AN AUTOMATED METHOD FOR REGIONAL AVALANCHE ALPHA-ANGLE CHARACTERIZATION BASED IN WESTERN CANADA

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ABSTRACT: The Avalanche Terrain Exposure Scale (ATES) is used to communicate spatial susceptibility to avalanche terrain (Statham and Campbell 2025). Historically, ATES maps were produced manually for small, high-use areas, however, advances in GIS, remote sensing, and automated terrain modelling now enable large-scale mapping (Jamieson and Campbell 2018; Huber et al. 2023). A new SAR-NIF project aims to produce ATES maps across Western Canada using the automated ATES (autoATES) protocol. A key component in autoATES is runout extent, calculated by the statistical runout model FlowPy. FlowPy primarily uses maximum alpha-angle, the angle between the avalanche crown and toe along the path of travel, to compute avalanche runout (D'Amboise et al. 2022; Huber et al. 2024). AutoATES v2.0 used a conservative 18° alpha-angle parameter to capture extreme runouts for all regions. However, a Coast Mountains study reported a minimum alpha-angle of 20.4°, indicating a need for regional calibration (Nixon and McClung 1993).

We propose a method for estimating regional avalanche alpha-angle parameters from operational avalanche occurrence records in western Canada. In this workflow, we use FlowPy to model an avalanche thalweg (flow path), statistically estimate a crown location, and locate a toe mass location using operational data to calculate regional alpha-angle distributions. Quality control removes unsuitable avalanche paths from statistics, reducing 153 initial paths to 40 retained. Across retained paths, alpha-angles ranged 21° to 56° for Bear Pass and 24° to 50° for Duffey Lake. Mean alpha-angles were 32° in both regions. The Bear Pass minimum closely matched the 20.4° Coast Mountains minimum, but other results differed (Nixon and McClung 1993). The absence of start-zone data, the operational nature of the dataset, and the limited number of retained paths introduce substantial uncertainty. However, the program can easily accommodate new datasets, improved thalweg routing, or the implementation of alpha-beta or runout-ratio regression models.

KEYWORDS: Automated Avalanche Terrain Mapping; FlowPy; Runout Simulation; Model Validation; Alpha-Angle

1. INTRODUCTION

Avalanche terrain maps have traditionally supported hazard management and land-use planning but are increasingly being used to communicate terrain severity to recreational users and workers (Harvey et al. 2018; Jamieson and Campbell 2018; Statham and Campbell 2025). The creation of these maps has historically been restricted to small areas due to a reliance on local experts, site visits, and field surveying (Jamieson and Campbell 2018), but recently, advances in Geographic Information Systems (GIS), widespread global elevation data, and open-source modelling tools have made it possible to produce avalanche terrain and runout maps over large-scale areas (Bühler et al. 2022; Huber et al. 2023).

The Avalanche Terrain Exposure Scale (ATES) classifies avalanche terrain into 5 categories based on physical terrain characteristics (Statham and Campbell 2025). AutoATES was developed to facilitate large-scale ATES classification across large regions by modelling select physical characteristics (Toft et al. 2024). The Search and Rescue New Initiative Fund (SAR-NIF) project "Large-scale avalanche terrain exposure scale mapping for mountainous regions in Canada" of the Simon Fraser University Avalanche Research Program aims to develop the novel, open-source autoATES v3.0 model chain and produce ATES maps for recreationalists spanning every avalanche forecast region in western Canada.

The open-source AvaFrame:com4FlowPy (generally referred to as FlowPy) runout model is a central component of the autoATES modelling chain used to simulate avalanche flow and overhead exposure (Sykes et al. 2026). FlowPy is a statistical avalanche model that simulates avalanche flow based primarily on user-defined runout and forest friction parameters (D'Amboise et al. 2022; Huber et al. 2024), which are calibrated purely from observed avalanche runout records. In contrast, dynamic avalanche models use simplified physics equations and location-specific friction coefficients and mass as parameters calibrated from detailed localized datasets, but these types of datasets are typically not available for large-extent map-

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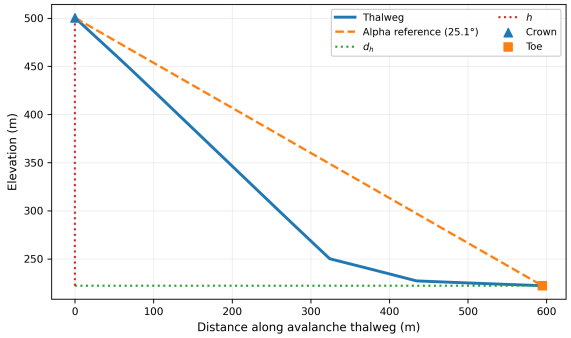


Figure 1: Alpha-angle geometry.

ping in North America (Jamieson et al. 2018a; Jamieson and Campbell 2018). Due to the simplicity and accessibility of the FlowPy model, large areas have been mapped at a very low computational cost in Austria, Norway, Canada, Switzerland, the Pyrenees, and Bulgaria supporting public-facing avalanche terrain hazard decision-support systems globally (Huber et al. 2023).

