An Empirical-Statistical Model for Landslide Runout Distance Prediction in Indonesia

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ABSTRACT

There have been many attempts and methods for predicting landslide-affected areas; empirical methods, numerical methods, and laboratory models are commonly used for prediction. Laboratory and numerical models require an input of parameters that are difficult to determine accurately. At the same time, empirical statistical methods use statistical methods based on historical data of landslide events to form an empirical model. Statistical analysis of empirical observations builds a possible relationship between disaster area characteristics and slide behavior because it does not require detailed mechanics of avalanche movement; the empirical-statistical model is a simple and practical tool in the initial assessment to predict the sliding distance of an avalanche that will occur. The main discussion of this study is that the volume of avalanches (V) has a more significant influence than the height of the slope (H) on the length of the avalanche (L) that occurs. Fifty-nine data on landslide events that have occurred in Indonesia are used to a prediction model for landslide events reviewing the slope geometry parameters in the form of H, slope (θ), and V and discussing the main factors that affect the sliding distance of avalanches that have not been discussed in research in the Indonesian territory. The analysis shows that H has a significant effect on the sliding distance of the avalanche compared to V. The best model produced to predict the sliding distance of the avalanche is $L = 6.918\ H^{0,840}$ and produces an average error rate of 29% for the landslide measurement data.
Keywords: *Landslide, Statistic Model, Landslide Runout Prediction*

ABSTRAK

Metode untuk memprediksi area yang terdampak longsor telah banyak dilakukan, salah satu metode yang cukup andal adalah metode statistik yang didasarkan pada historikal data kejadian longsor yang pernah terjadi untuk membentuk model empiris. Pembahasan utama dari penelitian ini adalah volume longsoran/sumber longsoran (V) memiliki pengaruh yang besar dibanding ketinggian lereng (H) pada panjang luncuran longsoran (L) yang terjadi, untuk membuktikan hal tersebut 59 data kejadian bencana longsoran yang pernah terjadi di Indonesia digunakan sebagai dasar dalam penelitian guna mendapatkan model prediksi kejadian longsor di kawasan lain di Indonesia dengan meninjau parameter geometri lereng berupa ketinggian lereng (H), kemiringan lereng (θ) dan volume sumber longsoran (V) serta membahas faktor utama yang berpengaruh terhadap jarak luncur longsoran yang yang belum di bahas pada penelitian sebelumnya di Wilayah Indonesia yang dilakukan oleh Qarinur (2014). Analisis menunjukkan bahwa parameter ketinggian lereng (H) memiliki pengaruh signifikan pada jarak luncur longsoran dibanding kemiringan lereng (θ) dan volume sumber longsoran (V). Model terbaik yang dihasilkan untuk memprediksi jarak luncur longsoran adalah $L = 6,918\ H^{0,840}$ dan mengasilkan tingkat kesalahan rata-rata sebesar 29% terhadap data pengukuran longsoran di lapangan.
Kata kunci: *Prediksi Jarak Luncur longsor, Longsoran, Model Statistic-Empiris*

1. INTRODUCTION

Slope failure is a complex phenomenon that causes landslides and results in severe damage. Topography, climate, geology, and land use are the factors that cause slope collapse (Nordiana et al., 2018). Predicting the extent of the impact of a landslide event is very important as input in the mitigation strategy and retrofitting structure plans, including restrictions on land use. However, topographical factors, landslide mass mechanics, and slope properties predict landslide distances complicated (Roering et al., 2005). Cracks becomes a problem when the ingression of aggressive and harmful substance penetrates to the concrete gap (Ekaputri et al., 2018). Making landslide models in the laboratory is not an easy job because heterogeneity modeling of flow materials in the field is hard to replicate in the laboratory (Ward & Day, 2006). Statistical modeling relates the physical properties of slopes to landslide-affected areas (McKinnon, 2010). The statistical-empirical method that makes empirical models based on statistical analysis of landslide event data helps predict the travel distance of various landslides (Rickenmann, 1999). Heim (1932) began analyzing the predicted impact of landslides by observing the characteristics of past landslides characteristics to avoid losses due to future landslides (Hungr et al., 2005). Statistical models can be used as a primary analysis tool in landslide prediction because the initial conditions of landslides and the parameters when landslides take place are difficult to determine (Crosta et al., 2006). The empirical model describes the sliding distance of the avalanche based on the relationship between parameters obtained from observations of landslide events in the field. However, this model produces a less clear interpretation, so that geometric, geomorphological, and volume changes are needed to reduce errors from the resulting model [6]. Empirical models for landslide prediction have been developed in many studies, including Devoli (2009) conducted an analysis of 367 landslide events and concluded that landslide mobility (H/L) is a function of volume (V)(Devoli et al., 2009). Legros (2002) proposed that the sliding distance of the landslide is entirely influenced by the avalanche's source, not the slope's height (Legros, 2002). Based on this hypothesis, it is necessary to analyze how the volume of the avalanche source influences the occurrence of landslides in Indonesia. Qarinur (2014) analyzed the occurrence of landslides in Indonesia until 2013 and provided various predictive models based on geometric parameters that were reviewed both based on the causes and movement mechanisms (Qarinur, 2015). How the influence or contribution of each parameter to the resulting model and has not analyzed the effect of the volume of the avalanche source on the prediction of the sliding distance, it is crucial to analyze it as a proposal in determining the parameters in the empirical models of advanced landslide predictions.

