type.

To further quantify RA types, the aspect ratio ($L/\text{Average width} = L^2/A$) was used to capture the morphological characteristics of deposits (Li LP et al., 2022). Results indicate that channelized RAs generally exhibit significantly higher aspect ratios than other types (Fig. 4). Aside from channelized RAs, few cases have an aspect ratio exceeding 7. Since aspect ratio is also influenced by other factors, differences among the remaining four RA categories are considered minor.



Fig. 3. Rock avalanches in different confinement conditions. a–Typical unconfined RA; b–channelized RA; c–nontypical laterally confined RA; d–f–channelized RA transformed from frontally confined type; g–nontypical frontally confined RA; h–typical frontally confined RA; i–typical unconfined RA; j–k–channelized RA; l–m–nontypical frontally confined RA.

3.2. Geometric characteristics of the 63 rock avalanche cases

The relationships among runout distance (L), fall height (H), volume (V), total area (A), and the H/L ratio are illustrated in Fig. 5. As shown in Figs. 5a, d, f, runout distance (L) strongly correlates with volume (V) and fall height (H), suggesting that greater fall heights and larger volumes increase gravitational potential energy, leading to extended runout. A strong correlation between volume and total area is

also evident in Fig. 5f, consistent with previous studies. Conversely, relationships between the H/L ratio and variables such as H , L , or V are less clear on a logarithmic scale, as shown in Figs. 5b, c, e.

Previous studies have highlighted the importance of the H/L ratio as an indicator of RA mobility. While some researchers suggest an H/L threshold of 0.6 (Locat P et al., 2006), others propose lower thresholds such as 0.4 or 0.32

(Corominas J, 1996). Statistical analysis of the cases in this study (Fig. 5b) reveals that approximately one-fourth of RAs have an H/L ratio exceeding 0.32, with several cases surpassing 0.4. Observing these high H/L cases via remote sensing imagery reveals typical fluidized geomorphological features (Figs. 3j–m), indicating that an H/L threshold below 0.6 may be appropriate. In fact, similar RAs in terms of fall height and volume exhibit considerable variability in H/L ratio (Figs. 5b, e), suggesting that H/L ratio may not be a statistically reliable predictor on its own.

In Fig. 5, subtle distinctions between RA types are

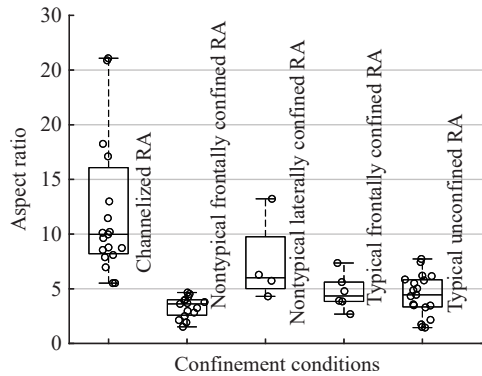


Fig. 4. Box plots of aspect ratios for the 63 rock avalanches in different confinement conditions.

observable. For example, unconfined RAs tend to cover greater distances for similar fall heights and occupy larger areas for comparable volumes (Figs. 5a, f). Meanwhile, channelized RAs tend to travel farther for comparable volumes (Fig. 5d). However, the dispersion within the data introduces variability that weakens these distinctions.

This study also draws attention to RAs with short runout distances, small volumes, and low fall heights. The RA with the shortest runout in this database, the Nayong RA (Zhu YQ et al., 2019), has a runout of less than 1 km yet displays typical fluidized geomorphological and sedimentological characteristics (Fig. 3i). Similarly, a recent RA in Xinjing, Inner Mongolia, exhibited a runout of less than 1 km (Wang QK et al., 2024). Certain RAs also feature low fall heights; for instance, the Naga RA has a fall height of 210 m, while the Nayong and Sutherland RAs have fall heights around 270 m, and the Chisca RA around 330 m. Analysis of smaller-volume RAs reveals three cases (Nomash RA, Nayong RA, and Pink Mountain RA) with volumes below $1 \times 10^6 \text{ m}^3$, which is beneath the typical threshold for RAs (Fischer L et al., 2012). Interestingly, all these are modern events. Scatter plots comparing RA age and volume suggest that smaller-volume RAs are more common in recent times than in ancient records, likely due to erosion effects that may have removed evidence of smaller ancient RAs (Fig. 6). These findings highlight the potential risk posed by smaller or low-elevation RAs, which