Maximum-extent alpha-angle is a key FlowPy parameter for computing runout scenarios in autoATES (Sykes et al. 2026). Alpha-angle is the angle formed between the highest point of an avalanche's crown and the lowest point of its runout along an avalanche thalweg (Figure 1; Jamieson, 2018). An avalanche thalweg is the 3-dimensional path an avalanche took from its crown to its toe (Spannring et al. 2026). Avalanche runouts and alpha-angles have an inverse relationship, where lower alpha-angles indicate larger relative runouts. In FlowPy, the alpha-angle provides a baseline for maximum runout estimations and forest and terrain factors may lessen the extent depending on path geometry (D'Amboise et al. 2022; Huber et al. 2024).

Actual recorded alpha-angle distributions vary between avalanche paths, influenced heavily by path geometry and forest conditions, but consistent behavior can be observed between paths in a region (Jamieson et al. 2018b). The regional applicability of statistical runout models is supported by significant historic observations suggesting that, when scaled properly, avalanche runouts form characteristic distributions within mountain ranges (McClung and Mears 1991; Nixon and McClung 1993; Jones and Jamieson 2004; Johnston et al. 2012).

AutoATES v2.0 uses a conservative 18° alpha-angle parameter in FlowPy to ensure a margin of safety for user-oriented hazard products (Sykes et al. 2026). However, this approach has the potential to lead to unnecessarily conservative runout estimates in regions with higher local alpha-angles. To address this challenge for autoATES v3.0, we are presenting a partially-automated method for calculating regional avalanche alpha-angle parameters based on an operational dataset in western Canada. Using a 5-step workflow, we calculate avalanche thalwegs to create an alpha-angle distribution for each path and region using estimated runout locations. Resulting distributions could be used to derive input parameters for autoATES v3.0 (Sykes et al. 2026). These parameters characterize typical and infrequent runout scenarios that are integral to distinguishing avalanche hazard in a region for autoATES.

2. METHODOLOGY

2.1. Study Regions

Our study regions are the highway corridors of Bear Pass (B.C. Highway 37A), near Stewart, B.C., and Duffey Lake (B.C. Highway 99), near Pemberton, B.C. The avalanche risk along these highway corridors is actively managed by the Avalanche Safety Program of the British Columbia Ministry of Transportation and Transit (BC-MoTT). Local teams of avalanche safety technicians monitor conditions and avalanche activity throughout the winter and manage the associated risk with temporary avalanche safety measures such as the proactive triggering of avalanches with explosives and temporary closures when necessary.

Bear Pass is located within a maritime snowpack (Shandro and Haegeli 2018) and is characterized by complex, up to 2000-meter-long avalanche paths spanning from sea level to 2300 meters. Start zones occasionally include glaciers, icefalls, and seracs. Dense forests give way to rugged terrain around 1000 meters in elevation. Bear Pass has a total of 90 identified avalanche paths, of which 76 affect the road.

Duffey Lake is located in a transitional snowpack (Shandro and Haegeli 2018) and is characterized by consistent, up to 1000-meter-long gullies spanning 600 to 2300 meters along many long, straight ridgelines. Moderately dense forests give way to gentle alpine terrain around 1800 to 2000 meters. Duffey Lake has a total of 114 identified avalanche paths, of which 77 affect the road.

2.2. Dataset

BC-MoTT has recorded avalanche occurrences at both of our study sites since the 1970s. Observation rates vary between paths from over 10 times a year to a few times a decade. The Bear Pass

dataset contains 30,784 occurrences, while the Duffey Lake dataset contains 4,068 occurrences. Each occurrence record has a "Toe Mass Distance" observation, the measure BC-MoTT uses to describe the distance from the highway fog line, the painted line delineating the shoulder, to the bottom of an avalanche's debris pile. Toe Mass Distance is treated as a signed distance from the highway reference measured along the terrain profile and provides an approximate location for the bottom of the avalanche for alpha-angle calculation. Additional avalanche occurrence attributes recorded include avalanche size, avalanche moisture, deposit length, depth, and width.

