AutoATES v2.0: Automated avalanche terrain exposure scale mapping

Håvard B. Toft[1,2]*, John Sykes[3,4], Andrew Schauer[4], Jordy Hendrikx[5,6,2] and Audun Hetland[2]
[1] Norwegian Water Resources and Energy Directorate, Oslo, Norway
[2] Center for Avalanche Research and Education, UiT the Arctic University of Norway, Tromsø, Norway
[3] SFU Avalanche Research Program, Department of Geography, Simon Fraser University, Canada
[4] Chugach National Forest Avalanche Center, Girdwood, AK, USA
[5] Antarctica New Zealand, Christchurch, New Zealand
[6] Department of Geosciences, UiT the Arctic University of Norway, Tromsø, Norway

Corresponding author address:
Håvard B. Toft, Norwegian Water Resources and Energy Directorate, Oslo, Norway; tel: +47 454 82 195; email: htla@nve.no

Keywords: ATES, GIS, snow, avalanche,

~~*Throughout the paper, we will use the terms: model and algorithm interchangeably, but they convey the same meaning.*~~

Abstract

~~Snow covered mountains attract an increasing number of people. . At the same time our changing climate will lead to more precipitation which in turn elevates the risk of avalanches in many regions globally.~~ A~~A~~valanche risk assessments is complex and challenging, with terrain assessment as one of the most fundamental factors. To aid ~~peoples~~people's terrain assessment, Parks Canada developed the Avalanche Terrain Exposure Scale (ATES), a ~~terrain classification~~ system that classifies the severity of avalanche terrain into five classes from ~~0, no avalanche~~non-avalanche terrain to ~~4~~ extreme terrain. Manual classification ~~of~~ is laborious and dependent on ~~experts~~expert's assessments. To ease the process Larsen and~~t~~ his ~~collegues~~colleagues developed an automated ATES ~~algorithm~~model (~~avalanche assessment model~~ AutoATES v1.0).~~.~~ ~~"" Althogh~~Although the model allowed ~~for a large scale~~large-scale ~~avalanche classification~~mapping, it~~it~~ had some significant limitations. This paper ~~present~~presents an improved AutoATES v2.0 ~~algorithm~~model improving the potential release area (PRA) model, utilizing the new Flow-Py runout simulation package and incorporating forest density data in the PRA, Flow-Py and in a newly developed post-forest-classification step. ~~model with updated run-out modelling capabilities, inclusion of forest data and an improved classification of potential release areas (PRA).~~ AutoATES v2.0 ~~The model~~ has also been rewritten in ~~open source~~open-source software making it more widely available. The paper ~~include~~includes a ~~verification~~validation ~~study~~ of the model measured against two consensus maps made by three experts at two ~~manual expert classification at two~~ different locations in Western Canada.~~.~~

~~This paper documents substantial improvements to the original automated avalanche terrain exposure mapping (AutoATES v1.0) algorithm. The most significant drawbacks of AutoATES v1.0 have been addressed by including forest density data, improving the avalanche runout estimations in low-angle runout zones, accounting for overhead exposure and open-source software. The algorithm also supports the new ATES v2.0 terrain class 'extreme' terrain. We used two benchmark maps from Bow Summit and Connaught Creek to validate the improvements from AutoATES v1.0 to v2.0.~~ For Bow Summit, the F1 score (a measure of how well the ~~algorithm~~model performs) improved from 64.~~01~~% to 77.~~30~~%. For Connaught Creek, the F1 score improved from 40~~39.81~~% to 71.~~38~~%. The main challenge limiting large-scale mapping is the determination of optimal input parameters for different regions and climates. In areas where AutoATES v2.0 is applied, it can be a valuable tool for avalanche risk assessment and decision-making. Ultimately, our goal is for AutoATES v2.0 to enable efficient, regional~~large~~-scale, and potentially global ATES mapping in a standardized manner rather than based solely on expert judgement.

1. Introduction

Snow avalanches lead to a yearly average of ~~Approximately~~ 140 fatal accidents ~~result from snow avalanches~~ in Europe and Northern America ~~annually~~ (Techel et al., 2016, 2018; Birkeland et al., 2017)~~(Techel et al., 2016, 2018; Birkeland et al., 2017). In recent decades, most of these fatalities have been related to the recreational use of avalanche terrain (Engeset et al., 2018).~~ ~~In~~ More than 9~~8~~0% of fatal avalanche accidents are related to recreational activity and triggered by~~90% of cases,~~ the victim or someone in their party ~~group triggered the avalanche~~ (Schweizer and Lütschg, 2001; Techel and Zweifel, 2013; Engeset et al., 2018)~~(Schweizer and Lütschg, 2001)~~. This means that avalanche accidents are not random, but rather a result of ~~less than optimal~~less-than-optimal decisions. Strengthening ~~peoples~~people's ability to make better decisions by raising awareness, providing information and education is important and may ultimately save lives. To do so, m~~M~~any countries have established ~~an~~ avalanche forecasting services ~~to increase awareness of and help mitigate the risk of avalanches and focus on increased public education~~ (Engeset et al., 2018). However, d~~D~~espite ~~the availability of public regional avalanche forecasting in many countries~~access to updated avalanche forecast, ~~assessing the avalanche risk is a complex task for backcountry recreationists~~ . t~~T~~he~~due to the~~ complexity and variability of the ~~spatial and temporal variability of snow~~~~in~~of the snowpack still leaves avalanche risk management a complex task. The inherent lack of feedback from the environment also turn avalanche terrain into~~increases the complexity and~~. ~~This results in~~ a wicked learning environment~~,~~ ~~where feedback is not always reliable~~ (Fisher et al., 2022)~~(Fisher et al., 2022)~~. Reliable information and ~~decision making~~decision-making support are therefore crucial. The most efficient method to mitigate the avalanche hazard is to choose appropriate terrain for the given avalanche conditions (Thumlert and Haegeli, 2017).

~~The avalanche risk is managed by performing detailed assessments of, factors such as i.e., weather, snowpack, and signs of instabilities or by the use of travel techniques / safety equipment (e.g. airbag, transceiver, probe, and shovel) at a regional scale. Another efficient method to mitigate the avalanche hazard is using appropriate terrain for the avalanche conditions (Thumlert and Haegeli, 2017).~~

Assessing avalanche terrain may be intuitive for avalanche professionals (Landrø et al., 2020)~~(Landrø et al., 2020)~~;~~,~~ however, this may not be the case for recreational users of avalanche terrain. To aid non-professionals terrain assessment Parks Canada developed t~~T~~he A~~a~~valanche T~~t~~errain E~~e~~xposure S~~s~~cale (ATES v1.0). This is a terrain classification system ~~developed by Parks Canada~~ to communicate the potential exposure to avalanches and thus how difficult~~complex~~ avalanche management would be in ~~complexities and risks of traveling in~~ different types of ~~avalanche-prone~~ terrain (Statham et al., 2006)~~(Statham et al., 2006)~~. The complexity of avalanche terrain is the result of interactions of multiple release areas, tracks, and deposition areas. Within these three areas, other factors like, e.g., terrain traps or forest density, could make terrain management more complex due to a more severe outcome.