This study will analyze the review factors, including the height of the slope (H), the slope (θ), and the volume of the avalanche source (V), to determine the factors that most influence the prediction of the sliding distance of landslides in the Indonesian region. Where these parameters can be obtained before landslides occur to facilitate the analysis of predictions of landslide events in other places, besides that the statistical model is suitable for use in conditions similar to the analytical model (Rickenmann, 2007) for that it is vital to analyze the occurrence of landslides in an area to get a suitable model to predict landslide events in other areas in Indonesia. Similar area. This research will also produce the best glide distance prediction model that can be used in the territory of Indonesia based on the parameters reviewed.

2. METHODE

This study uses simple linear regression analysis to describe the relationship between the dependent variable, namely the landslide distance to the free variable, namely the height of the slope, and multiple linear regression to describe the relationship between the landslide runout distance (L), which is the dependent variable with two independent variables consisting of slope height (H) and slope angle (θ). Modeling will be carried out with the SPSS statistical aid program. Classical assumption tests carried out in this study include normality, heteroscedasticity, F test, and T-test. Table 1 shows the level of relationship between variables determined based on the coefficient of determination in the resulting model.

The parameters considered in the geometric approach can be seen in Fig. 1, where these parameters consist of slope height (H), landslide runout distance (L), and slope angle (θ). These parameters can be known before the landslide slope, so prediction models that use the known parameters before landslides occur are needed to support the mitigation plan.

Table 1. Interpretation of the coefficient of determination (Sugiyono, 2014)

R2	Interpretation
0-0,199	Negligible correlation

0,2-0,399	Low correlation
0,4-0,599	Moderate correlation
0,6-0,799	High correlation
0,8-1	Very high correlation

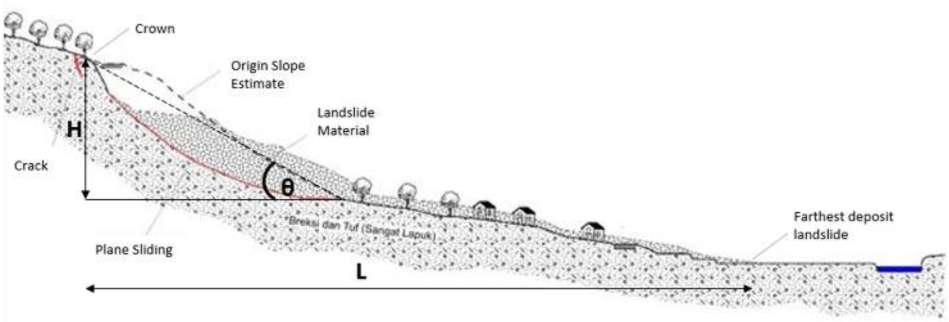

Fig. 1. Geometric parameters (Hungr et al., 2005)

Another parameter that is also commonly reviewed in predicting landslide runout distances is the volume of landslides (V). However, this parameter is difficult to find in existing landslide reports, so in this study, the data of unknown landslide volume is obtained through the empirical approach of Eq. (1) proposed by Li (1983) in (Karnawati, 2006), where the area of the landslide is a function of the volume for the landslide type of rock mass fall.

$$V = 0{,}00048\ A^{1{,}76} \tag{1}$$

Eq. (2) proposed to estimate the volume of landslides that occurred based on the landslide area with a determination coefficient value of 0,99 and can be used in any region because the data sources come from various regions of different countries (Amirahmadi et al., 2016).

$$V = 2{,}482\ A^{1{,}024} \tag{2}$$

A total of 59 landslides in Indonesia during 2015-2021 were used in this study. The data obtained from the PVMBG, the reports were processed by interpreting existing image data with the parameters required in the analysis, as shown in Fig. 1. The data in **Error! Reference source not found.** obtained includes the height of the slope (H), the landslide travel distance (L), and the slope angle (θ).