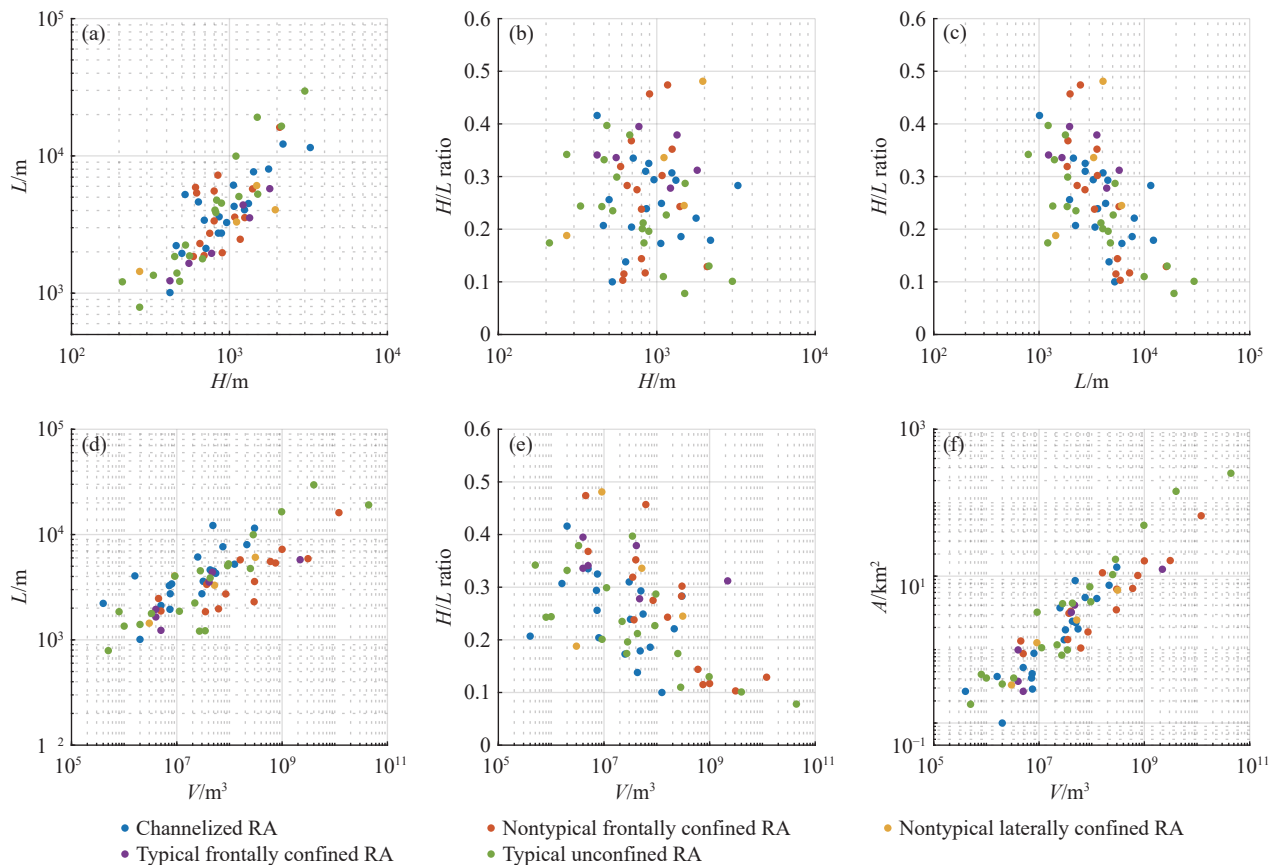


Fig. 5. Scatter plots of geometric parameters for the 63 rock avalanches. a–Runout (L) vs. fall height (H); b– H/L ratio vs. fall height (H); c– H/L ratio vs. runout (L); d–runout (L) vs. volume (V); e– H/L ratio vs. volume (V); f–total area (A) vs. volume (V). The data points are categorized by five confinement conditions: Channelized, nontypical frontally confined, nontypical laterally confined, typical frontally confined, and typical unconfined.

may not be as rare as previously believed.

A distinctive contribution of this study is the introduction of WoS as a new parameter. Fig. 7 plots WoS against V on a logarithmic scale, showing a significant positive correlation, highlighting WoS as a possible alternative to V in developing runout prediction models. Using traditional regression methods with various loss functions, a regression model relating V and WoS was determined. The optimal model, $V = (460.40 \times 10^{-9}) \times WoS^{2.8024}$, achieved a notable R^2 of 0.9408 and a MAPE of 49.32%. No significant differences were observed in WoS and V patterns among different confinement categories in this study.

4. Construction of runout prediction models

4.1. Selection of input and output parameters

Previous research has demonstrated a close relationship among runout distance, area, volume, and fall height (Strom A et al., 2019). Findings from the geometric analysis and Pearson correlations based on the dataset (Fig. 8) further support this relationship. Consistent with scatter plot observations (Fig. 5), the H/L ratio shows a weak correlation

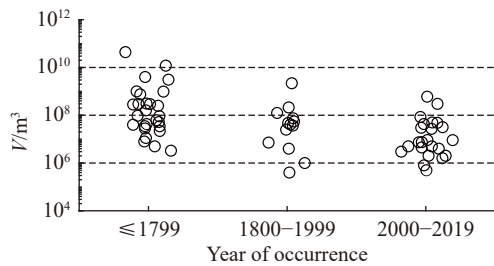


Fig. 6. Scatter plots showing the relationship between year of occurrence and volume of the 63 rock avalanches.

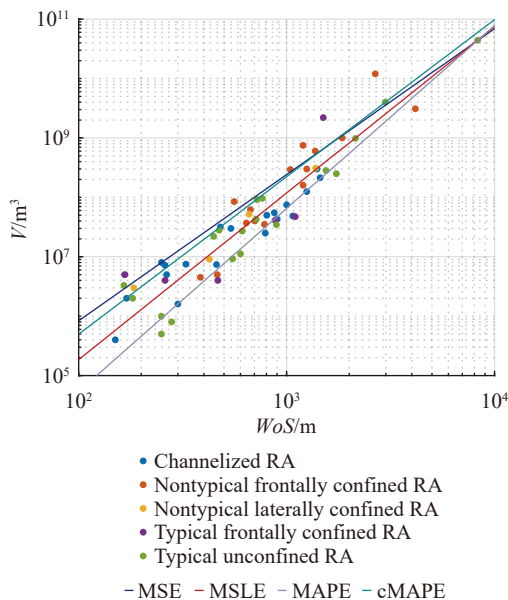


Fig. 7. Scatter plots and regression models illustrate the relationship between source area width and volume of the 63 rock avalanches.

with other parameters, while L has a significant Pearson correlation with V , H , and WoS . Therefore, L is selected as the target variable for prediction in this study.