Originally, ATES v1.0 categorized popular backcountry routes into three levels: Simple (1), Challenging (2), and Complex (3). With the growing adoption of ATES, its application expanded beyond individual routes to spatial zones, such as the initiative by Avalanche Canada which mapped several thousand square kilometers of avalanche terrain (Campbell and Gould, 2013). An update to the system led to ATES v2.0, which introduced two new classes: Non-avalanche terrain (0) and Extreme (4). This revised version also expand the scope of ATES to include spatial representations like zones, areas, and corridors. The updated scale is referred to as ATES v2.0 and a more thorough description can be found in Statham and Campbell (2023).

ATES classification has been used to provide guidelines for terrain use linked to people's specific avalanches management skills (CAA, 2016) or for recreational purposes (Campbell and Gould, 2013; Thumlert and Haegeli, 2017; Larsen et al., 2020; Schumacher et al., 2022). ATES mapping has also been used to describe backcountry users' terrain preferences recorded by GPS (i.e., Hendrikx et al., 2022; Johnson & Hendrikx, 2021; Sykes et al., 2020).

The development of ATES maps for Avalanche Canada from 2009 through 2012 was done using a combination of manual mapping and a GIS-assisted workflow (Campbell and Gould, 2013). ATES zoning was labor intensive, relied heavily on expert judgement and as a result ATES maps were typically only available in high-use areas. Campbell and Gould (2013) identified the limitations of this method and presented a more quantifiable zonal model that could leverage GIS tools for more systematic terrain classification.

~~The terrain was initially clustered in three classes and graded from The system was recently updated to include two additional terrain classes: Non-avalanche terrain (0), and Extreme (4).The updated system is referred to as ATES v2.0. Statham and Campbell, 2023).~~

~~ATES is a commonly used classification scheme worldwide and quantifies the avalanche terrain into an easy-to-understand rating: simple (class 1), challenging (class 2), and complex (class 3) terrain. A more detailed technical description of these classes is presented in Statham et al. (2006) and also reproduced in Larsen et al., (2020). Recently, the ATES classification scheme has been updated to include two additional ratings; non-avalanche (class 0, optional) and extreme (class 4) terrain to complement the current ATES classes from 1-3 (Statham and Campbell, 2023).~~

~~Avalanche hazard mapping has been common practice for decades to calculate the potential consequence of different avalanche scenarios related to infrastructure (Schläppy et al., 2013). The maps are often calculated for a specific return period (i.e., the probability of a given magnitude avalanche every 100 years) and determines the likelihood of an avalanche (sometimes with specific impact pressures) within a defined area. The return periods vary by application, and by country (DIBK, 2017; BFF and SLF, 1984). In recent years, it has become more common to undertake classify an assessment of avalanche terrain zoning, where the aim is to divide theRecent work has classified avalanche terrain (e.g., ATES) and provided guidelines for terrain use avalanche terrain into different zones or classes (e.g., ATES) depending on a specific skill level (CAA, 2016) or for recreational purposes (Campbell and Gould, 2013; Schmudlach and Köhler, 2016; Thumlert and Haegeli, 2017; Harvey et al., 2018; Larsen et al., 2020; Schumacher et al., 2022). In addition to mapping to inform users, ATES mapping has also been used as an important component to assess and measureto describe backcountry users terrain use preferences of backcountry users usingrecorded by GPS at a range of spatial scales (e.g., Hendrikx et al., 2022; Johnson & Hendrikx, 2021; Sykes et al., 2020).~~

~~This mapping was undertaken using a combination of manual mapping and GIS-assisted mapping workflowsF, rom 2009 through 2012, Avalanche Canada mapped several thousand square kilometers of avalanche terrain (Campbell and Gould, 2013). This initial ATES mapping was done using a combination of manual mapping and GIS-assisted mapping workflows. This work was labor intensive,which relied heavily on expert judgement and as a result ATES maps was typically only available in high-use areas. Campbell and Gould (2013) spelled out the need for a more quantifiable model and suggested a new spatial ATES model for GIS-assisted classification.Statham et al. (2006) noted that the ultimate goal would be to apply the ATES classification spatially to produce ATES maps across entire regions. From 2009 through 2012, Avalanche Canada mapped several thousand square kilometers of avalanche terrain (Campbell and Gould, 2013). This mapping was undertaken using a combination of manual mapping and GIS-assisted mapping workflows, which relied heavily on expert judgement. As part of this work, Campbell and Gould (2013) identified the need for a more quantifiable model and suggested a new zonal ATES model for GIS-assisted classification. Therefore, the majority of large-scale mapping of ATES have been limited by the manual labor needed to generate maps. As a result, ATES is, therefore, typically only available in high-use areas. due to the number of resources needed to generate ATES maps.~~

An automated model to classify avalanche terrain would~~ill~~ need the following components; 1) A model of potential release areas (PRA) for avalanches and 2) a run-out simulation which is an estimation of where and how far an avalanche would slide.

Formatert: Blokkjustert

The first attempt at a fully automated ATES ~~classification~~ model was made by Larsen et al. (2020) using a combination of the zonal and technical model of ATES (Campbell and Gould, 2013; Statham et al., 2006)~~(Campbell and Gould, 2013; Statham et al., 2006)~~.

Larsen et al. (2020)~~The authors~~ developed an automated ATES (AutoATES v1.0) ~~algorithm~~model that was able to maket~~ produces spatial~~ ATES ~~maps~~ zones for all of Norway, using only a digital elevation model (DEM) as input. This simple approach to terrain characteristics does not consider overhead exposure into account and the performance of the simple avalanche runout simulation is also insufficient in flatter terrain. In addition, ~~The main limitations of this work were that~~ the ~~algorithm~~model did not account for forest ~~d~~density, which has been found to be ~~significantly associated with avalanche release~~to be one of the most important factors for ATES classification (Delparte, 2008, Schumacher et al 2022).~~ata, or overhead exposure, and the performance of the simple avalanche runout simulation was insufficient in flat runouts.~~ A final challenge was that the~~The~~ ~~algorithm~~model was ~~also~~ heavily dependent on proprietary software (Larsen et al., 2020), thereby increasing the monetary and computing costs to operate the model~~,~~ ~~and also~~and limiting open-source~~s~~ access.

1.1 Improving potential release areas (PRA) ~~algorithm~~model.

In AutoATES v1.0, Larsen et al. (2020) used the PRA ~~algorithm~~model developed by Veitinger et al. (2016) due to its continuous raster output ranging from 0 to 1. The model uses windshelter, roughness, slope angle and forest density as inputs. However, the forest density is only processed as a binary input, meaning that the input is either forested or non-forested. If an area is defined as forested, it is not processed by the PRA ~~algorithm~~model and defined as a non-PRA. Sharp (2018) improved the PRA ~~algorithm~~model by incorporating forest density as a parameter in the fuzzy logic operator, making the interaction of forest density dynamic and equally important compared to roughness, slope angle and windshelter.

In AutoATES v1.0, Larsen et al. (2020) utilized the PRA model by Veitinger et al. (2016), which outputs a continuous range of values between 0 and 1. This model considers factors such as windshelter, terrain roughness, slope angle, and forest density. Originally, forest density was only a binary input, effectively categorizing areas as either 'forested' or 'non-forested'. In the binary approach, any 'forested' area was not further processed by the PRA model and was simply labeled as non-PRA. In 2018, Sharp improved the PRA model by including the forest density parameter in what's known as a fuzzy logic operator. Fuzzy logic, unlike binary, does not restrict inputs to yes-or-no values; instead, it allows for degrees of truth. For instance, instead of an area being classified as simply 'forested' or 'not forested,' it could be 'somewhat,' 'mostly,' or 'completely' forested. This method acknowledges the nuances in forest density and treats it with equal importance to other factors like roughness, slope angle, and wind shelter. The PRA establishes the baseline for where avalanches may release and is used as an input for the avalanche runout simulations.

