New empirical-statistical tools for the analysis of rock avalanche runout

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ABSTRACT
Rock avalanches are important geohazards to consider in mountainous terrain. Rock avalanche mobility is often characterized using the ratio of the elevation difference and horizontal distance between the crest of the source zone and distal toe of the deposit, H/L. A general inverse correlation between rock avalanche volume and H/L has been found by several researchers. Regression analyses on H/L versus volume data has been performed for rapid, probabilistic estimates of rock avalanche runout. In the present study, previously-published rock avalanche datasets have been supplemented with a new compilation of 48 previously-published Canadian case studies. A computer-based tool has been developed to allow users to digitize a runout path and estimate probability of runout exceedance bounds for a given volume, or the volume required to obtain a given probability of exceedance, using any of the compiled datasets for the statistical analysis.

RÉSUMÉ
Les avalanches rocheuses sont des aléas géologiques importants dans les régions montagneuses. La mobilité des avalanches rocheuses est souvent caractérisée par le rapport entre la différence en élévation et la distance horizontale entre la crête de la source et extrémité du dépôt, H/L. Par le passé, une corrélation générale inverse entre le volume des avalanches rocheuses et leurs valeurs de H/L fut décrite par plusieurs chercheurs. Des analyses de régression entre H/L et les données volumétriques ont été conduites pour fournir un estimé initial de la distance de parcours possible d'une avalanche rocheuse. Dans l'étude présente, une banque de données existante fut augmentée par une nouvelle compilation de 48 études de cas Canadien publiées indépendamment précédemment. Un outil-informatique fut développé pour permettre à l'utilisateur de numériser une trajectoire de parcours et d'estimer la probabilité qu'un parcours excède une limite pour un certain volume ou le volume requis pour obtenir une probabilité de dépassement spécifique, en utilisant une des banques de donnée compilées dans cette étude pour les analyses statistiques.

1 INTRODUCTION

Rock avalanches are important geohazards to consider in mountainous terrain, despite their relatively infrequent occurrence, because they can travel long distances and result in complete destruction along their travel path. Rock avalanches are an extremely rapid (>5 m/s), massive, flow-like motion of fragmented rock from a large rock slide or rockfall (Hungr et al. 2014). Members of the public and infrastructure are exposed to rock avalanche hazards, and decision makers are tasked with determining whether or not the associated risks are tolerable, or even credible. Runout analyses are used to estimate the zone of impact of a rock avalanche and help with land-use and evacuation decisions.

Often it is advantageous to make probabilistic estimates of runout to better communicate the range of possible outcomes, and the uncertainty around these predictions. A probabilistic estimate is especially important if the objective is to quantify and evaluate the risk to people and infrastructure. This paper presents a screening level rock avalanche runout prediction tool that uses a compilation of previously published rock avalanche runout datasets and a newly compiled dataset from western Canada to generate probabilistic runout estimates.

1.1 Objective

The objective of this work is to provide a simple, screening level prediction tool for rock avalanche runout. To achieve this objective, a dataset of rock avalanche events from the western Canadian cordillera was compiled to augment existing runout databases. A predictive tool has been developed to allow for visual representation of the potential hazard estimated from statistical analysis of the runout dataset(s).

In the future, the goal is to make the compilation of events freely available in an online database, to allow new case studies to be added along with additional descriptive details of the events, allowing more refined estimates to be made as more information becomes available. The work supporting this objective is ongoing with various platforms currently being evaluated.

1.2 Empirical Runout Analysis

Empirical runout models can be used to perform slope risk assessments and aid land-use decision making and emergency response in mountainous regions. In situations where a project is in its initial development stage or during the management of emergency situations, the time, data, and cost necessary for conducting a detailed mechanistic analysis is not practical. Detailed field investigation and

numerical modelling of site-specific conditions that could influence rock avalanche runout is appropriate at later stages of the project development, or when high consequence scenarios have been identified.