Table 2. Landslide data recapitulation (PVMBG, 2021)

No	Location	θ (deg)	H(m)	L(m)	A (m2)	No	Location	θ (deg)	H(m)	L(m)	A (m2)
1	Ngentos	28	34	164	8400	35	Saguling	40	4	17	4532
2	Kalijering	22	99.4	480	44757	36	Ciloto (Desa Sindanglaya)	60	10	75	-
3	Cimanggu	15	40	140	4000	37	Karangkobar (Desa Slastri)	41	10	100	-
4	tegalrejo	32	13	75	2531	38	Cisarua (Desa Batulayang)	53	15	130	-
5	Sidosari	25	5.4	30	276	39	Arjasa (Dusun Rayap)	41	20	60	-
6	basongan	45	2.6	30	360	40	Nanggung (Kp. Ciguha)	25	10	31	-
7	Kemloko III	34	9	40	7.14	41	Desa Malasari	35	9	30	-
8	Semen	28	95	490	20825	42	Pandanarum (Hutan Pinus)	52	42	200	2100
9	Parongpong	48	18	56.75	3188	43	Pacitan (Desa Ponggok)	59	100	283	118920.7
10	Cimagrib	25	30	70	14738	44	Dusun Jati, Arjosari	30	89	105	-
11	Urug	20	35	200	27918	45	Dusun Buyutan, Punung	25	113	320	-
12	Nglegok	26	7	106	-	46	Dusun Ngasem RT1	35	36	107	-
13	Margalaksana	27	27	67	7160	47	Nanggung (Kp. Citalahab)	60	2	10	-
14	Cibeber	30	13	50	1639	48	Gedangsari	30	2	15	-
15	Cikalong Wetan	50	10	30	1448	49	Dusun Wage, Cilebak 1	40	11	48	-
16	Kayangan	60	20	60	7695	50	Dusun Wage, Cilebak 2	40	5	17	-
17	Cipanas	60	40	101.2	1245	51	Desa Kenteng, Sempor	30	40	196	7539.84
18	Onan Rungu	78	10	36	-	52	182. Desa Donorati	15	8	22	-
19	Patrang (Mojan)	35	19	110	1889	53	183. Kampung Karanganyar	30	10	20	-
20	Jelbuk	50	4,5	24	228	54	183. Jalan Puspahiang	40	8	12	-
21	Arjasa	45	5	36	850	55	193. Desa Salopa	45	18	105	-
22	Cipanas	60	10	30	-	56	194. Desa Cipelah	35	5	40	-
23	277. Desa Cijulang	40	2.8	23	-	57	271. Desa Leuwibatu	28	50	168	-

Table 3. Landslide data recapitulation (PVMBG, 2021)

No	Location	θ (deg)	H(m)	L(m)	A (m2)	No	Location	θ (deg)	H(m)	L(m)	A (m2)
24	286. Desa Songa B	60	35	125	4600	58	272. Desa Cicangkang	23	35	76	-
25	290. Jln Nasional Kab. Majalengka	70	7	19.5	-	59	Jalur Sukaraja-Cikatomas	35	5	50	-
26	Kampung Suwidak	22	84	290	-	34	Karang Kencana	45	75	375	-
27	Kp. Bulukuning	10	2.5	10	-	A	tempuran	30	14	400	5508
28	Kp. Cibeureum	20	45	200	-	B	Karangkancana	45	75	375	-
29	Kampung Cibitung	45	10	30	-	C	Ciniru (Babakan)	36	52	305	-
30	Tegal Panjang	40	16	80	4080.5	D	Tegalombo (Desa Ploso)	30	40	180	-
31	Karangkancana	45	75	375	-	E	192. Kampung Cibojong	30	10	50	-
32	Karangkancana	29	35	125	-	F	192. Dusun Cisarua	30	20	90	-
33	Kebonagung	51	54	100	-						