FlowPy requires elevation, forest cover, and potential release area (PRA) rasters to compute avalanche runout (Huber et al. 2023). We use the ALOS global 30-meter digital surface model (DSM), Sentinel-2 canopy cover data, and a PRA raster generated through the autoATES workflow for this method (Toft et al. 2024). The DSM controls FlowPy's path-routing through terrain and persistence factors, which represent terrain-interaction and momentum respectively (D'Amboise et al. 2022). Forest cover data is used to apply friction and detrainment functions which reduce modelled runout distance in forested terrain (Huber et al. 2024). The PRA raster shows which pixels avalanches are allowed to originate from by ranking the likelihood of release based on slope, curvature, and forest factors (Toft et al. 2024).

In addition, our method for identifying likely avalanche thalwegs also requires avalanche path polygons, B.C. highway polylines, and PRA segment polygons. We received avalanche path polygons from BC MoTT, which outline the full extent of the avalanche path and extend from the top of the path to the highway intersection. B.C. highway polylines, which we downloaded from the provincial iMapBC database, show the centerline for each avalanche-controlled highway. A buffer of 3.5 meters was applied to this centerline to estimate the fog line for each side of the highway based on standard lane width (Government of British Columbia 2021). The buffer line closer to the avalanche path is used for each path. PRA segment polygons are derived from the PRA raster that comes from the autoATES workflow, representing individual start zones within an avalanche path (Sykes et al. 2026).

2.3. Estimating Alpha-Angle Distributions

Connecting the top of the start zone with the final runout location through an avalanche's thalweg allows for the calculation of alpha-angles for each occurrence and the creation of regional distributions. While recorded toe mass distances projected along the avalanche thalweg provide a reliable estimate for the location for the bottom of each recorded avalanche, start zone information is too sparse and coarse to estimate reliable locations for where each avalanche started. This poses a serious challenge for working with our analysis dataset. To still be able to take advantage of our datasets and estimate regional alpha-angles, we created a Python program with five main processing steps. While the first three steps are automated and executed for each avalanche path individually, Steps 4 and 5 are completed at the regional level and require manual inspection. Steps are:

(1) a pre-processing step, which prepares all the necessary files,

(2) a thalweg calculation step, which predicts likely avalanche flow paths,

(3) a thalweg selection step and alpha-angle calculation step, which chooses the most likely modelled start-zone and corresponding thalweg,

(4) a quality control step, where insufficient paths are removed, and

(5) an automated analysis step, where figures and statistics are generated.

2.4. Path-Level (1): Pre-Processing

Pre-processing prepares the inputs by clipping the regional rasters and vectors to the extent of the avalanche path and reprojecting and aligning inputs to the projection of the DSM.

2.5. Path-Level (2): Thalweg Generation

For thalweg generation, the FlowPy model is used to simulate avalanche runout with a raster representing avalanche flow. Post-processing filters are applied to convert this raster to a basic thalweg vector network, before aligning and extending the endpoint of each thalweg network in the path. The result of this section is a set of candidate avalanche thalwegs (Figure 2). A similar novel method calculates avalanche thalwegs during each routing step in the FlowPy process rather than in post-processing, creating an avenue for future thalweg comparisons (Spannring et al. 2026).

Runout Modelling In this step, FlowPy is run using a very low alpha-angle parameter of 10° to model each path's thalweg from its maximum runout. A key FlowPy output for determining