The Pearson correlation between H and L is notably strong at 0.77, while the correlations between H with V and WoS are comparatively weak. This suggests that H is essential for inclusion in the prediction model. The correlation between WoS and L , however, is higher than that between V and L . Additionally, WoS and V show a strong interrelationship, with a Pearson coefficient of 0.86, suggesting that only one of these variables may be needed as an input for L prediction. Although Pearson correlation revealed the pairwise relationships between geometric parameters, the interactions among multiple parameters still require further testing. In the next section, the performance of single-parameter models (WoS , V , and H), dual-parameter models (WoS and H , V and H), and a three-parameter model (WoS , H , and V) will be tested.

4.2. Traditional regression models

4.2.1. Comparison of single-parameter models with different loss functions

Table 3 lists nine traditional regression (TR) models developed for runout prediction. The first four models use the same input parameters but vary the loss functions, enabling a comparison of their effects. Figs. 9a–e display the differences in fit, error distributions, R^2 values, and mean absolute percentage error (MAPE) across the four WoS -based models.

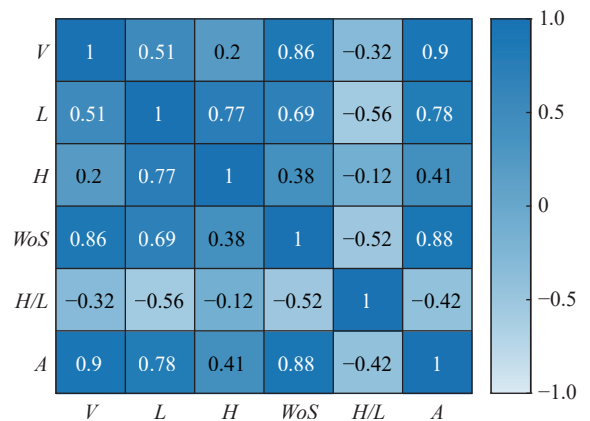


Fig. 8. Heatmap of Pearson correlation coefficients for geometry parameters of the 63 rock avalanches.

Table 3. Runout prediction models using various input parameters and various loss functions.

Model Name	Regression model
MSE-W	$L = 55.2066 \times WoS^{0.6681}$
MSLE-W	$L = 35.4424 \times WoS^{0.7099}$
MAPE-W	$L = 32.2506 \times WoS^{0.7076}$
cMAPE-W	$L = 26.8718 \times WoS^{0.7829}$
MSLE-V	$L = 1461.1 \times V^{0.2447}$
MSLE-H	$L = 2.3667 \times H^{1.0850}$
MSLE-WH	$L = 1.6497 \times WoS^{0.4265} \times H^{0.7270}$
MSLE-VH	$L = 15.1605 \times V^{0.1456} \times H^{0.7302}$
MSLE-VWH	$L = 4.2669 \times WoS^{0.2606} \times V^{0.0635} \times H^{0.7115}$

The model using MSE as the loss function achieves the highest R^2 (Fig. 9b), but has a broader error distribution and higher MAPE compared to the MSLE-based model (Fig. 9c). This result illustrates the limitations of relying solely on R^2 for model evaluation.

In Fig. 9d, the error distribution for the MAPE-based model is skewed to the left, indicating a tendency for underestimation. Conversely, the error distribution in the model based on cMAPE suggests a tendency for overestimation (Fig. 9e). Fig. 9f presents the MSLE-based model using V as a single parameter, which performs comparably to the MSLE-WoS model. Although the single H-based model achieves high R^2 and low MAPE (Fig. 9g), the proportion of errors within $\pm 25\%$ is significantly lower than that of the MSLE-V and MSLE-WoS models.

4.2.2. Multi-parameter traditional regression models

Given the strong performance of the MSLE-based single-

parametric models, dual-parameter models were also developed using MSLE. Figs. 10a, c present the fit surfaces, error distributions, R^2 values, and MAPE for models using WoS and H (MSLE-WH). Both R^2 and MAPE improve significantly over single-parameter models. Similarly, Figs. 10b, d show the results for models using V and H (MSLE-VH), which perform comparably to MSLE-WH models. This suggests that WoS is effective in predicting runout and may serve as a substitute for V in dual-parameter models.

A tri-parameter TR model incorporating WoS , V , and H was also developed. The error distribution, R^2 , and MAPE are shown in Fig. 10e. Compared to the dual-parameter models (Figs. 10c, d), the tri-parameter model shows slight improvements in MAPE and R^2 , with a higher peak.