The empirical model describes the travel distance of landslides based on the relationship between parameters obtained from observations of landslide events in the field but this model results in unclear interpretations. It needs geometric, geomorphological and volume change approaches to reduce the errors of the resulting model (Hungr et al., 2005). Empirical models for landslide prediction have been developed in many studies, including (Legros, 2002), which analyzed 203 landslide events and debris flow, which showed that the travel distance is directly proportional to the volume in the best prediction model. (Guo et al., 2014) analyzed 54 landslide events due to the Wenchuan earthquake showing that the rock type that makes up the slope, the volume of the landslide source, and the slope transition (β) are the main factors affecting the runout distance of the landslide. (Devoli et al., 2009) analyzed 367 landslide events and concluded that landslide mobility (H/L) is a function of volume (V). (Qarinur, 2015) analyzes landslide incidence in Indonesia until 2013 and proposes that the landslide distance is a function of the slope height in the best model.

3. RESULT AND DISCUSSION

The relationship of the parameters under review is obtained by plotting the data in scatter graph according to Fig. 2, where the relationship of the parameters under review is following the diagonal line, so it can be said that the residual value is usually distributed so that this regression model meets the assumption of normality.

The Heteroscedasticity test was also carried out on the input parameters for analysis as shown in Fig. 3, which shows the data points spread above and below point 0 on the X and Y axes and do not form a particular pattern, and it can be concluded that there is no heteroscedasticity symptom.