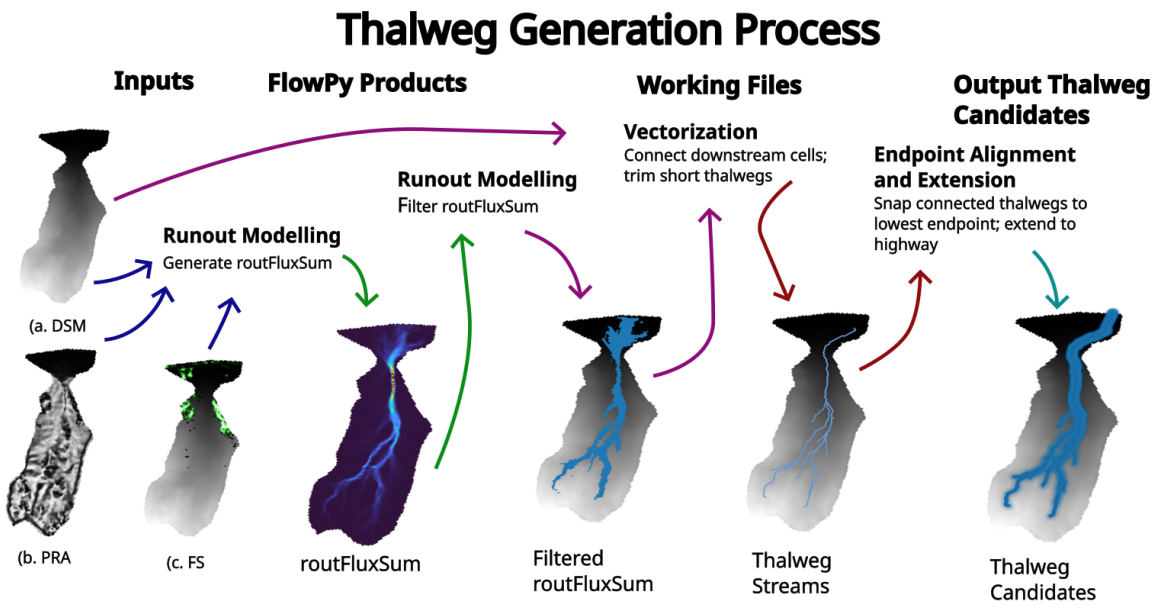


Figure 2: Thalweg generation workflow for Cornice, Bear Pass.

runout shape is routFluxSum, a raster representing the amount of modelled avalanche "flow" or flux through each pixel. A binary filter is applied to routFluxSum, keeping cells where the flux is greater than 50. For paths where the maximum flux is less than 100, cells are kept wherever the flux is more than half the maximum path flux, thus demarcating pixels of high avalanche flow. Thresholds were determined through testing to retain plausible avalanche routes in a path.

Vectorization Flow direction is modelled and applied to the generated binary routFluxSum layer during vectorization. A D8 flow-direction raster, a model showing which of the eight neighbor-cells each cell will flow into, is computed using WhiteBoxTools (Lindsay 2021) on the DSM. This direction raster provides the necessary connections to downstream cells in the filtered routFluxSum raster, which allows the creation of a thalweg network vector. Thalweg network vectors are composed of several thalweg candidates representing the different paths an avalanche can take.

Endpoint Alignment and Extension Each thalweg candidate is aligned to a common endpoint, then insignificant thalwegs are truncated from the network, before remaining candidates are extended to or beyond the highway. Candidate thalwegs are traced through the network toward the lowest connected endpoint. A significance filter is then applied, removing any thalweg candidates that are (a less than half the length of the longest candidate or (b) the shortest of two or more thalwegs within 60 meters. If the thalweg network does not contain geometry reaching the highway polyline, it is extended to and possibly beyond the highway over typically non-channelized, fan-like terrain. The length of the extension depends on the maximum distance required by the path's avalanche occurrences. The direction of the extension is based on the average direction in the last 100 meters of travel. If the extension climbs more than 10 meters on the opposite side of the valley before intersecting with the highway, it is removed.

2.6. *Path-Level (3): Alpha-Angle Calculation*

If exact start zones were known, they would be used to identify the relevant thalweg for the alpha-angle calculations. However, since we do not have that, relative likelihood scores are calculated from PRA segments to estimate the most likely thalwegs for the calculations. When multiple avalanche thalwegs exist within a path, the final thalweg is chosen by ranking the product of likelihood and area for the PRAs each thalweg begins in. This allows insignificant start zones to be avoided while ensuring likelihood plays the key role in selection. If this measure is tied, the PRA segment with the larger area is chosen; remaining ties are resolved by selecting the longest thalweg. The resulting final candidate avalanche thalweg is then extended in a straight line to the highest point within the PRA segment it ends in. This candidate is chosen as the final avalanche thalweg (Figure 3).

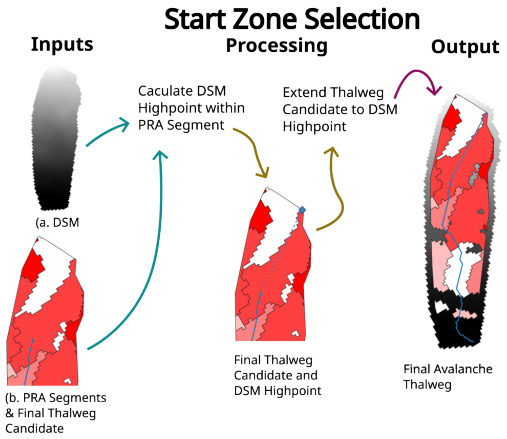


Figure 3: Start-zone selection for Cullen, Bear Pass.

With the final thalweg chosen, the elevation lost and horizontal distance travelled for each avalanche occurrence is computed. Avalanche alpha-angles are computed using

$$\alpha = \tan^{-1}\left(\frac{h}{d}\right),$$

where α = alpha-angle, h = 1-dimensional elevation difference, and d = 2-dimensional horizontal distance measured along the thalweg. Alpha-angles are calculated for each occurrence within the avalanche path, creating a path-level distribution of alpha-angles.

