Adjusting for uncertainty when combining runout estimates for extreme snow avalanches

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ABSTRACT

Many developments in or near snow avalanche terrain require a high-confidence estimate of dense or powder avalanche runout distance for a specified return period. In Canada, this runout is typically estimated along the centerline of the path using up to four sources: occurrence records, trim lines in vegetation, statistical runout models, and indirectly calibrated dynamic models. The uncertainty in the estimated runout distance and return period for each of these sources can vary. The proposed two-step method is largely a formal version of often undocumented methods traditionally used by some avalanche practitioners. First, each of the runout estimates is adjusted for the specified return period using models or expert knowledge. Second, each adjusted estimate is numerically weighted based on the practitioner's confidence in the estimate. Estimates with greater uncertainty are assigned lower weight according to the practitioner's lower confidence in the estimate. The combined runout estimate is the weighted average. Should substantial uncertainty remain that the runout will be exceeded for the specified return period (e.g. due to fewer runout estimate sources), a safety margin can be added. These steps in obtaining a high-confidence estimate of extreme runout distance can be documented in the report. A worked example is presented.

1. INTRODUCTION

Avalanche hazard and risk maps as well as some infrastructure planning projects require that impact pressure and hence velocity be well estimated in the runout zone of the avalanche path. The velocity in the runout zone is best obtained from an avalanche dynamic model fitted to a high-confidence runout (i.e. the design runout) for the return period required for the project and situation (e.g. T = 300 years). This design runout is commonly obtained by combining extreme runout estimates from various sources.

Up to four largely independent sources are available to estimate extreme runout in an avalanche path: occurrence records, trim lines in vegetation, statistical runout models, and indirectly calibrated dynamic models (Canadian Avalanche Association, 2002, p. 13-15; Canadian Avalanche Association, 2016, p. 25-28). Traditionally, some Canadian practitioners calculated the average of the runout estimates from these different sources, excluding the estimates in which they had low confidence. Some reports listed the sources used and then stated the design runout without explaining how it was obtained.

This paper describes a more transparent – and arguably improved – process for combining the runout estimates from different sources based on Jamieson and Campbell (2018). First, the time scale of each source is considered, and the corresponding runout estimate is adjusted to the design return period. Second, each adjusted estimate is numerically weighted based on the practitioner's confidence in the estimate. Adjusted estimates with greater uncertainty are assigned lower weight according to the practitioner's lower confidence in the estimate. The design runout – to which a dynamic model can be fitted – is the weighted average of the adjusted estimates.

Margreth (2014) and likely others have been previously mentioned numerical weighting of runout estimates. Referring to runout estimates from dynamic models, he proposed that for simple hazard situations in Switzerland that are similar to the paths used to calibrate the dynamic model, the weight applied to the estimates could be as high as 0.8. The weight would decrease to zero for complex hazard situations, especially when the model results do not fit observations or expert judgment. In North America, where statistical runout models are often used as a source of runout estimation, the weight applied to the statistical estimates would decrease similarly where the terrain and snow climate differ substantially from the paths used to calibrate the statistical models.

For many avalanche paths in Canada, extreme runouts from vegetation damage obtained from field surveys and air photos are – when available – of low uncertainty (i.e. good confidence), followed by statistical runout estimates for which uncertainty is typically moderate (i.e. fair confidence). Runouts from indirectly calibrated dynamic models are often of high uncertainty (i.e. poor confidence).

2. METHOD

As part of a book chapter, Jamieson and Campbell (2018) described the following two-step process of confidence-based weighting of runout estimates from different sources.

2.1 Step 1: Adjusting the runout estimates from each source to the relevant return period

Extreme runouts for a specific return period are often estimated based on four largely independent sources (e.g. Canadian Avalanche Association, 2002; Bründl and Margreth, 2015):

(1) Written (or sometimes oral) records of long running avalanches. In North America, the farthest recorded runout is typically extrapolated to adjust the runout to the design return period. This approach can be based on a single runout during an observation period that is often substantially shorter than the design return period. Alternatively, the runout for the design return period can be estimated by linearly regressing binned runouts on ln T, as described in Jamieson and Gould (2018). In this method, many runouts influence the regression and hence the predicted runout for the design return period.