4.3. Neural network regression models

In addition to loss functions, the choice of hypothesis

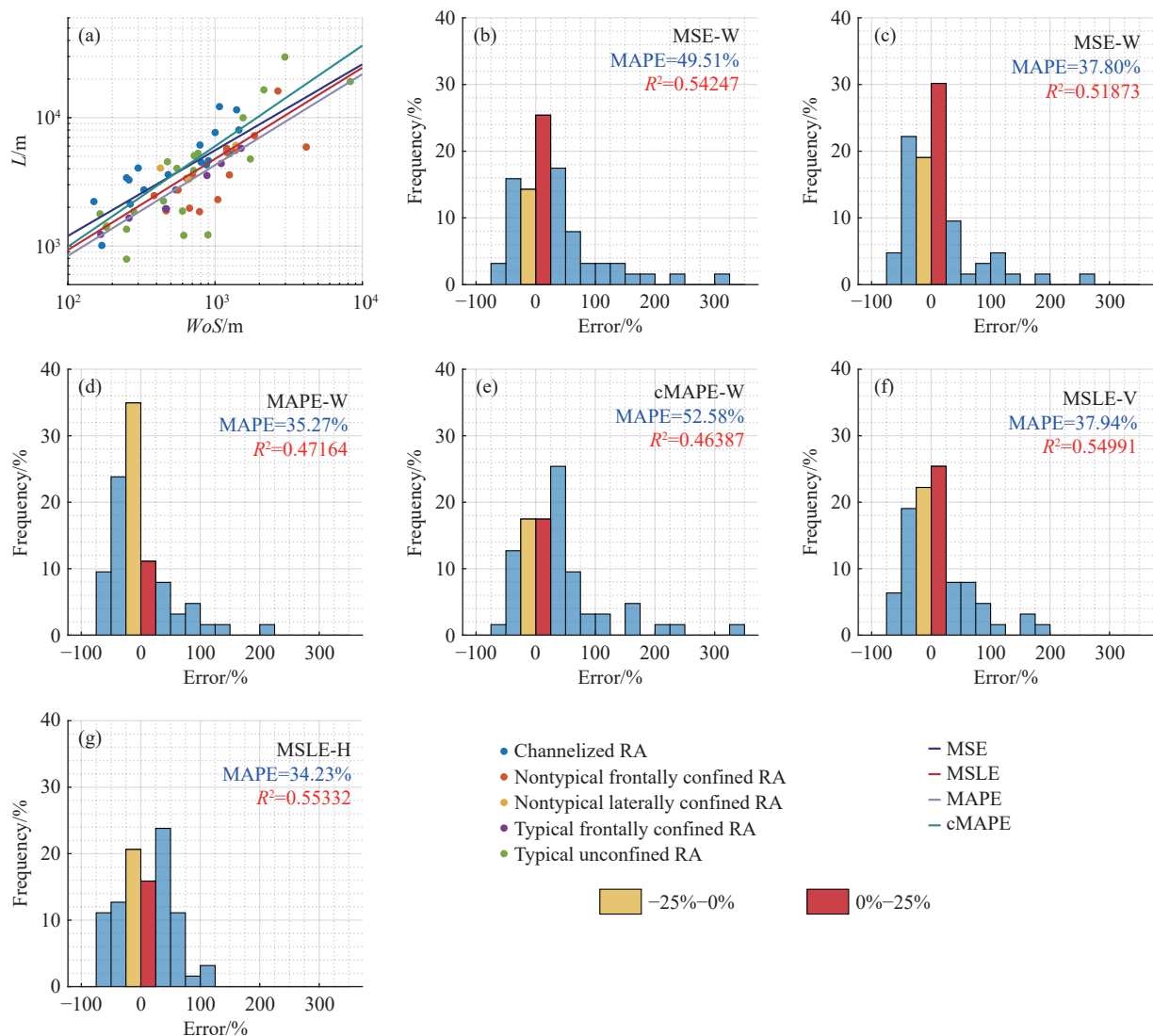


Fig. 9. Single-parametric models and their error distributions under different loss functions. a–Scatter plot of runout (L) vs. source area width (WoS) showing regression lines for MSE, MSLE, MAPE, and cMAPE loss functions; b–e–error distribution for models using WoS as the input parameter, optimized with MSE, MSLE, MAPE, and cMAPE loss functions, respectively; f–error distribution for the model using failure volume as the single input parameter based on the MSLE loss function; g–error distribution for the model using fall height as the single input parameter based on the MSLE loss function. R^2 and MAPE denote the goodness of fit and the mean absolute percentage error, respectively.