2.7. Region-level (4): Quality Control

After the thalweg calculations, avalanche paths are manually inspected to ensure we have a high-quality dataset for the statistical analysis. Paths that are (a) under 200 m, (b) could never impact the highway, and (c) have no clear track are discarded from the dataset. Thalwegs are manually inspected to ensure that (a) paths with too many thalweg networks starting at and/or ending in varying elevations and (b) paths with no complete thalwegs from top to bottom are also removed. Because Toe Mass Distance requires a valid highway intersection to calculate alpha-angles, remaining paths without intersection geometry are also automatically removed.

2.8. Region-level (5): Analysis

In this step statistics and visualizations are created by combining alpha-angle distributions from all retained paths in a region to produce regional distributions and visualizations. Analysis was completed using two occurrence datasets: one containing all recorded occurrences and one containing only size 3 or greater occurrences. On both the complete and filtered datasets, the minimum, mean, and maximum alpha-angle and several quantiles (0.05, 0.25, 0.50 (median), 0.75, and 0.95) are calculated for each region to capture their alpha-angle distributions and provide a point of comparison to existing literature. These regional statistics are calculated on an occurrence-weighted basis as opposed to a path-weighted basis, so each occurrence is ranked equally in the resulting distributions regardless of avalanche path. Using these distributions, avalanche thalweg plots displaying path profile over elevation and plots comparing alpha-angle over avalanche size, path, and region are generated to visualize the results.

3. RESULTS

3.1. Final Dataset

After manual quality-control steps, 35 valid avalanche paths remained for Bear Pass, while 39 remained for Duffey Lake. A final round of highway intersection validation left Bear Pass with 17 retained paths, containing a total of 5,248 occurrences, while Duffey Lake was left with 23 retained paths, containing a total of 2,588 occurrences. The Bear Pass dataset includes 50 years of records, compared to 41 years for Duffey Lake. On average, Bear Pass had 309 occurrences per path, compared with 113 occurrences per path on the Duffey Lake Highway. It is important to note that the median numbers of occurrences per path were 234 and 22, respectively. This reflects the tendency for observations to be concentrated in frequently avalanching, easily observable avalanche paths, particularly for Duffey Lake. Sixteen Bear Pass path datasets contained more than 50 occurrences, compared with eight path datasets for Duffey Lake. The Duffey Lake dataset is skewed towards smaller avalanches, with only 317 size 3+ avalanches compared to 1,858 in Bear Pass. For Duffey Lake, size 3+ avalanches comprise 12% of the retained dataset, compared to 35% for Bear Pass. In Duffey Lake, size 3+ avalanches are only represented in 17 of 23 paths, as opposed to 17 of 17 for Bear Pass.

3.2. Path-level Results

For each avalanche path in a region, a unique avalanche alpha-angle distribution exists along a

unique avalanche thalweg. Individual paths generally contain narrower alpha-angle distributions than the regional distribution, reflecting differences in path geometry and vegetation. Occurrences are typically concentrated around the highway, potentially a result of observational bias (Figure 4).

3.3. Region-level Results

Across all retained occurrences, Bear Pass alpha-angles span 35°, ranging from 21° to 56°, while Duffey Lake alpha-angles span 26°, ranging from 24° to 50°. Values pertinent to the infrequent scenarios include the minimum and p05 values, while values pertinent to the typical include the median/p50 and the mean (Table 1).

Table 1: Regional alpha-angle statistics.

Metric	Bear All	Bear 3+	Duffey All	Duffey 3+
Occurrences	5,248	1,858	2,588	317
Paths	17	17	23	17
Minimum	21°	21°	24°	25°
5th Percentile	24°	23°	28°	27°
Median	32°	30°	32°	29°
Mean	32°	30°	32°	30°
95th Percentile	39°	37°	36°	33°
Maximum	56°	43°	50°	38°

Comparing avalanche alpha-angles across sizes within a region presents a clear trend for Bear Pass and Duffey Lake. The median avalanche alpha-angle decreases as avalanche size increases, following expected avalanche behavior. The violin plots in Figure 5 also reveal the relatively narrower distribution of avalanche alpha-angle within a size for most of Duffey Lake when compared to Bear Pass. A majority of the avalanche size distributions between regions, with the exception of size 2.5 in Duffey Lake, have a clear grouping around the median and mean values.