(2) Vegetation damage identified in historical air photos, satellite imagery and field studies. Where avalanche runouts extend into forests in Canada, the trim line farthest down the path typically represents the runout of a dense-flow avalanche within the previous 50+ years. While the extent of the runout (trim line) is often measurable with low uncertainty, extrapolation of a single runout with a short time scale (e.g. 50 years) to a substantially longer return period (e.g. 300 years) may be required.

(3) Statistical models of extreme runout based on paths in the same mountain range (e.g. Lied and Bakkehøi, 1980; McClung and Mears, 1991). The return period for the paths used to calibrate the models is often 30 to 100 years. If the return period for the project is longer (e.g. 300 years), the runout estimate can be increased based on expert

judgement. Alternatively, where the return period can be estimated at a reference point in the runout zone, the runout for the design return period can be estimated using McClung's (2000) Space-Time model, which has been validated by Sinickas and Jamieson (2016).

(4) Indirectly calibrated dynamic models of extreme avalanches. Some of the older 1-dimensional models such as PCM (Perla et al., 1980) and PLK (Perla et al., 1984) yield runout estimates for a nominal return period of ~100 years. The runout can be adjusted with expert judgement for other return periods relevant to the project. Some of the input parameters for models such as AVAL-1D and RAMMS (Christen et al., 2002, 2010) have been published for specific return periods (WSL-SLF, 2005, 2017); if these are used, the predicted runout will not require adjustment.

2.2 Step 2: Combining the runout estimates based on the practitioner's confidence in each estimate

In this step, each adjusted runout is numerically weighted based on the uncertainty in the estimate, which depends on the situation, time scale of the runout estimate, and estimation method (e.g. vegetation damage, statistical model). Estimates with greater uncertainty are assigned lower weight wt_i according to the practitioner's lower confidence in the estimate. These are then combined to yield the confidence-weighted average runout (i.e. design runout) ro*:

$$\mathrm{ro}^* = \sum_i \mathrm{wt}_i \mathrm{ro}_i \,/\, \sum_i \mathrm{wt}_i \qquad [1]$$

When there are limited sources of runout estimates or all of the runout estimates lack good confidence, an "uncertainty buffer", often of 20 or more meters can be added to ro* based on expert judgment. Alternatively, a dimensionless uncertainty factor, say 1.1 could be applied to increase ro* past the reference point by 10%.

The uncertainty in the runout estimates from indirectly calibrated dynamic models warrants explanation. These models are considered indirectly calibrated because they are not fitted to an extreme runout in the path under consideration. The runouts predicted by such models depend strongly on input parameters, specifically on friction coefficients and for some models, on the release mass (or average release depth). These input parameters strongly influence runout but there has been little calibration of input parameters in Canada (Buhler et al., 2018). In western European countries such as Switzerland, some of the important input parameters have been calibrated by region and return period for the 1-dimensional model AVAL-1D (Christen et al., 2002; WSL-SLF, 2005). Also, for the 2-dimensional RAMMS model (Christen et al., 2010), the friction coefficients have been calibrated based on elevation, slope angle, slope curvature, flow volume and return period (WSL-SLF, 2017).

3. WORKED EXAMPLE OF ESTIMATING DENSE-FLOW RUNOUT

This section outlines a worked example for the dense-flow runout along the center-flow of hypothetical Path A for a 300-year return period.

It is helpful to select a reference point for the runouts along the centerline of the runout zone. In this example, the reference point is the β point where the slope angle decreases to 10° (Lied and Bakkehøi, 1980), so ro is the horizontal distance of the runout past the β point. When the runout estimate is towards the start zone from the reference point, ro is negative.

For Path A, horizontal runout estimates for various sources are shown in Fig. 1.