The earliest empirical runout relationship was developed by Heim (1932), who proposed that the distance a landslide will travel is proportional to its volume. He defined a "fahrböschung" angle, which is the tangent of the ratio of fall height (H) to horizontal runout distance (L) between the crest of the source zone and toe of the deposit (Figure 1). It was postulated that the effective friction coefficient of the sliding mass is equal the ratio of vertical to horizontal displacement by equating energy loss to work done (Heim 1932).
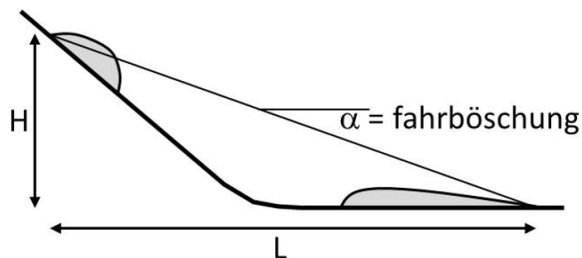

Figure 1. Fahrböschung angle definition, where H is the elevation difference between the source zone crest and toe of the runout and L is the plan distance between the source zone crest and toe of runout (after Heim, 1932).

Several authors have built on Heim's (1932) work to incorporate effects of path morphology, landslide type, and other independent variables such as runout length, excessive travel distance, inundation area, and potential energy. Whittall et al. (2017) demonstrated that when external influences such as path morphology and liquefiable substrate are controlled, volume-based fahrböschung angle relationships provide the most reliable runout estimate. This paper builds on volume-based runout relationships developed by Scheidegger (1973), Li (1983), Corominas (1996), and Hermanns et al. (2012). For consistency with these authors, the H/L vs. V relationship presented in this paper is in log-log space and volume is presented in terms of million cubic metres (M m^3).

2 METHODOLOGY

The two primary components of this work are the compilation of a dataset of western Canadian rock avalanches and the development of a computer-based probability of exceedance (P(E)) calculation and visualization tool for rock avalanche runout.

A literature review was conducted for published case histories of rock avalanche events in western Canada. To be included, an event needed to be primarily bedrock in the source zone and have a minimum event volume of 0.1 M m^3. Rock avalanche events were characterized primarily by their ratio of height versus length (H/L) and their deposit volume. The published values of H/L were compared with values estimated in Google Earth or from air photo analysis. In a few instances, modifications to the published values were made.

The Canadian examples were further characterized by attributes including: topographic constraints, substrate, source geology, and failure mechanism where information was available. Specific attributes used in the dataset are summarized in Table 1. The values of these attributes are intentionally general, so that key differences are highlighted, but statistically significant sample sizes will remain. The intention of this further classification is to potentially identify sub-trends within the data (similar to Whittall 2015), which may allow for more refined estimates of runout distances. Rock avalanches that moved across glaciers have not been included in this study at this time due to their distinctly greater mobility, as demonstrated by Evans and Clague (1988).

Table 1. Attributes and values used in Canadian rock avalanche dataset

Attribute	Possible Values
Topographic constraints[1]	Deflection, opposing wall, confined, or runup
Substrate	Fine grained soils, coarse grained soils, talus, colluvium, or bedrock
Source geology	Weak/highly weathered rock, or strong/fresh rock

[1]Adapted from Corominas (1996)

The screening level runout prediction tool uses the variation within the dataset as a proxy for the uncertainty in the runout distance for any given event. A linear regression with prediction intervals is fit to the data, assuming the statistical assumptions for a linear regression are valid (e.g. normally distributed errors about an unbiased mean). The logarithm of both the H/L ratio and volume is used to linearize the relationship, and for consistency with other authors as mentioned previously.

The analysis can be run in two ways. The first is to find the probability of runout exceedance along a user-defined path for a given rock avalanche volume, referred to as a path analysis. This type of analysis could be applied if a potentially unstable source zone was identified, and there was a need to estimate a probable inundation area. If a frequency-magnitude relationship is available for the source zone, this analysis can also be used to estimate encounter probabilities along the potential runout path. The second version of the analysis is to calculate the volume to obtain a certain probability of runout exceedance at a point along the runout path, referred to as a point analysis. This analysis could be used to estimate the credibility of a hazard, i.e. if the minimum volume for a certain P(E) is greater than the volume of the source zone, it is not credible. The graphical representation and statistical analyses have been implemented in RStudio (R Core Team 2015).