~~Two of the most used PRA algorithms are those developed by Bühler et al. (2013) and Veitinger et al. (2016). A key difference between the two algorithms is that the one from Bühler et al. (2013) produces a polygon-based output using roughness, curvature, slope angle and forest density. In contrast, the PRA from Veitinger et al. (2016) produces a continuous raster layer ranging from 0 to 1 due do its Fuzzy membership approach. The inputs are windshelter, roughness, slope angle and forest (binary). Both algorithms are considered to have a good performance, although Bühler and his collogues polygon-based algorithm was found to be slightly more accurate (Bühler et al., 2018).~~

~~In avalanche terrain classification~~zoning, ~~the main goal is to divide the terrain into different zones or classes representing different levels of exposure to avalanches~~areas of hazard, ~~using a defined classification scheme. Avalanche terrain, especially~~The complexity of avalanche terrain when

Formatert: Normal, Blokkjustert

formaterte: Skriftfarge: Automatisk

Formatert: Normal

formaterte: Skrift: (Standard) +Brødtekst (Calibri)

formaterte: Skrift: Fet

formaterte: Skrift: Fet

Formatert: Blokkjustert

formaterte: Norsk (bokmål)

formaterte: Norsk (bokmål)

formaterte: Skriftfarge: Mørk rød

formaterte: Skriftfarge: Mørk rød

~~complex is the result of interactions of multiple release areas, tracks, and deposition areas. Within these three areas, other factors like, ei.ge., terrain traps or forest density, could make terrain management more complex due to a more severe outcome. TThe two most important components in making a gooddeveloping a reliable avalanche terrain classification zoning algorithm are (1) the delineation of the start zone area, as defined by the potential release area (PRA) modelpotential release area (PRA) of an avalanche start zone, and (2) the avalanche runout distance and width, accounting for the track and deposition area (Sykes et al., 2022)(Sykes et al., 2022). An increase in accuracy in either of these components directly benefits avalanche terrain zoning models. Additional factors like forest density have also been found to be significant (Delparte, 2008; Schumacher et al., 2022).~~

~~The use of an appropriate PRA model to delineate the start zones of avalanche paths, is critical when creating a good avalanche terrain classificationzoning model (Sykes et al., 2022). The PRA establishes the baseline for where avalanches may release and is used as an input for the avalanche runout simulations. Manual classification of PRAs is time-consuming and often involves field observations, historic events review, and numerical simulations (Bühler et al., 2018)(Bühler et al., 2018). A range of different PRA algorithms based on GIS or remote sensing have been developed (Bühler et al., 2018, 2013; Maggioni and Gruber, 2003; Barbolini et al., 2011; Pistocchi and Notarnicola, 2013; Chueca Cía et al., 2014; Andres and Chueca Cia, 2012; Ghinoi and Chung, 2005; Veitinger et al., 2016)(Bühler et al., 2018, 2013; Maggioni and Gruber, 2003; Barbolini et al., 2011; Pistocchi and Notarnicola, 2013; Chueca Cía et al., 2014; Andres and Chueca Cia, 2012; Ghinoi and Chung, 2005; Veitinger et al., 2016).~~

~~The two most commonly used PRA algorithms are those developed by Bühler et al. (2013) and Veitinger et al. (2016). A key difference between the two algorithms is that the one from Bühler et al. (2013) produces a binary polygon-based output, while the one from Veitinger et al. (2016) produces a continuous raster layer ranging from 0 to 1. Both algorithms are considered to have a good performance, even although Bühler and his colloguesthe polygon-based algorithm was found to be slightly more accurate (Bühler et al. 2018). In prior automated ATES mapping work, Larsen et al., (2020) used the PRA algorithm of Veitinger et al. 2016 for the AutoATES v1.0 algorithm due to the continuous raster output. It is possible to include a binary forest parameter in the Veitinger et al. (2016) PRA model. However, the binary nature of the parameter results in coarse output, as the model removes all PRAs when the forest parameter takes the value 1. Sharp (2018) improved this PRA algorithm by incorporating forest density as a parameter in the fuzzy logic operator, making the forest interaction more dynamic.~~

1.2 Improvements for run-out simulations

There are several avalanche runout simulation models available to ~~which,~~ estimate the potential track and deposition area, given specific start zone inputs from the PRA model (Christen et al., 2010; Sampl and Zwinger, 2004; Tarboton, 1997; D'Amboise et al., 2022)~~, outputs the potential track and deposition area.~~. In principle, these runout models ~~could~~ ~~can~~can be divided into two categories: (1) process-based, which attempt to calculate all the physical properties involved, or (2) empirical models which are~~is~~ driven by data-based observations. ~~Which modelling approach to choose~~Selecting an appropriate modelling approach depends on the problem to be solved, data availability, the required accuracy and the spatial scale *(D'Amboise et al., 2022)*~~(D'Amboise et al., 2022)~~. Given access to highly detailed data and unlimited computational power, the process-based models outperform the data-based empirical models. However, given the limitations in computational power when processing large areas and the need for more accurate digital elevation models (~~DEMs~~DEM's) in many countries, the data-based model is more suitable for large-scale mapping applications.

Formatert: Blokkjustert

formaterte: Skrift: Fet

formaterte: Skrift: Fet

Formatert: Normal

formaterte: Utheving, Skrift: (Standard) +Brødtekst (Calibri), Ikke Kursiv, Skriftfarge: Svart, Engelsk (USA), Mønster: Klart (Hvit)

Two of the most common process-based simulation tools for avalanche hazard assessment are the RAMMS (Christen et al., 2010)~~(Christen et al., 2010)~~ and Samos-AT (Sampl and Zwinger, 2004)~~(Sampl and Zwinger, 2004)~~ models. Both models are made to simulate an accurate prediction of avalanche runout distances, flow velocities and impact pressures in a 3-dimentional space. These models are typically calibrated towards known avalanches with long return periods and define~~s~~ potential avalanche terrain. These models are suitable for avalanche terrain zoning, where the aim is to divide the potential avalanche terrain into different zones, across large spatial areas such as regional forecast areas or entire countries, these models are less suitable.

In contrast to the process-based models, data-based models are computationally inexpensive and can more easily be applied to large geographic areas. A common data-based method to delineate avalanche runout is applying the classical runout angle concepts and path routing in three-dimensional terrain (D'Amboise et al. 2022). Comparison of the model results to more computationally expensive simulation type models shows that they respond adequately for the delineation of broad scale terrain classification.

In prior automated ATES mapping work, Larsen et al. (2020), used the multiple flow direction ~~algorithm~~model D-infinity (Tarboton, 1997)~~(Tarboton, 1997)~~. This ~~algorithm~~model is coupled with the alpha~~travel~~ angle (also known as~~i.e.,~~ travel ~~alpha~~ angle). The D-infinity ~~algorithm~~model identifies the cells downslope of the starting cell for each PRA cell. The ~~algorithm~~model spreads downslope until a defined alpha angle is reached from the starting cell (as per Heim, 1932; Lied & Bakkehøi, 1980; Toft et al., 2023)~~(as per Heim, 1932; Lied & Bakkehøi, 1980; Toft et al., 2023)~~. While used in hydrology applications, a substantial weakness of the D-infinity ~~algorithm~~model is that it cannot appropriately model avalanche movement, which may occasionally flow in flat and uphill terrain.