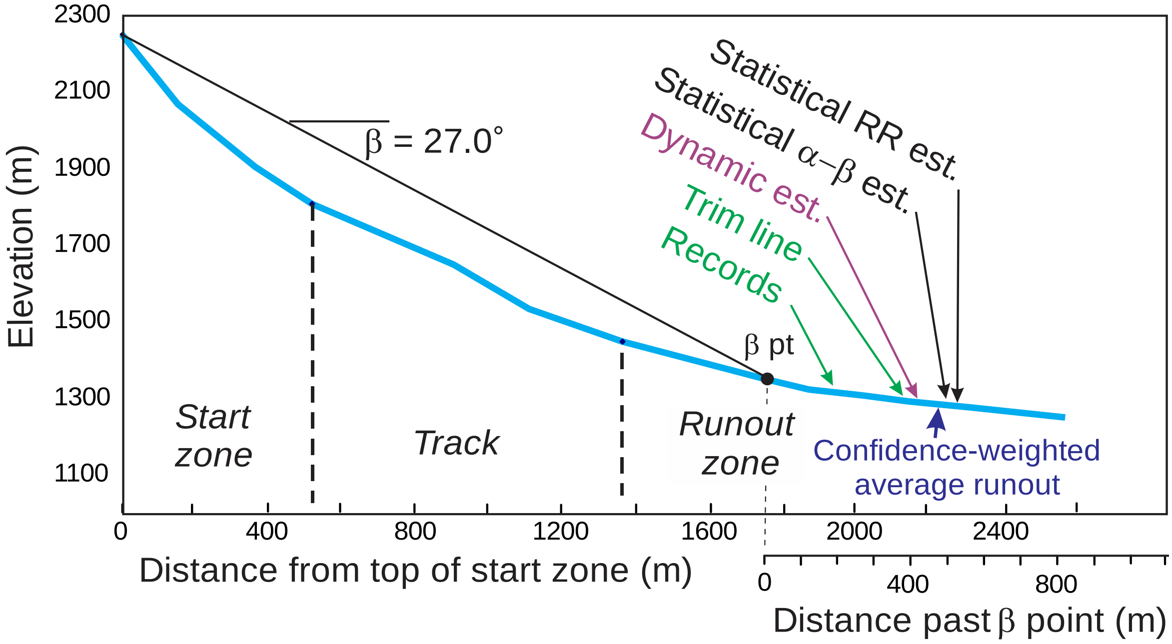

Figure 1 Hypothetical example of unadjusted dense-flow runout estimates from different sources along the centerline of an avalanche path (blue line): longest recorded runout (records), farthest vegetation damage (trim line), indirectly calibrated dynamic model and statistical models (α–β and Runout Ratio (RR)). These estimates are combined to determine the confidence-weighted average runout from a dense-flow avalanche ro* for the design return period.

The runout estimates from Fig. 1 are also given in Table 1 column 2 along with the associated time scale (column 3), which is either the return period for model estimates, or the elapsed years for the written or vegetation records. The ordinal ratings of confidence for each runout are shown in column 4. The numerical weights, wt_i, in column 5 are assigned by the practitioner based on the ordinal ratings of confidence in column 4. In this example, the weights range from 1 to 10 but other ranges of nonnegative numbers are acceptable since Eq. 1 is normalized by the sum of the weights.

In the written records of occurrences observed over 25 years, the longest runout is 200 m past the β point. The practitioner estimates that the 300-year runout would be 150 m farther, which is of poor confidence (wt = 1) since the observation interval is only 25 years long.

The forest damage (trim line) farthest along the path is 390 m past the β point. The trees just upslope of this are about 65 years old. The estimated 300-year runout is 70 m farther, which is of good confidence (wt = 10).

The α–β (Lied and Bakkehøi, 1980) and Runout Ratio (McClung and Mears, 1991) statistical methods yield runout estimates 490 and 515 m past the β point. The estimated 300-year runouts are 40 m past the runouts predicted by each of the two models. These are of fair confidence and each is assigned a weight of 3, giving these runout estimates less combined weight as the farthest forest damage and more weight than the dynamic model or the limited occurrence records.

Table 1 Dense-flow runout estimates along centerline of Path A and confidence levels for runout estimates and associated time scale. The column numbers are cited in the description of the weighting process in the text.

Column number					
1	**2**	**3**	**4**	**5**	**6**
Source of runout estimate	**Horizontal distance past β point (m)**	**Time scale: return period or elapsed time (years)**	**Confidence in runout for design return period**	**Weight wt_i**	**Horizontal distance past β point (m) ro_i (*T* ~300 year)**
Written records	200	25	Poor	1	350
Farthest forest damage from field survey and air photos	390	~65	Good	10	460
Statistical α–β model [a]	490	30 to 100	Fair	3	530
Statistical Runout Ratio model [a]	515	30 to 100	Fair	3	555
Dynamic model for dense-flow with friction coefficients	410	~100	Poor	1	440
Confidence-weighted average 300-year dense-flow runout					480

[a] To be conservative, especially for paths expected to run relatively longer than the paths used to calibrate the model parameters, a non-exceedance probability > 0.5 can be applied.