The workflow for the program is summarized in Figure 2. Both analysis methods start the same way, with a digital elevation model (DEM) and with northing and

easting values in metres entered by the user. The DEM is read into the program, and a hillshade is generated, onto which the user digitizes a runout path. The program extracts the elevation data from the DEM at each digitized point, and calculates the 2D profile to obtain the change in elevation from the top of the path to each digitized point (H), and the path distance (L) in metres.

For the path analysis, a potential landslide volume, in millions of cubic metres (M m^3), is entered by the user. A linear regression is generated for the user selected rock avalanche dataset in log-log space, and the H/L values for the target prediction intervals are calculated iteratively, then transformed out of log space. The points on the digitized path on either side of the calculated H/L values are then used to linearly interpolate the coordinates of the probability of exceedance point along the digitized path found in the analysis. The first digitized point has an undefined value for the H/L ratio, thus it is assigned a value of one for interpolation purposes. Once the points are found on the 2D profile, the equivalent points along the 3D path are found and plotted on the topography.
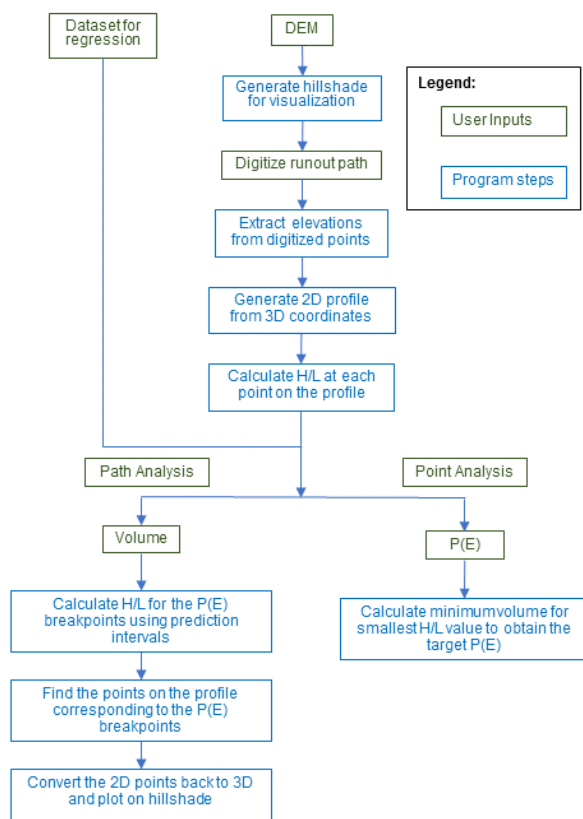

Figure 2. Flowchart showing the workflow for the path and point analyses.

The critical volume to obtain a specified probability of exceedance at a point can be found by entering the target probability of exceedance once the profile has been defined. The volume is varied iteratively until the prediction interval for the volume and the H/L value at the end of the digitized profile matches the target probability of runout exceedance.

3   DATABASE

A comprehensive public-domain literature search returned 48 previously published rock avalanche case histories in western Canada. Using the published values, augmented with analysis of aerial imagery, H/L, volume, and topographic constraints have been gathered for each case.

Topographic constraints are grouped into categories modified from Corominas (1996). Source geology is described in terms of fresh and strong rocks, and weak and weathered rocks based on mobility observations when liquefiable substrate and path channelization effects are removed (Whittall et al. 2017). Limited data was available for the travel path substrate. If not provided in the reference, the authors interpreted fine-grained soils, coarse-grained soils, talus, colluvium, or bedrock substrate categories from aerial photograph terrain evaluation and other local geology references.

Figure 3 is a comparison of the data from western Canada and other datasets compiled by Scheidegger (1973) (various locations), Li (1983) (Switzerland), Corominas (1996) (various locations), Hermanns et al. (2012) (Norway), Whitehouse (1981), Lee et al. (2009), McColl and Davies (2011), Barth et al. (2014) (New Zealand), and Zhan et al. (2017) (China). A comparison of linear regressions fit to each of the individual datasets - with the exception of the cases from New Zealand due to small sample size (8 observations) - and a regression fit using all available data are summarized in Table 2. As the regressions are performed on log-log transformed data, the slope, m, and intercept, b, constants in Table 2 correspond to an equation of the form:
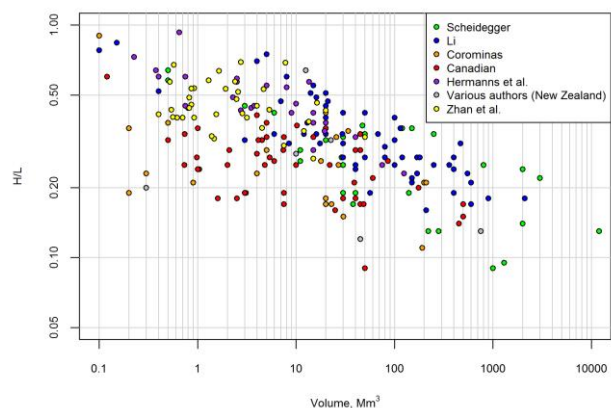
$$\log_{10}(H/L) = m * \log_{10}(V) + b \qquad [1]$$