4. DISCUSSION

4.1. Runout Statistics

For this autoATES-focused application of this method, typical and infrequent parameters are the primary desired outputs (Sykes et al. 2026). Possible candidates for calibrated parameters extracted from the regional distributions include: minimum, 5th percentile, median, and average (mean) alpha-angles. Filtering to avalanche sizes 2–3 for typical parameters, or avalanche sizes 3+ for extreme parameters could focus the dataset toward the intended runout scenario. Occurrence-based weighting was used for the statistics so that each recorded avalanche equally contributes to the regional distributions. Consequently, the paths with the most occurrences become over-represented while paths with fewer occurrences become underrepresented. Path-specific biases arising from unique terrain or vegetation could therefore inflate or deflate the output statistics.

4.2. Comparisons with Alpha-Angles in Existing Literature

The Canadian Coast Mountains, where our study regions are located, along with the Columbia and the Canadian Rocky and Purcell Mountains have had significant research based on field surveys and vegetative records (McClung and Mears 1991; Nixon and McClung 1993; Johnston et al. 2012). In a 1993 study of the Canadian Coast Mountains, the minimum alpha-angle was calculated to be 20.4°, while the mean alpha-angle was calculated to be 26.8° (Nixon and McClung 1993). This study region included 31 paths across the Coast Mountains. This minimum alpha-angle is very close to our calculated minimum of 21° from the Bear Pass dataset, but it is considerably lower than the 24° minimum calculated from the Duffey Lake region. The Coast Mountain study's mean value is considerably lower than that of the mean and median values for both Bear Pass and Duffey Lake, which range from 29°–32°. This difference could be due to the method for calculating alpha-angles. Occurrence data contains avalanches of all sizes, while vegetation records only portray extreme runout events. There are also numerous sources of uncertainty which could contribute to this difference. Due to the distinct methods, this comparison provides a contextual comparison rather than validation of results.

4.3. Limitations

Due to the operational nature of the dataset, there could be a sampling bias favoring large avalanches near to the highway; the opposite bias could also exist, favoring small or moderately-sized avalanches due to avalanche mitigation efforts on the highway. Observational uncertainty exists with the location of the toe of the avalanche from factors including poor visibility, distance from road, observer bias, and measurement method. Additionally, the high uncertainty in start zone location is passed on to the resulting distributions.

Out of an initial total dataset of 153 avalanche paths that impact the highways, only 40 passed

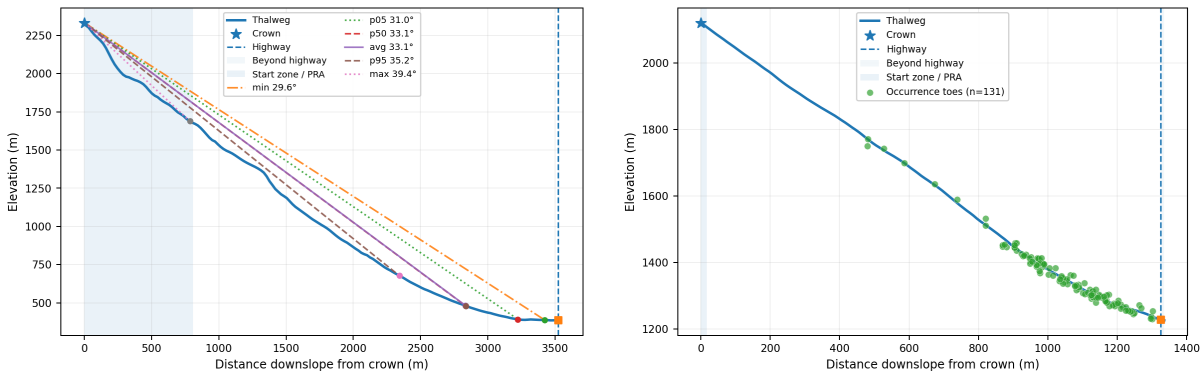


Figure 4: Example thalweg profiles showing individual occurrences for Eagle, Bear Pass (left) and occurrence quantiles for Rohr Ridge 1, Duffey Lake (right).

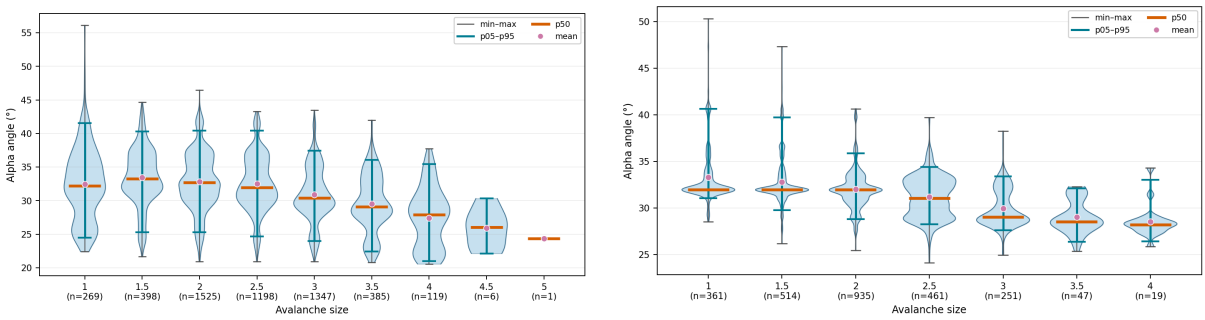


Figure 5: Alpha-angle distributions by avalanche size for Bear Pass (left) and Duffey Lake (right).