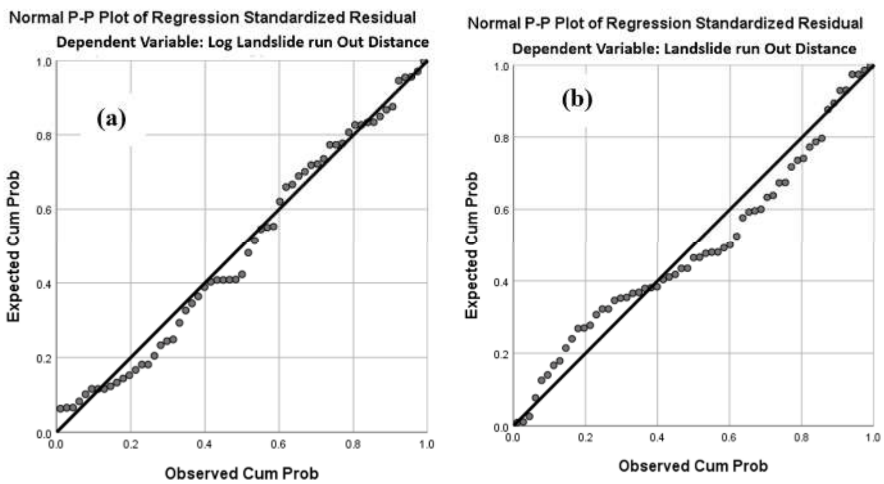

Fig. 2. Normality test of the relationship (a) H vs. L, (b) H, θ with L

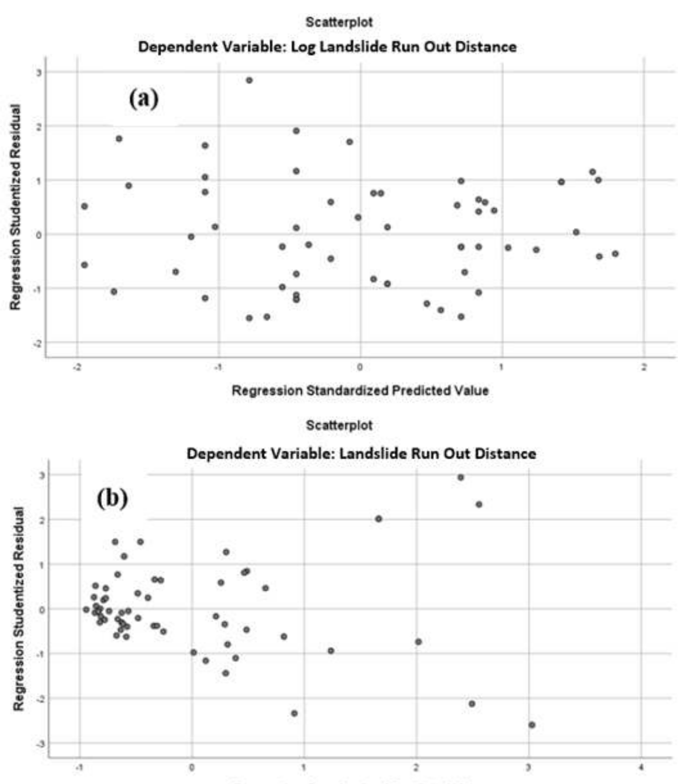

Fig. 3. Heteroscedasticity test relationship (a) H vs. L) (b) H, θ and L

The best numerical model from the statistical test is obtained if it meets the normality test, heteroscedasticity, the p-value is less than 0,005, which means that the regression model is appropriate. The T-test results in the value of tcount > ttable, indicating that the independent parameters affect the dependent variable. This study is limited to the effect of the geometric parameters on travel distance. The only parameters to be reviewed are the slope angle and the height of the slope. In the landslide distance model with a view of the height of the slope, a model is produced according to Eq. (3), where the model produces a coefficient of determination of 0,845 with a p-value 0,00 < 0,005, which means that the regression model is appropriate, the value of tcount > ttable is 17,648 > 2,003 which shows that the variable slope height affects the landslide distance.

$$Log\ L = 0{,}84 + 0{,}840\ Log\ H \text{ or } L = 6{,}918\ H^{0{,}840} \quad (3)$$

In the model that takes into account two independent variables of slope geometry that affect the travel distance, namely the height of the slope (H) and the slope angle (θ), the coefficient of determination is 0,843, the p-value of p-value 0,00 < 0,005 shows that the two variables under review have an effect to the landslide distance (H) the regression model has been appropriately used. Meanwhile, the tcount value on the effect of landslide height (H) is 17,022 > 2,003, which means that the landslide height affects the travel distance, meanwhile on the slope parameter (θ), the ttable value is equal to 0,779 < 2,003, so it shows that the slope angle parameter (θ) does not have a significant effect on the travel distance of the landslide. An empirical model that shows the relationship between landslide distance (L) with height (H) and slopes angel (θ) according to Eq. (4) as shown below,

$$L = 15{,}693 + 3{,}688\ H + 7{,}01\ tan\theta \quad (4)$$

The model in Eq. (4) shows that the geometric parameter in the form of the slope does not affect the travel distance of the landslide that occurs so that from the geometry factor that is reviewed, only the height of the slope has a significant effect on the landslide runout distance.

Although the coefficient of determination shows a strong relationship between the landslide distance parameters and the slope height, it is necessary to conduct a model test on field measurements using Eq. (5).

$$\frac{(L_{predicted} - L_{observed})}{L_{observed}} x100\% \tag{5}$$

Testing the proposed model is very difficult because validation using back-to-back analysis using post-hoc parameters only proves the model's adaptability (Iverson, 2003). In this study, the modeling results can be seen in Table 4, which shows the average error of the test. The model is done by comparing the proposed model with the field measurement data in **Error! Reference source not found.** points A to F, where the landslide prediction model proposed in this study produces a smaller average error value than the other proposed methods.

Table 4. Comparison of landslide runout distance prediction models

Predicting Model	Data Source	Researchers	Average Error for 6 Surveyed Landslides
$L = 6{,}918\ H^{0{,}840}$	59 Landslides	This paper	29 %
$L = 2.672\ H – 208.31$	32 landslides	Guo, et. all., (2014)	209 %
$L = 1{,}066\ H^{1.093}$	106 Landslides	Qarinur (2014)	74 %

Moriwaki (1987) states that the slope of the slope affects landslide mobility (Moriwaki, 1987). However, in modeling the landslide mobility (H / L), the coefficient of determination for the model is 0,091, as shown in Fig. 4. The parameter of slope angel has a weak relationship with landslide mobility. The significance value of 0,142 > 0,005 means that the selected regression model does not accurately describe the relationship between variables. The value of tcount 1,519 < ttable 2,069 means that the variable of the slope angel has no significant effect on the variable of landslide mobility.