Figure 3. Rock avalanche H/L versus event volume.

Table 2. Summary of linear regressions fit to datasets available for runout exceedance prediction

Dataset	n	m	b	R^2
Scheidegger	32	-0.155	-0.316	0.61
Li	58	-0.159	-0.237	0.61
Corominas[1]	20	-0.094	-0.520	0.25
Hermanns et al.	26	-0.181	-0.202	0.68
Zhan et al.	38	-0.057	-0.328	0.93
Canadian	48	-0.102	-0.520	0.31
All data	230	-0.129	-0.359	0.40

[1]The Bekkelaget slide was removed from the database following review of historical photos that concluded the motion was not primarily flow-like.

The collected datasets all have the same general trend of H/L being negatively correlated with volume, as shown in Figure 4. The coefficient of determination, R^2, for the regressions shows significant variation between the datasets. The R^2 values for the Scheidegger (1973), Li (1983), Hermanns et al. (2012), and Zhan et al. (2017) datasets are greater than 0.6, implying the linear model is a good fit to the data. The R^2 value for the regressions fit to the Corominas (1996) and Canadian datasets, and as a consequence, the regression fit to all available data is significantly below 0.6; which implies that the regression line alone is not a good predictor of the runout behaviour. To address the uncertainty around the predictions obtained directly from the regressions, we do not rely solely on the single value predicted by the regression line at a given volume, rather we look at the scatter about the regression, and describe the probabilities of exceedance as ranges as opposed to exact values.

The regressions fit to the Li (1983) and Hermanns et al. (2012) datasets agree well, and suggest a lower typical mobility (higher H/L ratio) than the overall regression. In contrast, the Canadian and Corominas (1996) regressions agree well, and imply higher typical mobility (lower H/L ratio) than the overall regression. The regression fit to the Scheidegger (1973) data is closest to the overall regression.

There are several potential explanations for this variation between the regressions. One potential difference is the variation in the dominant geological and physiographic conditions and topographic constraints amongst the events in each dataset. Another potential source of variation is the methodology used by the various authors to estimate event volumes and H/L ratios. The range of volumes in each database could also have an effect. For example, the Scheidegger (1973) dataset has the widest range of volumes, from 0.5 Mm³ to 20,000 M m³, and its regression line is closest to the overall regression, which is generated from a range of volumes from 0.1 Mm³ to 20,000 M m³. The regression line fit to the Zhan et al. (2017) dataset diverges the most from the others and has the narrowest range of volumes, between 0.04 M m³ and 50 M m³. The range of volumes for each individual dataset are shown graphically by the horizontal lines on Figure 4.
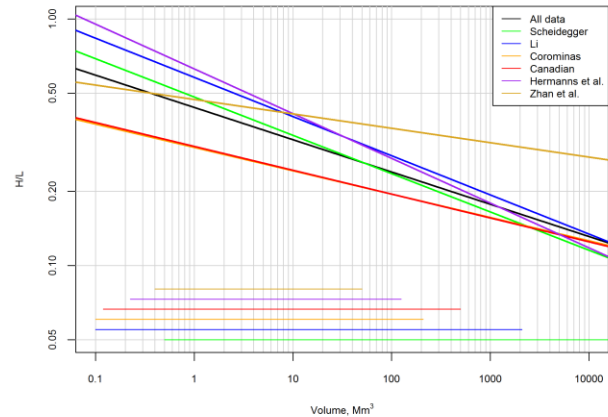

Figure 4. Comparison of the regression best-fit lines and the range of volumes for each dataset (indicated by the horizontal lines on the bottom).