quality control due to highway proximity, channelization, path size, or thalweg accuracy. This put both regions below the recommended 30-path minimum to perform statistical analysis (McClung and Mears 1991), reducing the number of usable occurrences from 34,852 to 7,836.

Our analysis used a 30-meter resolution for geospatial data and calculations which could have led to unrealistic or broken thalweg generation and angle calculation; a 10-meter or finer DSM resolution is typically recommended for alpha-angle analysis (Jamieson et al. 2018b).

5. CONCLUSION

The workflow for autoATES v2.0 uses a conservative, 18° alpha-angle (Sykes et al. 2026); however, a 1993 study covering similar regions found typical and minimum alpha-angles to be noticeably larger (Nixon and McClung 1993). With our methodology, we use the BC-MoTT dataset to extract alpha-angles from 7,836 individual occurrences. Occurrences provide a rough avalanche toe position, while a start zone is estimated based on release probability. Avalanche thalwegs, calculated for each path using outputs from the FlowPy statistical runout model, connect these points forming the basis for alpha-angles calculations. Novel alternative methods for thalweg calculation allow for future comparison opportunities (Spannring et al. 2026). Alpha-angles are then compared on a regional level to create distributions from which alpha-angle parameters for autoATES v3.0 could be statistically derived. Using these results as input parameters for future autoATES applications has the potential to reduce uncertainty in large-scale ATES maps by modelling infrequent, extreme avalanche runouts and typical, frequent runouts based on local observations.

Observation biases in occurrences, absent start zone information, low-resolution thalweg calculation, and a large number of currently-unusable paths and occurrences within each region create barriers to direct applications to autoATES. However, future research could decrease uncertainty and increase applicability by using high-resolution elevation data and occurrence data with exact start and end positions available in select areas across western Canada. Traditional hazard mapping and avalanche zoning practices typically include beta- and delta-angles, parameters derived from terrain features in the path, required for runout-ratio and alpha-beta regression models that help account for local path geometry in alpha-

angle analysis (Jamieson and Campbell 2018). These methods are well-documented for the Canadian Coast Mountains, the Canadian Rocky and Purcell Mountains, and the Columbia Mountains, areas across the SAR-NIF project extent (McClung and Mears 1991; Nixon and McClung 1993; Johnston et al. 2012). Avalanche thalwegs generated with our method provide a direct way to calculate the beta- and delta-angle for each path. Implementing these regression models could allow for increased validation of resulting statistical data, potentially reducing the severity of path geometry-caused, occurrence-weighted biases. Rigorous improvement of the method could provide an opportunity for application across the new (SAR-NIF) project, “Large-scale avalanche terrain exposure scale mapping for mountainous regions in Canada”, by contributing empirically calibrated, localized avalanche alpha-angle parameters for typical and infrequent runout scenarios across all of Avalanche Canada’s forecast regions.

REFERENCES

Bühler, Y., Bebi, P., Christen, M., Margreth, S., Stoffel, L., Stoffel, A., Marty, C., Schmucki, G., Caviezel, A., Kühne, R., Wohlwend, S., and Bartelt, P. (2022). Automated avalanche hazard indication mapping on a statewide scale. In: Nat. Hazards Earth Syst. Sci. 22, pp. 1825–1843. https://doi.org/10.5194/nhess-22-1825-2022.

D’Amboise, C. J. L., Neuhauser, M., Teich, M., Huber, A., Kofler, A., Perzl, F., Fromm, R., Kleemayr, K., and Fischer, J.-T. (2022). Flow-Py v1.0: a customizable, open-source simulation tool to estimate runout and intensity of gravitational mass flows. In: Geosci. Model Dev. 15, pp. 2423–2439. https://doi.org/10.5194/gmd-15-2423-2022.

Government of British Columbia (2021). Geometric Design Guidelines for B.C. Roads.

Harvey, S., Schmudlach, G., Bühler, Y., Dürr, L., Stoffel, A., and Christen, M. (2018). “Avalanche terrain maps for backcountry skiing in Switzerland”. In: Proceedings of the International Snow Science Workshop. Innsbruck, Austria, pp. 1625–1631.