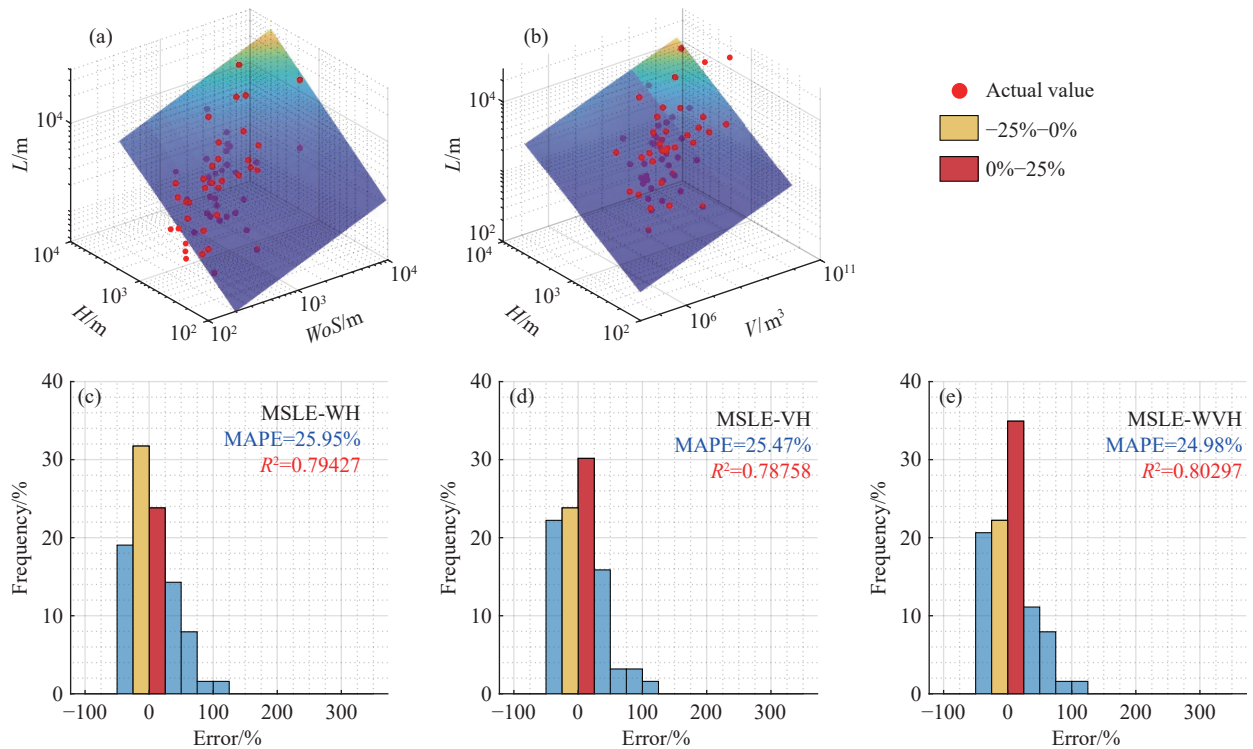


Fig. 10. Multi-parametric regression models and their error distributions based on the MSLE loss function: a–3D prediction surface for runout (L) using source area width (WoS) and fall height (H) as input parameters (MSLE-WH model); b–3D prediction surface for runout (L) using failure volume (V) and fall height (H) as input parameters (MSLE-VH model); c–e–error distributions for the MSLE-WH, MSLE-VH, and MSLE-WVH (tri-parameter model incorporating WoS , V , and H) models, respectively. R^2 and MAPE denote the goodness of fit and the mean absolute percentage error, respectively.

function—defining the relationship between input and output variables—also affects TR model performance. Since selecting an optimal hypothesis function can be challenging, this study applies neural network regression (NNR), which does not require explicit specification of functional forms. Given the effectiveness of MSLE in reducing the impact of large values, it was chosen as the loss function for the NNR model. Due to MATLAB's Neural Net Fitting tool lacking direct support for custom loss function, this study applied a logarithmic transformation to the parameters, approximating the effect of using MSLE as the loss function.

Fig. 11 presents the fit curves, error distributions, and MAPE for various NNR models. The NNR-W model uses WoS as a single parameter; NNR-V uses volume; NNR-WH and NNR-VH are dual-parameter models using (WoS , H) and (V , H); and NNR-WVH is the tri-parameter model incorporating WoS , V , and H . With the exception of the tri-parameter model, the other models exhibit smooth and continuous prediction surfaces, due to monotonicity constraints.

4.4. Determination of the optimal runout prediction model

Compared to TR models, both single- and dual-parameter NNR models show narrower error distributions and lower MAPE, indicating superior performance (Figs. 9, 10, 11). To compare model performance, the cumulative errors within $\pm 25\%$ and $\pm 50\%$ are summarized in Fig. 12. Multi-parameter models, whether TR or NNR, consistently outperform single-

parameter models, with over 80% of errors falling within $\pm 50\%$. Notably, NNR models have a higher proportion of predictions within $\pm 25\%$ compared to TR models. The single-parameter model using WoS outperforms the model using V , though this advantage diminishes in multi-parametric models. Consequently, WoS is considered a potential replacement for V but does not significantly outperform it.

Based on Fig. 12, the NNR-WH is determined as the optimal model for predicting the runout of rock avalanches, achieving prediction errors within $\pm 25\%$ with a probability of 63.5% and within $\pm 50\%$ with a probability of 95.2%. This model achieves a MAPE of 23.22% and an R^2 of 0.85.

5. Discussion

5.1. Data uncertainty and its sources

A major source of uncertainty in this study stems from the ambiguous historical processes of ancient RAs. Evidence suggests large landslides may have occurred multiple times in the same location. For instance, multiple RAs have been identified in the Siachen area (Ekström G and Stark CP, 2013), frequent collapses have been documented at Baige (Tian SF et al., 2020), and two significant events have been recorded at the American Copper Mine (Moore JR et al., 2017). Furthermore, ancient RA deposits may undergo reactivation over time, adding further uncertainty.

Another key source of uncertainty is related to the complex and varied friction reduction mechanisms of RAs.