Work is ongoing to present these datasets in an open-access website. An open-access format will allow researchers and practitioners worldwide to use and contribute to the data with the objective of increasing the quantity and quality of data available to perform screening level, probability-based analysis.

4   PREDICTIVE TOOL

The predictive tool allows the user to select which dataset they want to use for the regression analysis (or if all available data is to be used). The requested data is pulled in from the online database to perform the regression analysis. Two hypothetical case studies are shown to demonstrate the predictive tool.

The two examples are shown using a randomly selected site in British Columbia as a means of demonstrating the tool. Elevation data were obtained from the Canadian Digital Elevation Model Mosaic for the area between 50.178° and 50.271° north latitude and 122.739° and 122.915° west longitude, and was converted to UTM coordinates using Global Mapper v18. A volume of 2M m³ was input, and the Canadian dataset was selected. A hypothetical path was digitized from a point of high elevation, and travels down a hanging alpine valley before entering a broad river valley. The analysis was run to obtain the probability of exceedance lines shown in Figure 5.

The probabilities of exceedance are presented as ranges: greater than 0.95, 0.68 to 0.5, 0.5 to 0.34, 0.24 to 0.05, 0.05 to 0.01, and less than 0.01. The output is presented as a range of probabilities to help demonstrate the uncertainty inherent in the analysis. As this is intended to be a screening level tool, presenting the results as ranges is also done to avoid implying a higher level of precision than is warranted.
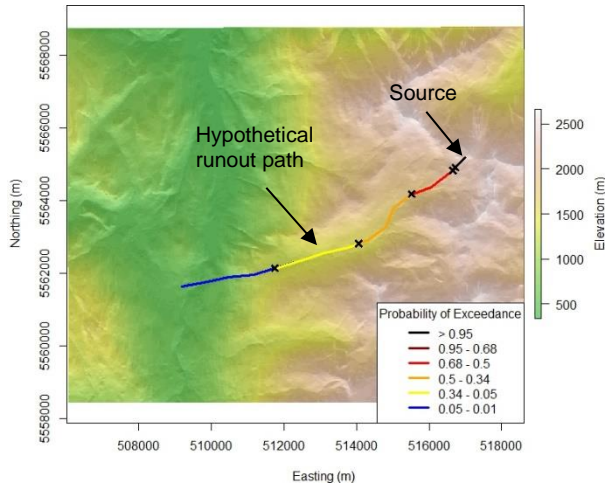
Figure 5. Probability of runout exceedance plotted along a user-specified runout path for a hypothetical 2 M m³ rock avalanche in BC.

The probability of exceedance is shown along the H versus L profile in Figure 6. It can be seen in both Figures 5 and 6 that the probability of exceedance drops rapidly moving away from the source zone as the hypothetical path transitions from the steep source zone into the more gently sloping valley. The hanging valley morphology results in a concave profile through the alpine valley, resulting in a gradual reduction of H/L. There is an inflection point at approximately 7,000 m along the profile where the path enters the river valley when the H/L values increase again before starting to decline again at approximately 8,000 m.
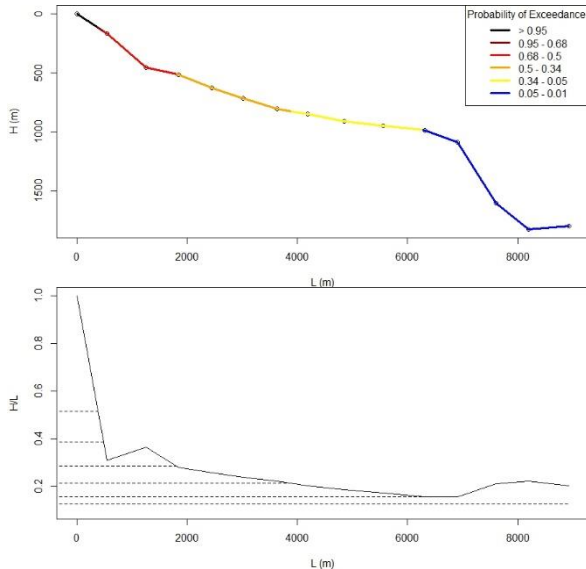

Figure 6. Probability of exceedance plotted on the H versus L profile (top), and the calculated H/L values plotted along the length of the profile. H/L values corresponding to the plotted probabilities of exceedance are indicated by the dashed lines (bottom).