Recently, D'Amboise et al. (2022) presented a new customizable simulation package (Flow-Py) to estimate the runout distance and intensity (the effect from the runout simulation at a specific location) of avalanches. The model utilizes persistence-based routing instead of terrain-based routing, enabling the simulation to respond appropriately to flat or uphill terrain. Where the D-infinity ~~algorithm~~model only considers flow direction, the Flow-Py ~~algorithm~~model also considers flow process intensity. ~~They~~Both ~~algorithm~~models use the same stopping criteria to estimate the runout distance by defining the alpha angle from the initial starting cell.

2. Model development

The main objective of the AutoATES v2.0 model is to improve large-scale spatial ATES mapping, update the mapping to reflect recent changes in ATES v2.0 and improve the model workflow. For AutoATES v2.0 to be a viable option for large-scale ATES classification, the model performance should be at least as accurate as manual mapping.~~In this paper, we will present improvements´ll address thefor the significant drawbacks of AutoATES v1.0 by including forest density data, improving avalanche runout estimations in low-angle runout zones, accounting for overhead exposure and making the algorithm available as open-source software. The new algorithm will also support the new ATES v2.0 standard with the exception of class 0 – non avalanche terrain.~~

~~2. Model motivationdevelopment~~

~~The main objective of the AutoATES v2.0 algorithm is to improve large-scale spatial ATES mapping, update the mapping to reflect recent changes in ATES which include the two new terrain classes (0 and 4), and improve the model workflow. Manual ATES classification using avalanche experts is time-consuming and expensive (Sykes et al., 2020) which, limitsting large-scale mapping. For AutoATES v2.0 to be a viable option~~

formaterte: Skrift: (Standard) +Brødtekst (Calibri), 11 pkt, Engelsk (USA)

formaterte: Skriftfarge: Automatisk

formaterte: Skriftfarge: Automatisk

formaterte: Skriftfarge: Automatisk

Formatert: Normal

formaterte: Skriftfarge: Automatisk

Formatert: Blokkjustert

~~for large-scale ATES classification, the model performance should, on average, be as accurate as manual mapping or better.~~ ~~be at least as accurate as manual mapping.~~

~~**2.1 Model description**~~

~~This paper aims to document the improvements made to the AutoATES v1.0 algorithm initially developed by Larsen et al. (2020). In AutoATES v2.0, the influence of the forest density has been included by integrating the parameter into the PRA model (as per Sharp, 2018), track and the deposition area. The TauDEM runout model (Tarboton, 2005)(Tarboton, 2005), which uses the previously mentioned D-infinity algorithm and is known to perform poorly in flat deposition areas (Larsen et al. 2020), has been replaced by the new Flow-Py model which also has the option to include forest density data (D'Amboise et al. 2022). Another advantage of the Flow-Py model is a separate output layer which enables the model to quantify the overhead exposure from multiple avalanche paths, which is an important consideration in the updated ATES model. To improve the classification in forested areas, a new post-forest-classification step is added to the algorithm. Finally, the model now also includes the new ATES class for extreme terrain (Statham and Campbell, 2023)(Statham and Campbell, 2023) and steps to improve delineation of terrain traps.~~

2.1.~~2~~ ~~Implementation~~Implementation

To secure a broad adaptation of the new AutoATES model it is important that the model is open-source and easy to use. The v1.0 ~~algorithm~~model was written using proprietary software. We have resolved this by rewriting the entire v2.0 ~~algorithm~~model into the programming language Python using widely available and open-source modules. The AutoATES v2.0 model is available on GitHub (Toft et al., 2023)~~(Toft, Sykes, et al., 2023)~~.

2.2~~3~~ Input data

The minimum input data required to run the full AutoATES v2.0 is a DEM and forest density raster (a digital representation of the terrain/elevation and forest density) ~~, both~~ using the GeoTIFF format. It is also possible to run the ~~algorithm~~model with only a DEM as input, but the output would then only be valid for open, non-~~vegetated~~ forested terrain. Both rasters must have a matching spatial resolution and ~~, extent, and~~extent and be defined using a projected coordinate system. The ~~algorithm~~model has been tested with spatial resolutions ranging from 5 to 30 m (cell sizes), but it should be possible to run other spatial resolutions.

Our parametrization for forest density allows for various metrics of forest density inputs. The ~~algorithm~~model is designed to work with stem density, percent canopy cover, basal area or~~and~~ no forest (only for mapping of open terrain). The forest type must be defined ~~using a string~~ in the beginning of the Python script ~~('stems', 'pcc', 'bav' orand 'no_forest')~~. Forest density influences snow accumulation and snowpack stability, with denser forests generally reducing the risk of avalanches (Bebi et al., 2009).~~.~~

2.3~~3~~.1 Percent canopy cover

Canopy cover has a direct relationship with radiation balance and can impact formation of persistent weak layers as well as give an estimate of the degree of snowfall intercepted by trees prior to falling onto the snowpack (Bebi et al., 2009). Forest canopy also impedes wind transport of snow reducing the formation of wind slabs. Percent canopy cover is a widely used metric that quantifies the extent of forest density by measuring the proportion of the ground area obscured by tree canopies when viewed from above. Percent canopy cover can be estimated using various methods~~,~~ including aerial photography, satellite imagery, remote sensing techniques, and ground-based measurements. The resultant parameter used in our model has a value ranging from 0~~0~~ to 100. ~~to 100.~~

2.3~~3~~.2 Stem density

Formatert: Blokkjustert

Formatert: Blokkjustert

Formatert: Blokkjustert

Stem density is a metric used to quantify the number of tree stems (trunks) per unit area, typically expressed as stems per hectare or stems per square meter, which provides insight into forest structure and composition. Stem density can influence the snowpack stability and avalanche initiation, as a higher stem density generally results in more trees obstructing and anchoring the snow, thereby reducing the likelihood of avalanche occurrence (Bebi et al., 2009). Stem density can be measured through various techniques, including field surveys, aerial imagery analysis, or remote sensing data. The resultant parameter used in our model can have a value ranging from zero~~0~~ to ~~infinity, and~~a couple of thousands (depending on minimum stem diameter) and is stated in number of stems~~ density~~ per hectare.

2.3~~3~~.3 Basal area

The basal area is a unit used to describe the sum of the cross-sectional areas of all trees within a given space, specifically those in the dominant, co-dominant, and high intermediate positions within the forest canopy. It's a measure of the density of trees and is quantified in square meters per hectare ~~The basal area represents the total cross-sectional area of all living trees in the dominant, co-dominant, and high intermediate crown positions and is measured in~~ ~~m^2/hectare~~ (Sandvoss et al., 2005)~~(Sandvoss et al., 2005)~~. The advantage with basal area over ~~crown cover~~canopy cover and stem density ~~is~~are that it incorporates the size of trees in addition to the number of trees and is a more direct measurement of the density of the forest vegetation. The basal area value can have any value starting from zero upwards. While theoretically, there is no upper limit to this value, practically it is generally capped at around 60 square meters per hectare to reflect realistic forest conditions.