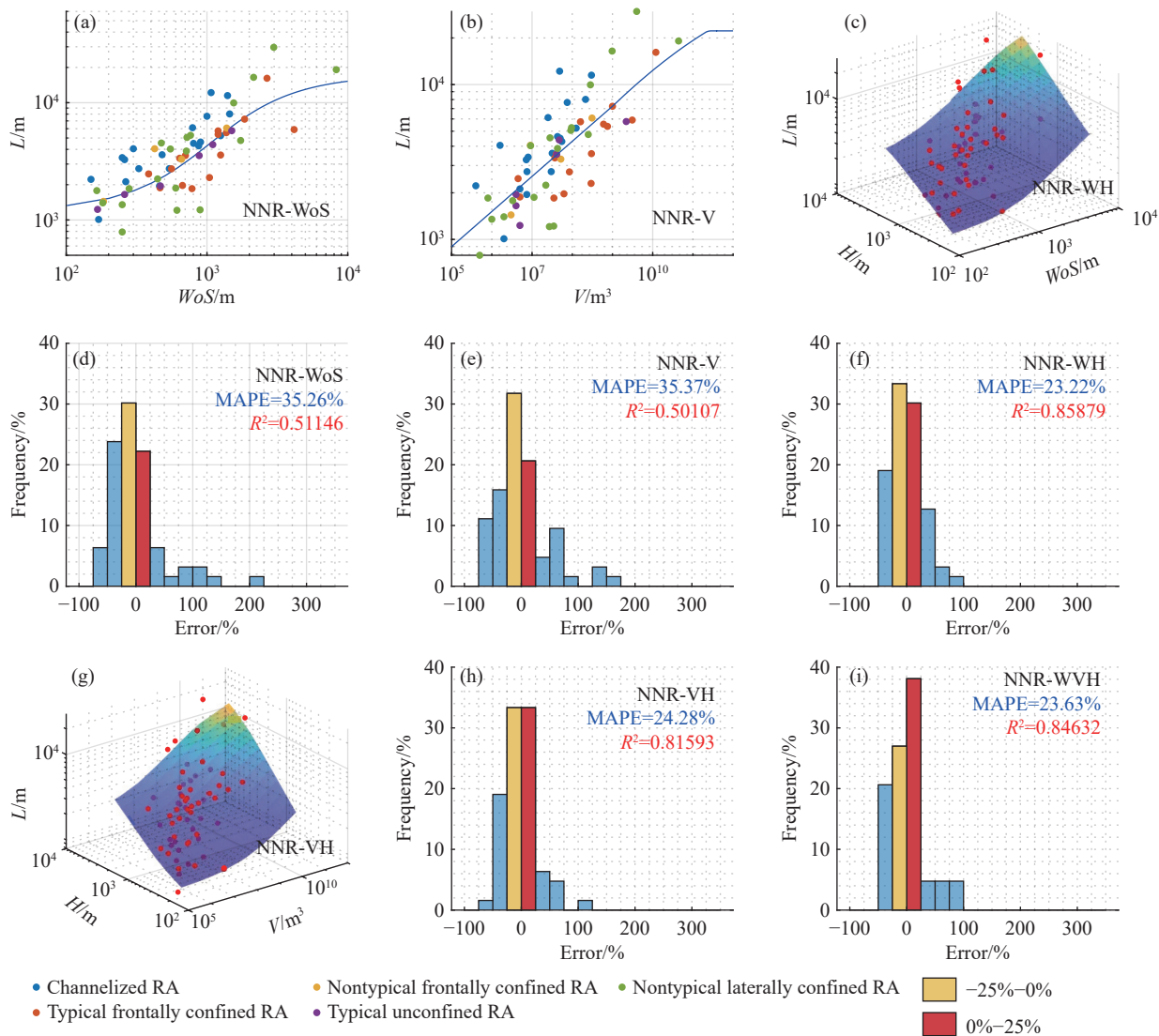


Fig. 11. Regression models and their error distributions based on the neural network regression (NNR) approach. a, b—scatter plots and regression curves for single-parameter models using source area width (WoS) and failure volume (V), respectively; c, g—3D prediction surfaces for dual-parameter models using (WoS , H) and (V , H), respectively; d–f—error distributions for the NNR- WoS , NNR- V , NNR- WH , respectively; h, i—error distributions for the NNR- VH and NNR- WVH models. R^2 and MAPE denote the goodness of fit and the mean absolute percentage error, respectively.

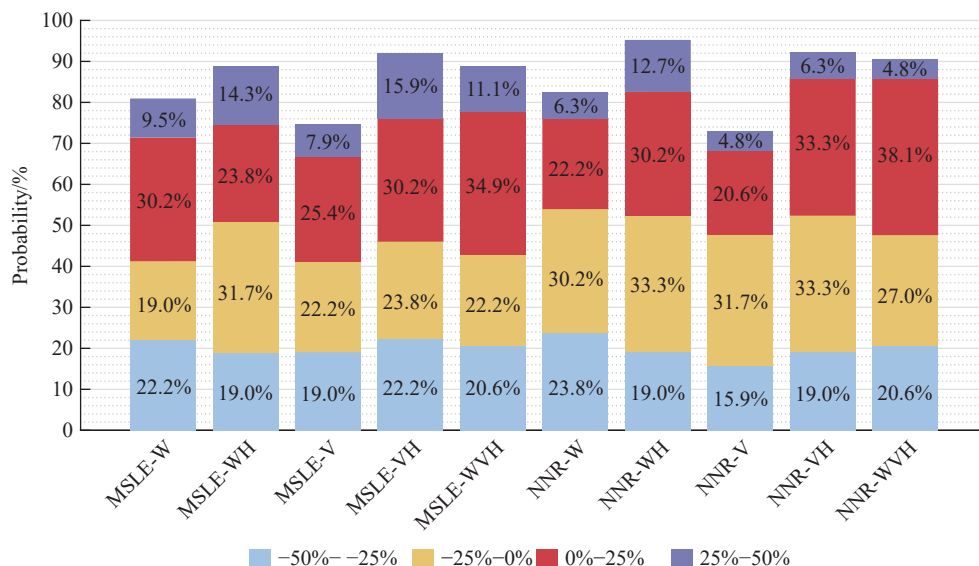


Fig. 12. Probability distributions of prediction errors across different regression models.