Directly applying the H/L ratio can result in the probability of exceedance increasing along the profile, as opposed to a monotonic reduction moving away from the source as is expected. To address this, probability of exceedance breakpoints are only output at decreasing probabilities. For example, 0.05 probability of runout exceedance occurs at approximately 6,300 m, near the inflection point on the profile on Figure 6. Although the average slope of the profile increases further along the profile, the probability of the runout reaching that point cannot exceed a point upslope that it would have to pass to obtain that runout distance.

Using the logarithm of the H/L ratio and volume to create a linear regression with prediction intervals results in the uneven spacing between the H/L values of probability of exceedance breakpoints indicated by the dashed lines in Figure 6. Although the range of H/L values corresponding to a range of probability of runout exceedance values decreases with the H/L value, the results in Figure 5 show an increase in the length of each probability of runout exceedance segment. This is a result of the convex slope profile which results in a reduction of average slope at lower elevations.

Using the path data shown in Figure 5, the analysis was re-run to estimate the minimum size of a rock avalanche to obtain P(E) = 0.25 at the end point of the line, based on data from the Canadian rock avalanche dataset. As demonstrated with the path analysis, a concave slope profile can result in an increase in probability of exceedance for points further along the profile. To address this, the minimum volume required to achieve the specified probability of exceedance is calculated using the minimum H/L value along the profile. The volume obtained from the analysis is 27 M m³, as shown in Figure 7. For comparison, if the combined rock avalanche database is used, the minimum volume estimate is 100 M m³.
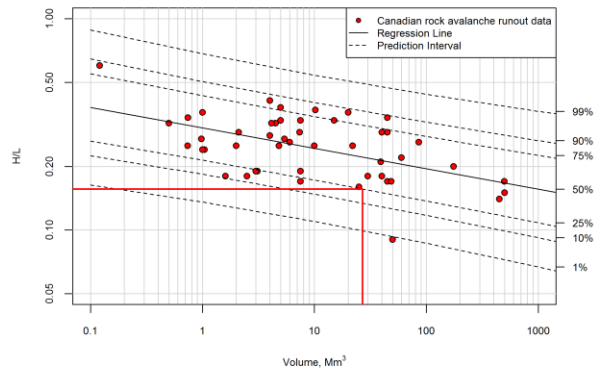

Figure 7. Estimation of the minimum volume required for a probability of runout exceedance greater than 0.25 for the end point of the hypothetical runout path shown in Figure 5.

5 CONCLUSIONS

Empirical methods remain in common usage to estimate the potential areas impacted by rock avalanche events. In many applications, such as quantitative risk assessment, a single value to predict the runout extent of a potential rock avalanche is less desirable than a range of potential outcomes. This paper is an introduction to an empirical-statistical method that uses the variability within H/L versus volume data as a proxy for the probability of runout exceedance. Data has been collected from five previously published studies on rock avalanche runout, as well as 48 cases from western Canada obtained through a comprehensive literature review and desktop mapping exercise.

Linear regressions have been fit to the H/L versus volume data, and prediction intervals are generated for each regression, including the combined dataset. These are compared to H/L values along a profile, and with a given volume, the profile is divided into probability of exceedance bounds. Alternatively, the profile can be used to estimate the minimum volume required to obtain a specified probability of exceedance at the end point of the profile.

This method has been implemented in a computer-based tool that produces runout exceedance probability ranges for a path, or calculates a minimum volume required to obtain a specified probability of exceedance at a point. The probability a rock avalanche will reach a given location along a user specified path can be found using one of five H/L vs. V relationships, or the complete dataset of 230 events.

Work is ongoing to refine the statistical model that is used for the runout exceedance probability estimation. Using parametric statistical models as opposed simple linear regression will be tested to see if a more robust estimation of the runout exceedance probability can be made, while still having a simple tool that can be applied to minimally characterized sites at a screening level.

Statistical analyses require robust datasets. Other researchers are encouraged to use and contribute to this database to continually improve the quantity and quality of the data.

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