~~The resultant parameter used in our model can have a value ranging from zero0 to infinity, andinfinity and is stated in~~ ~~m^2 per hectare.~~

2.4~~4~~ Model components

The AutoATES v2.0 ~~algorithm~~model is split into two main components: (1) pre-processing and (2) the AutoATES classifier. In the pre-processing step, the DEM and forest density rasters are used as input for the start zone PRA ~~algorithm~~model. When the PRA calculations are~~are~~ complete, the PRA and DEM are~~is~~ used to calculate the avalanche runout using the Flow-Py component. When all the key components are calculated, they are used as input for the AutoATES classifier which assigns the final ATES classes for each raster cell (Figure 1).

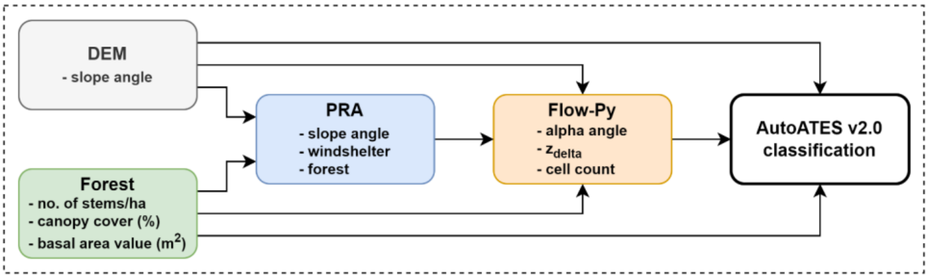


Figure 1: The main components of the AutoATES v2.0 ~~algorithm~~model. First, a pre-processing step is completed to calculate all the necessary raster layers using PRA and Flow-Py. Finally, the AutoATES classifier is used to assign the final ATES classifications.

2.4~~4~~.1 PRA

The AutoATES v1.0 ~~algorithm~~model (Larsen et al., 2020) incorporated the PRA model developed by Veitinger et al. (2016) to calculate the potential release areas. This PRA model (v1.0) uses slope angle, roughness and windshelter as input parameters. Sharp (2018) modified this ~~algorithm~~model to also include forest density. The models apply Cauchy membership values to determine how important each parameter is. A Cauchy

formaterte: Skrift: (Standard) +Brødtekst (Calibri), Skriftfarge: Svart, Engelsk (USA)

Formatert: Blokkjustert

Formatert: Blokkjustert

membership value reflect how strongly an input variable belongs within a certain set~~The algorithms utilize Cauchy membership values to assign the importance of each parameter~~ (Jang et al., 1997). A Cauchy membership value~~s~~ must be defined for each input variable (Eq. 1).

formaterte: Mønster: Klart (Hvit)

Formatert: Blokkjustert

$$\mu(x) = \frac{1}{1+\left(\frac{x-c}{a}\right)^{2b}} \tag{1}$$

Formatert: Blokkjustert

where $\mu(x)$ is the Cauchy membership value;~~,~~ x is an input variable (e.g., slope angle, windshelter, or forest);~~,~~ and a, b, and c are parameters which control the weight of each input variable. We use the membership values suggested by Veitinger et al. (2016) for slope angle and windshelter, while using the value suggested by Sharp (2018) for stem density (Figure 2). In our modified version of the PRA model (v2.0), we have chosen to remove the roughness parameter due to the scale issues with 5-30 m cell sizes (t~~.~~he original PRA ~~algorithm~~model was made to work with a 2 m cell size). ~~-~~The removal of roughness makes it less ideal for higher resolution ~~DEMs~~DEM’s (< 5 m cell sizes), see section 4.1.4 for a discussion around this. We have also defined~~ some~~ new membership functions for canopy cover and basal area based on input from Parks Canada avalanche experts and through testing of the AutoATES model on our two study areas. These values could be fine-tuned for specific datasets and applications~~different inputs~~ to improve the performance of the PRA model.

Formatert: Blokkjustert

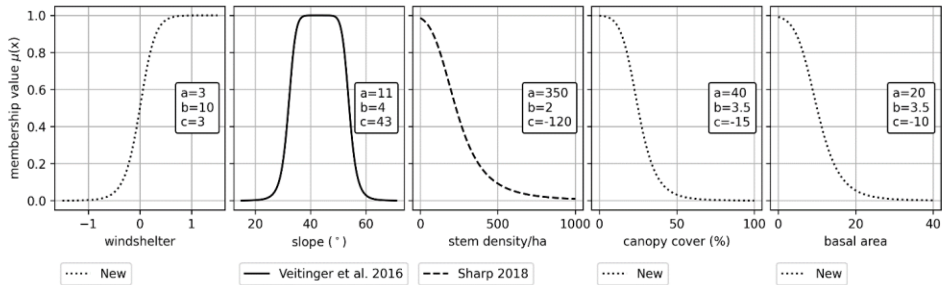


Figure 2: The different Cauchy functions used by Veitinger et al. (2016) and Sharp (2018) for slope angle and stem density. The values a, b and c are inputs for the Cauchy membership value (Eq. 1). ~~-~~We have suggested new membership values for windshelter, canopy cover (%) and basal area. We recommend that these values are fine-tuned for specific datasets and applications~~,~~. R~~r~~ead a more in-depth discussion of this in section 4.3.

formaterte: Skrift: Ikke Kursiv, Mønster: Klart

The Cauchy membership values from slope angle, windshelter and forest density are~~is~~ used as inputs for the fuzzy operator. We use the same “fuzzy AND” operator used by both Veitinger et al. (2016) and Sharp (2018), originally defined by Werners (1988)~~(1988)~~. The PRA value is therefore defined as follows in Eq. 2:

Formatert: Blokkjustert

$$\mu_{PRA}(x) = \gamma \cdot \min(\mu_s(x), \mu_w(x)\mu_f(x)) + \frac{(1-\gamma)+(\mu_s(x),\mu_w(x)\mu_f(x))}{3}, \tag{2}$$

$$x \in X, \gamma \in [0,1]$$

Formatert: Blokkjustert

With three fuzzy sets slope angle $\mu_s(x)$, windshelter $\mu_w(x)$, forest density $\mu_f(x)$ and with γ defined in Eq. 3 as:

$$\gamma = 1 - \min(\mu_s(x), \mu_w(x)\mu_f(x)) \tag{3}$$

Formatert: Blokkjustert

The PRA output is a continuous layer ranging between 0 (not likely) to 1 (very likely). Most data-based runout models need release areas in a binary format where 0 is no potential release areas, while the potential release areas are encoded as 1. To convert the PRA layer to a binary format, we select a cut off threshold ($PRA_{threshold}$)

where all pixels above this value ~~is considered~~are included in the ~~a~~ potential release area for the runout modelling. We found the PRA$_{threshold}$ from Larsen et al. (2020) to be too conservative for our study areas and have therefore increased the value to 0.15. The PRA$_{threshold}$ could be adjusted depending on whether frequent or more extreme avalanche scenarios are of interest.

We have also adjusted how the windshelter index is calculated. Using a 2 m DEM, Veitinger et al. (2016) resampled the DEM by a factor of 5 (from 2 m to 10 m) and applied a 11x11 sliding window (a technique where a fixed-size segment of data moves over the entire data set one step at a time). ~~.~~This is according to the recommendations of Plattner et al. (2006), ~~(2006),~~ which found the optimal radius to be 60 meters, followed by a secondary optimal radius of 250 m~~eters~~. To achieve the same results, we removed the down sampling factor of 5 and used the 10 m DEM directly to calculate the windshelter index. If other DEM resolutions are to be used, the windshelter index should be adjusted accordingly to use either 60 m (recommended) or 250 m as the radius around each cell. This could be done by either resampling the spatial resolution or changing the size of the sliding window.