The indirectly calibrated dynamic model with a nominal return period of 100 years predicts a runout 410 m past the β point. The estimated 300-year runout is 30 m farther along the runout zone. Confidence is poor (wt = 1) because these models are sensitive to the inputs including the friction coefficients and release mass (or average release depth).

Using Eq. 1, the weighted average 300-year runout for dense-flow avalanches ro* is calculated to be 480 m past the β point. This can be used to *directly calibrate* a dense-flow dynamics model, which will yield a high-confidence estimate of velocity at any point in the runout zone.

Sections like this one can be included in reports to increase transparency.

REFERENCES

Bründl, M., Margreth, S., 2015. Integrative risk management – The example of snow avalanches. In: Snow and Ice-Related Hazards, Risk, and Disasters, Haeberli, W., Whiteman, C., (eds.), Elsevier, Amsterdam, Netherlands, pp. 263-301.

Buhler, R., Argue, C., Jamieson, B., Jones, A., 2018. Sensitivity analysis of the RAMMS avalanche dynamics model in a Canadian transitional snow climate. In: Proceedings of the International Snow Science Workshop, Innsbruck, Austria, Oct 7-12, 2018, pp. 767-771.

Canadian Avalanche Association, 2002. Guidelines for Snow Avalanche Risk Mapping and Determination in Canada, McClung, D.M., Stethem, C.J., Jamieson, B., Schaerer, P.A. (eds.), Canadian Avalanche Association, Revelstoke, British Columbia Canada.

Canadian Avalanche Association, 2016. Technical Aspects of Snow Avalanche Risk Management - Resources and Guidelines for Avalanche Practitioners in Canada, Campbell, C., Conger, S., Gould, B., Haegeli, P., Jamieson, B., Statham, G., (eds.). Canadian Avalanche Association, Revelstoke, British Columbia, Canada.

Christen, M., Bartelt, P., Gruber, U., 2002. AVAL-1D: An avalanche dynamics program for the practice, INTERPRAEVENT 2002 in the Pacific Rim, Matsumoto, Japan, Congress publication 2, pp. 715-725.

Christen, M., Kowalski, J., Bartelt, P., 2010. RAMMS: Numerical simulation of dense snow avalanches in three-dimensional terrain. Cold Reg. Sci. Tech., 63(1-2), 1-14.

Jamieson, B., Campbell, C., 2018. Avalanche mapping, in: Jamieson, B. (ed.). In: Planning Methods for Assessing and Mitigating Snow Avalanche Risk, Canadian Avalanche Association, Revelstoke, British Columbia, Canada, pp. 199-212.

Jamieson, B., Gould, B., 2018. Avalanche hazard assessment, in: Jamieson, B. (ed.), In: Planning Methods for Assessing and Mitigating Snow Avalanche Risk, Canadian Avalanche Association, Revelstoke, British Columbia, Canada, pp. 143-156.

Lied, K., Bakkehøi, S., 1980. Empirical calculations of snow avalanche run-out distance based on topographical parameters. J. Glaciol., 26(94), 165-177.

Margreth, S., 2014. Avalanche hazard assessment – application of RAMMS in practice. Presentation at the RAMMS Workshop at the 2014 International Snow Science Workshop, Banff, Alberta, Canada.

McClung, D.M., 2000. Extreme avalanche runout in space and time. Canadian Geotechnical Journal, 37, 161-170.

McClung, D.M., Mears, A.I., 1991. Extreme value prediction of snow avalanche runout. Cold Reg. Sci. Tech., 19, 163-175.

Perla, R.I., Cheng, T.T., McClung, D.M., 1980. A two-parameter model of snow-avalanche motion. J. Glaciol., 26(94), 197-207.

Perla, R.I., Lied, K., Kristensen, K., 1984. Particle simulation of snow avalanche motion. Cold Reg. Sci. Tech., 9, 191-202.

Sinickas A., Jamieson, B., 2016. Validating the Space-Time model for infrequent snow avalanche events using field observations from the Columbia and Rocky Mountains, Canada, Arctic, Antarctic and Alpine Research, 48(1), 177-197.

WSL-SLF, 2005. AVAL-1D Manual, WSL Institute for Snow and Avalanche Research SLF, Davos, Switzerland.

WSL-SLF, 2017. RAMMS rapid mass movements simulation – a numerical model for snow avalanches in research and practice. RAMMS Avalanche User Manual v.1.7, WSL Institute for Snow and Avalanche Research SLF, Davos, Switzerland.