Studies have shown that RA runout distances are significantly affected by the material properties of the path traveled (Aaron J et al., 2017). In this database, two channelized RAs—Meager Mountain RA and Yigong RA—traveled over 10000 m, ranking sixth and fifth, respectively. The hypermobility of these RAs can be attributed not only to their substantial fall heights but also to the entrainment of ice or water, which likely reduced friction and enhanced mobility (Guthrie RH et al., 2012; Kang C et al., 2017).

Measurement uncertainties of key parameters are also important. Previous research has identified volume as the parameter most susceptible to inaccuracies. Generally, simpler, more readily measurable parameters yield greater accuracy and utility. Mitchell A et al. (2020), for example, attempted to incorporate average width in runout prediction modeling; however, this measure, derived from dividing area by runout distance, captures the dynamic nature of movement rather than a fundamental controlling factor in RA kinematics. To address this, this study introduces the *WoS* for predicting RA runout. The strong correlation observed between *WoS* and *V*, along with successful model predictions using *WoS*, supports its role as a practical substitute for volume in accurately predicting RA runout distances.

5.2. Implications of loss functions and evaluation criteria

Previous studies have shown that RAs' geometric parameters often display linear relationships when plotted on a logarithmic scale, which has led to the widespread use of logarithmic transformations in runout prediction models (Strom A et al., 2019; Mitchell A et al., 2020; Liu H et al., 2021; Wen BP and Guan LC, 2022). However, limited research has examined how such transformations might affect modeling outcomes.

In this study, the effects of different loss functions on traditional regression methods were compared. MSE is the most widely used loss function in regression, minimizing the sum of squared errors. However, due to the squaring of errors, larger values disproportionately influence results, yielding a more accurate fit for high-value data points. In contrast, MSLE can reduce the impact of large values on the regression outcome. Since the value of *L* is typically greater than 1, the difference between MSLE and $\frac{1}{n} \sum \left(\frac{\log \hat{y}}{\log y} \right)^2$ is minimal. Consequently, the MSLE-based regression model aligns closely with results obtained using parameter logarithmization, suggesting that logarithmic transformations in previous studies do not introduce significant errors. Nevertheless, MSLE introduces asymmetry in handling positive and negative errors, which could lead to bias. Meanwhile, MAPE-based models tend to underestimate results, as larger actual values reduce the error term, leading the optimization process to de-emphasize these points. Conversely, models using cMAPE may overestimate results, as smaller predictions yield large errors, prompting the model to increase predictions to minimize error. Given these characteristics, this study recommends using the MSLE as the

loss function in runout regression prediction models, unless logarithmic transformation has been applied.

Goodness of fit (R^2) is commonly used to describe model fit quality. However, our observations suggest R^2 may not be as determinative for runout prediction models as often assumed. In fact, R^2 is particularly suited to evaluating MSE-based models, while MAPE is useful for assessing relative error. However, MAPE still remains insufficient as a sole evaluation criterion. In risk prediction, it is crucial to determine the probability of outcomes falling within specific error ranges. Therefore, error distributions provide a more comprehensive assessment. This study specifically evaluated the frequencies of prediction errors within ranges of −50% to 50% and −25% to 25%. For instance, with the MSLE-WH model, there is a 55.5% probability that prediction error will fall within −25% to 25% and an 88.8% probability that error will be within −50% to 50%. This insight can guide more direct recommendations for risk mitigation. This study anticipates that this evaluation framework, based on examining error distributions and likelihoods within specific ranges, will not only enhance landslide risk prediction but also inspire further advancements in the field.

5.3. Insights from the novel runout prediction model

The selection of input parameters for model construction is critical. A key advancement in this study is the introduction and comprehensive validation of source area width as an effective alternative to failure volume for constructing runout prediction models. *WoS*, as a more easily measurable parameter, demonstrates robust predictive reliability across both traditional regression method and neural network regression approaches, consistently showing strong potential as a substitute for *V*. Although multi-parameter models improved predictive performance relative to single-parameter models, the tri-parameter models did not demonstrate substantial gains over dual-parameter models. Given *WoS*'s ease of measurement and predictive strength compared to *V*, this study advocates for prioritizing a combination of *WoS* and *H* to develop more efficient and accurate runout prediction models for RAs.

To address the impact of the hypothesis function on traditional regression models, this study also employed an NNR approach for constructing the runout prediction model, thereby addressing limitations associated with traditional regression methods. Comparative analysis of model performance (Fig. 12) reveals that the NNR-WH model achieved the highest accuracy, with a MAPE of 23.22%, an R^2 of 0.85, and 63.5% of prediction errors within the range of −25% to 25%, and 95.2% within −50% to 50%. These results underscore the superior predictive accuracy of the NNR approach and suggest that NNR holds considerable promise for developing RA regression models, particularly for complex future applications involving multiple parameters.