2.~~4~~4.2 Avalanche simulation

The Flow-Py model developed by D'Amboise et al. (2022) is used for the avalanche simulation of the potential track and deposition area. It is similar to the TauDEM ~~algorithm~~model utilized in AutoATES v1.0 which uses the alpha angle to limit the flow (Larsen et al., 2020; Tarboton, 1997). Flow-Py also includes a flow process intensity parameter which makes it able to handle mass movement in flat and uphill terrain, significantly improving the output compared to ~~the previous model~~AutoATES v1.0. Another advantage ~~with~~of the FlowPy model is the additional output layers which represent~~s~~ the overhead exposure. We utilize the cell count and z_{delta} layer by scaling the two layers from 0-100 and taking their average value which represents the overhead exposure layer. In the AutoATES v2.0 ~~algorithm~~model it is possible to select cell count, z_{delta} or both to represent the overhead exposure. The layer enables us to quantify the exposure from different release areas at every raster cell. We use the forest detrainment module of Flow-Py which makes it possible to use forest density as an input layer to limit spreading and runout distance. An in-depth description of the Flow-Py simulation package can be found in D'Amboise et al. (2022).

2.~~4~~4.3 AutoATES classifier

When the pre-processing of PRA and Flow-Py is completed, the AutoATES classifier uses a set of map algebra equations to define each ATES class. The following raster layers from the pre-processing step are used as input in the AutoATES classifier:

- Slope angle (calculated from the DEM)
- Forest density (provided by the user, as per section 2.3.1-2.3.3)
- PRA (calculated from the DEM and forest data)
- Runout distance as a function of alpha angle (calculated from PRA and Flow-Py)
- Overhead exposure (cell count, z_{delta} or both) (calculated from PRA and Flow-Py)

The first step of the AutoATES classifier is controlled by adjustable thresholds for slope angle, runout distance, overhead exposure and island filter size (Table 1). Using these parameters, the AutoATES model outputs a preliminary, and conservative, layer with the categorical classes (1) simple, (2) challenging, (3) complex and (4) extreme terrain by keeping the maximum value ~~between~~of the 3 input rasters.

Table 1: The recommended input parameters for AutoATES according to Sykes et al. (2023). The encoding describes the name of each parameter in the AutoATES ~~algorithm~~model.

Input parameter	Class	Range	Encoding
Slope angle threshold (SAT)	Simple (1)	< 18°	SAT12=18°
	Challenging (2)	18 – 28°	SAT23=28°

Formatert: Blokkjustert

formaterte: Skrift: (Standard) +Brødtekst (Calibri), Skriftfarge: Svart, Engelsk (USA)

Formatert: Blokkjustert

Formatert: Blokkjustert

Formatert: Blokkjustert

Formatert: Blokkjustert

	Complex (3) Extreme (4)	28 – 39° > 39°	SAT34=39°
Alpha angle threshold (AAT)	Simple (1) Challenging (2) Complex (3)	< 24° 24° – 33° > 33°	AAT12=24° AAT23=33°
Overhead exposure (OE)	Simple (1) Challenging (2) Complex (3)	< 5~~0~~ 5~~0~~ – 40~~350~~ > ~~3~~40~~50~~	OE12=5~~0~~ OE23=40~~350~~
Island filter size (ISL_{size})			30,000 m^2

The second step of the AutoATES classifier is to reduce the exposure in certain ATES classes depending on forest density. The forest density is applied in a secondary step to increase the importance of the forest density criteria. The forest density layers are divided into four different categories with different thresholds for each forest density input (Table 2).

Table 2: The recommended input parameters for AutoATES according to Sykes et al. (2023). The encoding is the same for all three forest types, but the forest input type can be defined by a string ~~('no_forest', 'pcc', 'stems' or 'bav')~~ in the AutoATES script. ~~describes the name of each parameter in the AutoATES algorithm. Only one of the forest inputs can be used at the time, the encoding is therefore identical for all three forest density types.~~

Input parameter	**Class**	**Range**	**Encoding**
~~**Forest density**~~**Canopy cover (%)** ~~(Percent canopy cover)~~	Open Sparse Moderate Dense	0 – 20~~%~~ 20 – 55~~5%~~ 55 – 75~~%~~ 75 – 100~~%~~	TREE1=20 TREE2=55 TREE3=75
~~**Forest density**~~**Stem density (no. of stems/ha)** ~~(stem density/ha)~~	Open Sparse Moderate Dense	0 – 100 100 – 250 250 – 500 > 500	TREE1=100 TREE2=250 TREE3=500
~~**Forest density** (basal area)~~**Basal area (m^2/ha)**	Open Sparse Moderate Dense	0 – 10 10 – 20 20 – 25 > 25	TREE1=10 TREE2=20 TREE3=25

Once the forest density parameter has been coded into the four classes of forest density (~~ie~~~~.~~e.g., open, sparse, ~~moderate~~moderate, and dense), as a function of the forest density input parameter used, we mapped these categorical descriptors on to ATES classes (Table 3).

Table 3: Forest criteria applied to the second step of the AutoATES.

		Initial ATES rating			
Forest criteria		**Simple (1)**	**Challenging (2)**	**Complex (3)**	**Extreme (4)**
Open	PRA & Runout	Simple (1)	Challenging (2)	Complex (3)	Extreme (4)
Sparse	PRA & Runout	Simple (1)	Simple (1)	Challenging (2)	Complex (3)
Moderate	PRA	Simple (1)	Simple (1)	Challenging (2)	Complex (3)
	Runout	Simple (1)	Simple (1)	Simple (1)	Complex (3)
Dense	PRA	Simple (1)	Simple (1)	Simple (1)	Challenging (2)
	Runout	Simple (1)	Simple (1)	Simple (1)	Complex (3)

Finally, the island filter size is applied removing clusters smaller than a specified area and incorporating it to the surrounding class. The filter size is not a new addition to the ~~algorithm~~model as it is a part of the v1.0 ~~algorithm~~model, but Sykes et al. (2023)~~(2023)~~ found that a filter size of 30,000 m^2 (Table 1) was the optimal

Formatert: Blokkjustert
Formatert: Blokkjustert
formaterte: Skrift: Ikke Kursiv
formaterte: Skrift: Ikke Kursiv
Formatert: Blokkjustert
Formatert: Blokkjustert
formaterte: Skrift: Fet, Ikke Kursiv
formaterte: Ikke Hevet/ Senket
Formatert: Blokkjustert
Formatert: Blokkjustert
Formatert: Blokkjustert
formaterte: Skriftfarge: Tekst 1
Formatert: Blokkjustert
formaterte: Skriftfarge: Tekst 1
Formatert: Blokkjustert
formaterte: Skriftfarge: Tekst 1
formaterte: Skriftfarge: Tekst 1
Formatert: Blokkjustert
formaterte: Skriftfarge: Tekst 1
Formatert: Blokkjustert

filter size for all the spatial resolutions tested. ~~The additional step improves the accuracy of challenging (2) and complex (3) terrain, and in some cases in extreme (4) terrain.~~

2.5~~5~~ AutoATES outputs

The outputs from AutoATES v2.0 have the same spatial resolution as the input. The following outputs are available:

- Continuous PRA
- Flow-Py raw outputs (D'Amboise et al. 2022).
- Preliminary ATES classification of slope angle
- Preliminary ATES classification of runout distance
- Preliminary ATES classification of overhead exposure
- Forest density criteria
- AutoATES v2.0
- AutoATES v2.0 with island size filter

2.6~~6~~ Model ~~assessment~~validation

To evaluate the performance of AutoATES v2.0, we use two Canadian benchmark maps made explicitly for Connaught Creek, British Colombia and Bow Summit, Alberta Canada (Figure 3). These are the only locations that have manually mapped maps using the ATES v2.0 model (Sykes et al., 2023). The benchmark maps were made by combining individual maps from a panel of three experts, utilizing methodologies such as Geographic Information Systems (GIS), remote sensing imagery, local knowledge, and field-based investigations. Sykes et al. (2023) provide an in-depth description of how the benchmark maps were developed.