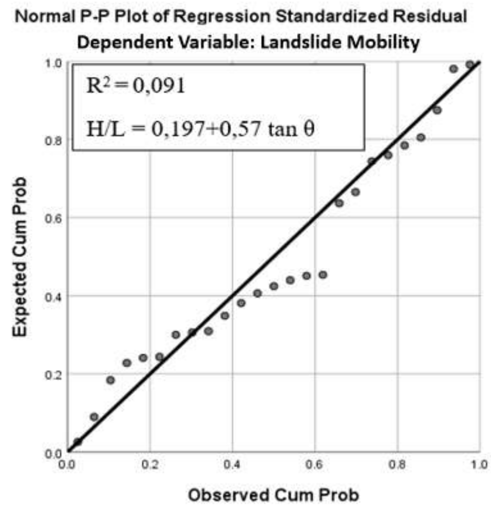

Fig. 4. The relation between landslide mobility (H/L) and slope angle (θ)

The landslide runout distance is entirely influenced by the source, not the height of the slope (Legros, 2002). Fig. 5 (a) the effect of landslide volume (V) on landslide runout distance (H) results in a coefficient of determination of 0,442, which shows the relationship between variables at a moderate level with a significance value of 0,000 > 0,005 means that the regression model chosen is suitable to describe the relationship between variables. The value of tcount 4,270 > ttable 2,069 means that the landslide volume variable has a significant effect on the variable landslide mobility where the landslide volume data is obtained from the approach according to Eq. (1). At the same time, Fig. 5 (b) shows the analysis results for the volume of landslides using Eq. (2), where the coefficient of determination shows the relationship between the landslide volume and the landslide runout distance has a moderate level of 0,442. From the model between the landslide runout distance (L) to the volume of landslides (V), it has a moderate effect on the relationship between the variables, which is much lower than the coefficient of determination resulting from the relationship between the landslide runout distance variable (L) and the slope height (H), so that the variable slope height has a strong influence compared to the volume of landslides on the length of the landslide.

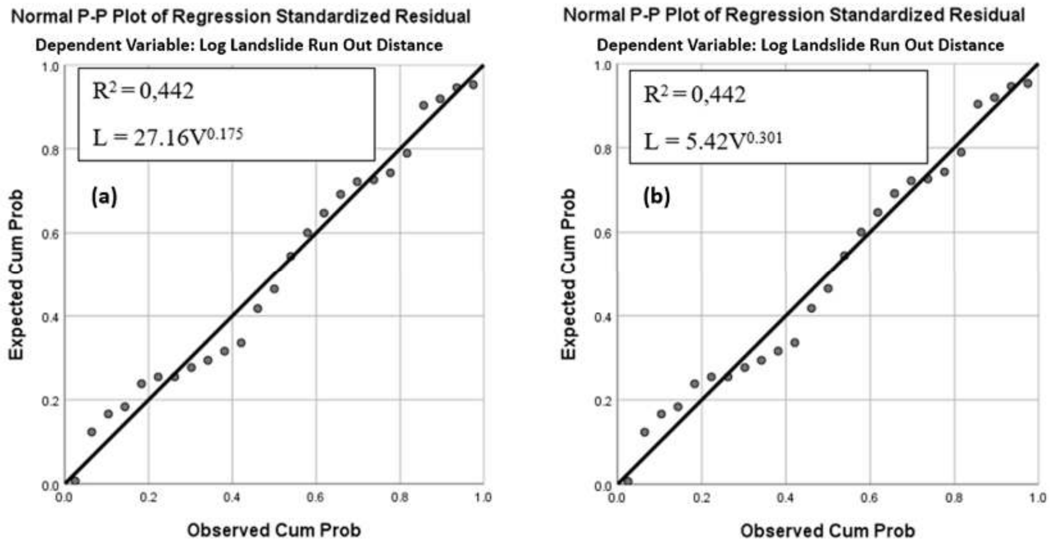

Fig. 5. The relation between landslide runout distance with landslide volume (a) according to Eq. 1 (b) according to Eq. (2)

4. CONCLUSION

Slope height is the main factor that affects the landslide runout distance that occurs compared to the volume of landslides, while the slope angle does not significantly affect the travel distance of the landslide that occurs. Based on the analysis, the best model for predicting landslide runout distances is $L = 6{,}918\ H^{0{,}840}$, with an average error of 29% compared to field events.

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Moriwaki, of the Runout Distance of a Debris • X ˜ e Š ° * Hiromu M0RIWAKI Synopsis An analysis of the landslide data, shows that there exists a linear relationship between the " runout height/runout distance " and the " tangent of slope in the source area, "whic, (1987).