Huber, A., Hesselbach, C., Oesterle, F., Neuhauser, M., Adams, M., Plörer, M., Stephan, L., Toft, H. B., Sykes, J., Mitterer, C., and Fischer, J.-T. (2023). “AutoATES Austria – testing and application of an automated model-chain for avalanche terrain classification in the Austrian Alps”. In: Proceedings of the International Snow Science Workshop. 8–13 October 2023. Bend, OR, USA, pp. 929–936.

Huber, A., Saxer, L., Spannring, P., Hesselbach, C., Neuhauser, M., D’Amboise, C. J. L., and Teich, M. (2024). “Regional-scale avalanche modeling with com4FlowPy – potential and limitations for considering avalanche-forest interaction along the avalanche track”. In: Proceedings of the International Snow Science Workshop. Tromsø, Norway, pp. 587–594.

Jamieson, B., ed. (2018). Planning Methods for Assessing and Mitigating Snow Avalanche Risk. Revelstoke, British Columbia, Canada: Canadian Avalanche Association.

Jamieson, B. and Campbell, C. (2018). “Avalanche mapping”. In: Planning Methods for Assessing and Mitigating Snow Avalanche Risk. Ed. by Jamieson, B. Revelstoke, British Columbia, Canada: Canadian Avalanche Association.

Jamieson, B., Jones, A., and Argue, C. (2018a). “Avalanche dynamic models”. In: Planning Methods for Assessing and Mitigating Snow Avalanche Risk. Ed. by Jamieson, B. Revelstoke, British Columbia, Canada: Canadian Avalanche Association.

Jamieson, B., Jones, A., and Sinickas, A. (2018b). “Statistical runout estimation”. In: Planning Methods for Assessing and Mitigating Snow Avalanche Risk. Ed. by Jamieson, B. Revelstoke, British Columbia, Canada: Canadian Avalanche Association.

Johnston, K. S., Jamieson, B., and Jones, A. S. T. (2012). Estimating extreme avalanche runout for the Columbia Mountains and Fernie area Rocky Mountains of British Columbia, Canada. In: Can. Geotech. J. 49, pp. 1309–1318. https://doi.org/10.1139/t2012-079.

Jones, A. S. T. and Jamieson, B. (2004). Statistical avalanche-runout estimation for short slopes in Canada. In: Ann. Glaciol. 38, pp. 363–372. https://doi.org/10.3189/172756404781814960.

Lindsay, J. B. (2021). WhiteboxTools: An advanced geospatial data analysis platform. GitHub repository, available at: `https://github.com/jblindsay/whitebox-tools`.

McClung, D. M. and Mears, A. I. (1991). Extreme value prediction of snow avalanche runout. In: Cold Reg. Sci. Technol. 19, pp. 163–175. https://doi.org/10.1016/0165-232X(91)90006-3.

Nixon, D. and McClung, D. M. (1993). Snow avalanche runout from two Canadian mountain ranges. In: Ann. Glaciol. 18, pp. 1–6. https://doi.org/10.3189/S0260305500011162.

Shandro, B. and Haegeli, P. (2018). Characterizing the nature and variability of avalanche hazard in western Canada. In: Nat. Hazards Earth Syst. Sci. 18, pp. 1141–1158. https://doi.org/10.5194/nhess-18-1141-2018.

Spannring, P., Hesselbach, C., Huber, A., Wirbel, A., Oesterle, F., Sykes, J., Mariani, A., Knies, D., and Fischer, J.-T. (2026). “Towards an automated avalanche thalweg analysis to identify and compare avalanche terrain”. In: Proceedings of the International Snow Science Workshop. Whistler, BC, Canada.

Statham, G. and Campbell, C. (2025). The Avalanche Terrain Exposure Scale (ATES) v.2. In: Nat. Hazards Earth Syst. Sci. 25, pp. 1113–1137. https://doi.org/10.5194/nhess-25-1113-2025.

Sykes, J., Knies, D., Haegeli, P., and Anthony-Malone, K. (2026). “AutoATES v3.0: Automated ATES Mapping at Scale Across Western Canada”. In: Proceedings of the International Snow Science Workshop. Whistler, BC, Canada.

Toft, H. B., Sykes, J., Schauer, A., Hendrikx, J., and Hetland, A. (2024). AutoATES v2.0: Automated Avalanche Terrain Exposure Scale mapping. In: Nat. Hazards Earth Syst. Sci. 24, pp. 1779–1793. https://doi.org/10.5194/nhess-24-1779-2024.