For the model validation, the benchmark maps are compared against the AutoATES v2.0 model described above using the optimized parameters from Sykes et al. (2023). Input data for the validation model is a 26 m ALOS DEM combined with forest density data (basal area) from the British Columbia Vegetation Resource Inventory (BC VRI). For more information about the input data, see Sykes et al. (2023).

Formatert: Blokkjustert

formaterte: Engelsk (USA)

formaterte: Engelsk (USA)

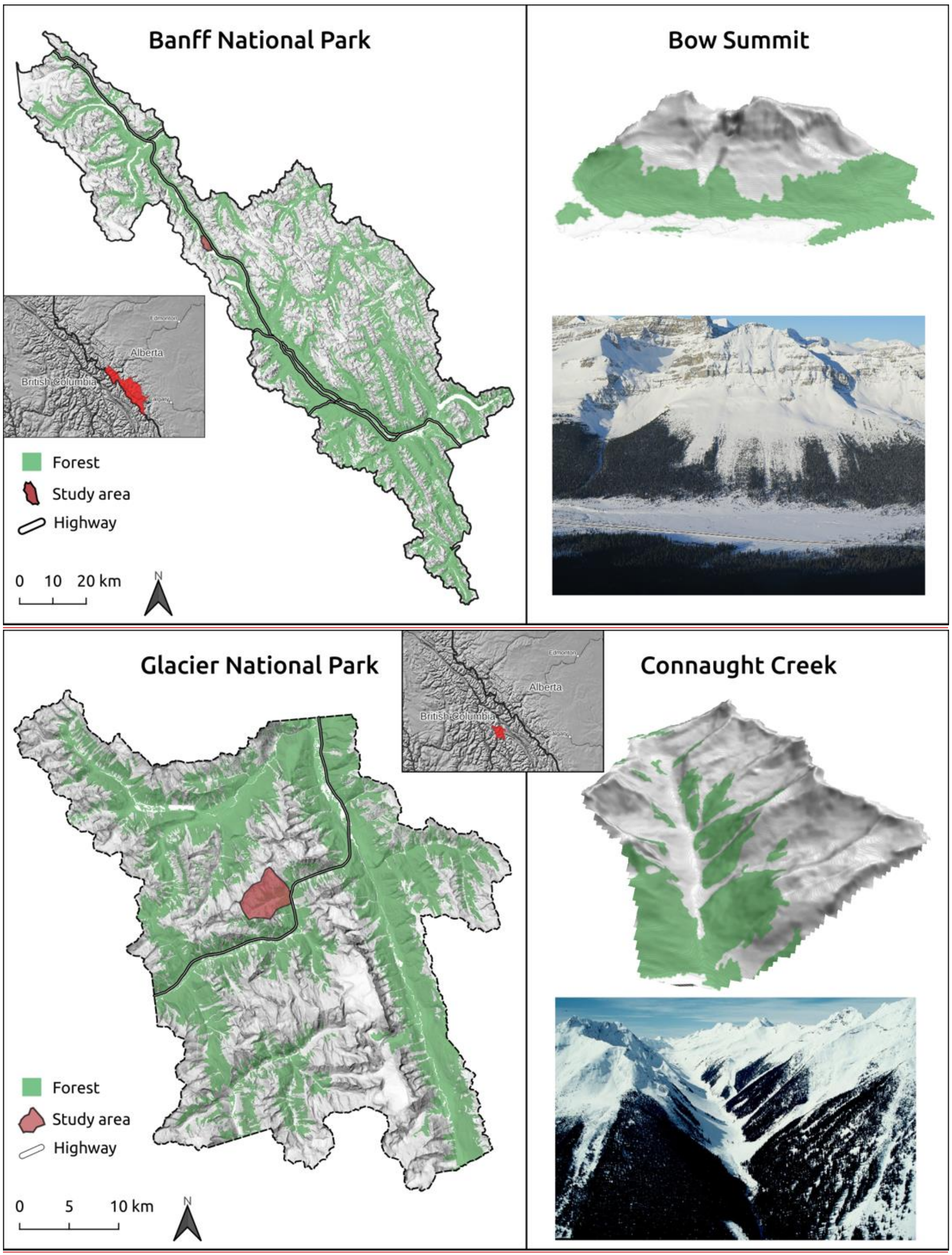


Figure 3: Two areas where benchmark maps for the updated ATES are available in Glacier and Banff National Park. An overview of the greater area with the study areas in 3D view and overview photo (adapted from Sykes et al., 2023).

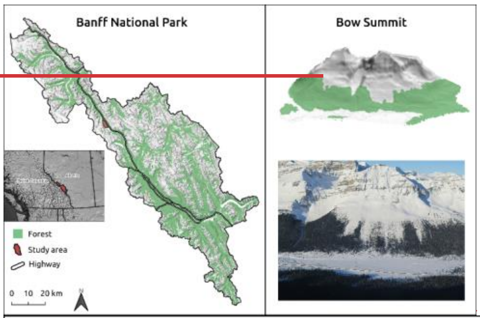
formaterte: Skrift: 10 pkt, Ikke Fet, Skriftfarge: Svart