However, the NNR model may exhibit greater uncertainty when predicting trends with sparse or incomplete datasets. For

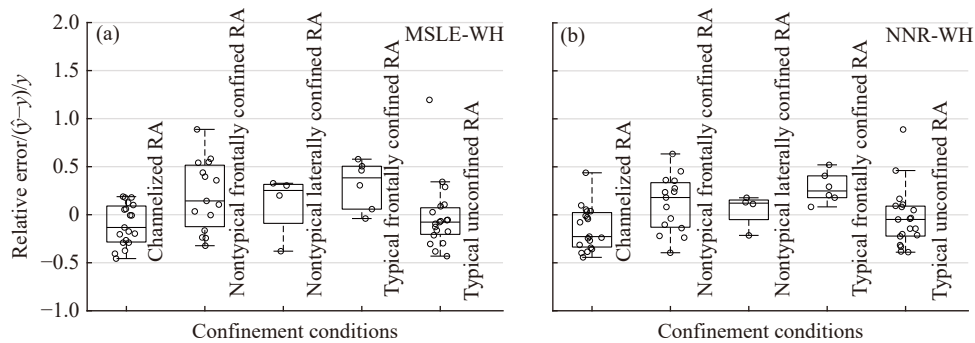


Fig. 13. Error distribution of different confinement conditions based on a-MSLE-WH model and b-NNR-WH model.

instance, as shown in Fig. 11a, when WoS exceeds 1000 m, the prediction curve flattens, suggesting a lack of physical realism in which runout distances remain stable despite increasing WoS . This phenomenon may reflect limitations in model sensitivity or data sparsity. Therefore, while the NNR model demonstrates high performance, its results should be carefully scrutinized, particularly in extrapolated regions of the data.

Although this study did not separately build the model for different confined RAs, the prediction models from total dataset also offer insights into RA mobility under different confinement conditions (Fig. 13). Figs. 13a, b show that different regression methods do not alter the general pattern of error distribution across confinement types. Unlike the aspect ratio distributions observed for confined versus unconfined RAs (Fig. 4), there is little difference in error distributions between channelized and unconfined RAs. This finding contrasts with previous studies suggesting that channelized RAs experience lower energy dissipation (Nicoletti PG and Sorriso-Valvo M, 1991). One possible explanation is that the sinuous topography and frequent impacts in channelized terrain dissipate more energy, offsetting any mobility benefits from confinement. Furthermore, Fig. 13 reveals that both typical and atypical frontally confined RAs exhibit lower mobility, as indicated by the error overestimation. These differences in error distribution across confinement types support the feasibility of developing distinct runout prediction models tailored to each confinement category. Future work will focus on investigating the characteristics of different confinement types and constructing subcategory-specific models.

This study provides preliminary evidence supporting the promise of a novel runout prediction model based on source area width. Compared to previous studies, this research enhances the intuitive understanding of model performance by employing error distributions, thereby offering a methodological framework for future study. However, several questions remain unresolved. Future efforts should focus on improving database quality, streamlining automated parameter extraction processes, and enhancing machine learning model accuracy. These advancements are essential for addressing the remaining challenges and refining the predictive capabilities of RA runout models.

6. Conclusions

This study presents the development and evaluation of a global database comprising 63 RA cases, comparing the performance of runout prediction models constructed using traditional regression methods and neural network regression. Key findings and conclusions are summarized as follows.

(i) A high-quality global database of 63 RA cases was established, with an enhanced classification of confinement conditions. Analysis of the relationship between RA age and volume suggests that the frequency of smaller-volume, lower-fall-height events may be substantially underreported in existing statistics, potentially due to erosional effects.

(ii) Incorporating source area width (WoS) as an alternative predictor for runout distance has proven to be a feasible replacement for volume, validated through both traditional and neural network regression analyses. This substitution not only simplifies measurements compared to volume assessments but also improves model accuracy and practicality, making it particularly valuable for rapid, on-site RA evaluations.

(iii) Examination of different loss functions in traditional regression models for runout prediction highlighted the effectiveness of the MSLE as the loss function, given its capacity to manage large input variations. This finding underscores the importance of selecting an appropriate loss function for reliable RA runout predictions. Furthermore, this study introduces a preliminary framework for evaluating prediction models using MAPE and error distributions, offering improved practical utility for risk prediction.

(iv) Based on comparative analysis of various traditional and neural network regression models, an optimal model was developed using WoS and fall height (H) as parameters. This model achieves a MAPE of 23.22% and an R^2 of 0.85, with prediction errors falling within the range of -25% to 25% at a probability of 63.5% and within -50% to 50% at a probability of 95.2%.

Overall, this study contributes to RA modeling by proposing novel prediction models and introducing innovative methodologies for model construction and performance evaluation. These advancements provide a foundation for enhanced predictive accuracy and practical applicability in RA runout risk assessment.

CRedit authorship contribution statement

Jian Chen and Rui-chen Chen conceived of the presented idea. Rui-chen Chen, Sheng Ma, Zi-ang Yan and Qian Shi carried out the data collection and analysis. All authors discussed the results and contributed to the final manuscript.

Declaration of competing interest

The authors declare no conflicts of interest.

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