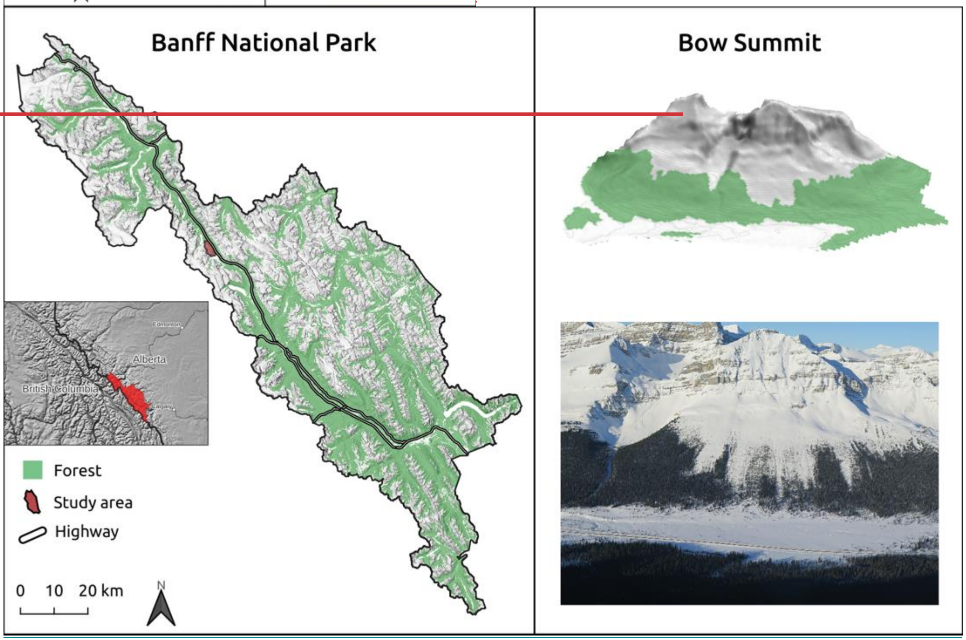
Formatert: Blokkjustert

We use the metrics a~~A~~ccuracy, precision, recall, and F1-score ~~are essential metrics for~~to evaluate~~ing~~ the performance of the~~a~~ model. These metrics provide a more detailed assessment, accounting for class imbalance and varying prediction results. They have been widely used in various fields, including avalanche literature (e.g., Keskinen et al., 2022)~~(e.g., Keskinen et al., 2022)~~. For a more in-depth understanding of these metrics and their sources, see Liu et al. (2014), who provides a comprehensive review of evaluation metrics for classifiers.

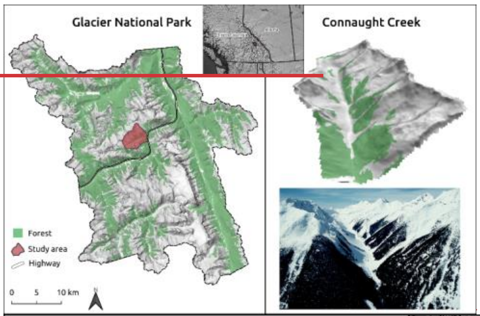
3. Results and validation

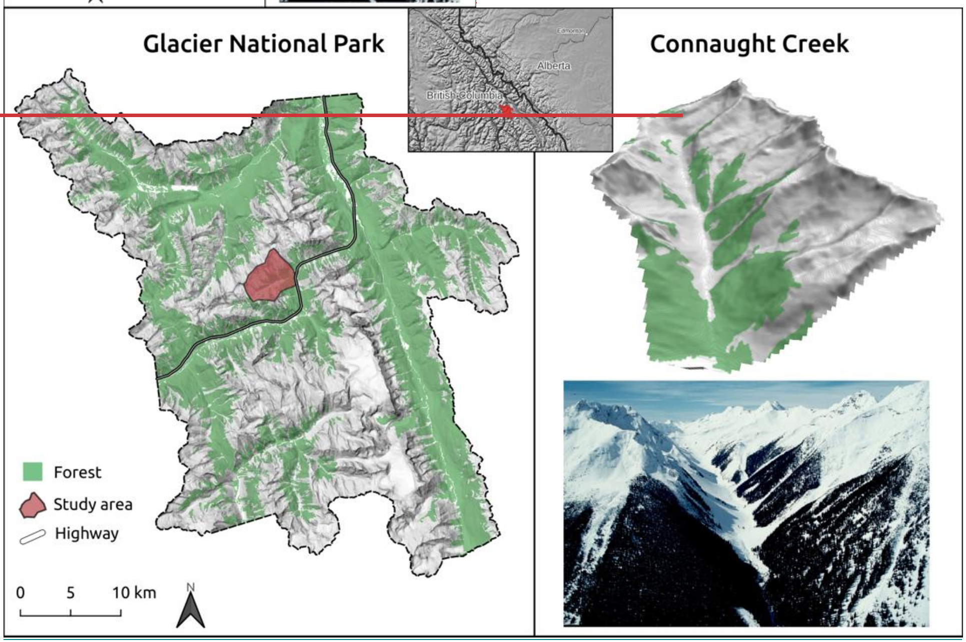
~~In order to~~To ~~evaluate the performance of AutoATES v2.0, we use two Canadian benchmark maps made explicitly for Connaught Creek, British Colombia and Bow Summit, Alberta Canada (Figure 3). These are the only locations that have manually mapped maps using~~ the ~~the new 5 class ATES~~ v2.0 ~~model (Sykes et al., 2023)(Statham and Campbell, 2023). The benchmark maps were made by combining individual maps from a panel of three experts, utilizing methodologies such as Geographic Information Systems (GIS), remote sensing imagery, local knowledge, and field-based investigations. Statham et al.~~Sykes et al. ~~(2023) provide an in-depth description of how the benchmark maps were developed.~~





Formatert: Blokkjustert



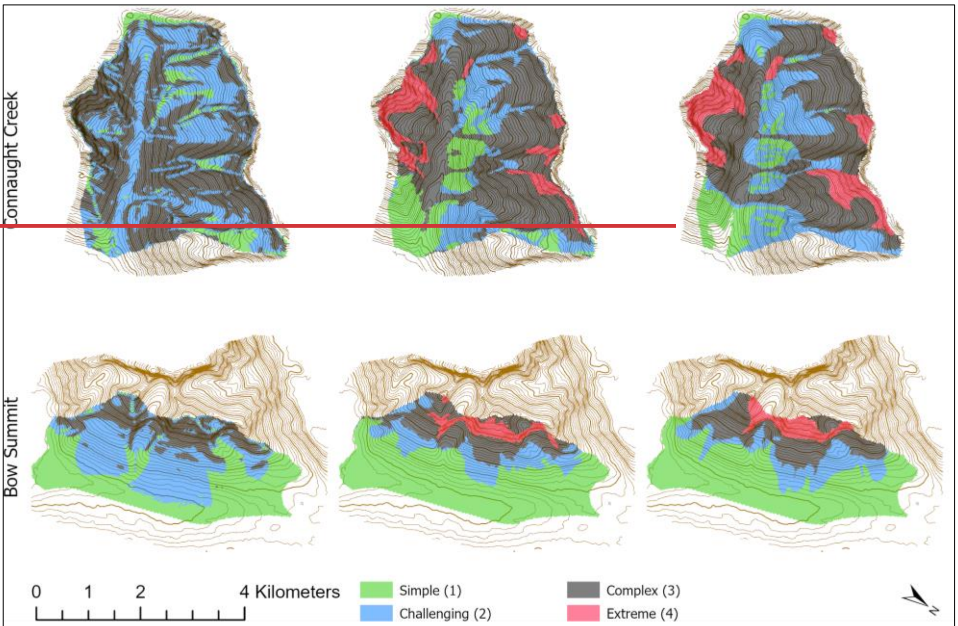


~~Figure 3: Two areas where benchmark maps for the updated ATES are available is in Glacier and Banff National Park. An overview of the greater area with the study areas in 3D view and overview photo~~ (adapted from Sykes et al., 2023)~~.~~.

3.1. Model accuracy

There is no true validation dataset for AutoATES due to differences in scale between automated and manual methods, but we believe the new benchmark maps made by Sykes et al. (2023) provides the best spatial validation maps to date. In figure 4, we visualize the differences between AutoATES v1.0, v2.0 and the ATES benchmark maps for Connaught Creek and Bow Summit.

Formatert: Blokkjustert


Connaught Creek
Bow Summit
0 1 2 4 Kilometers
Simple (1)
Challenging (2)
Complex (3)
Extreme (4)

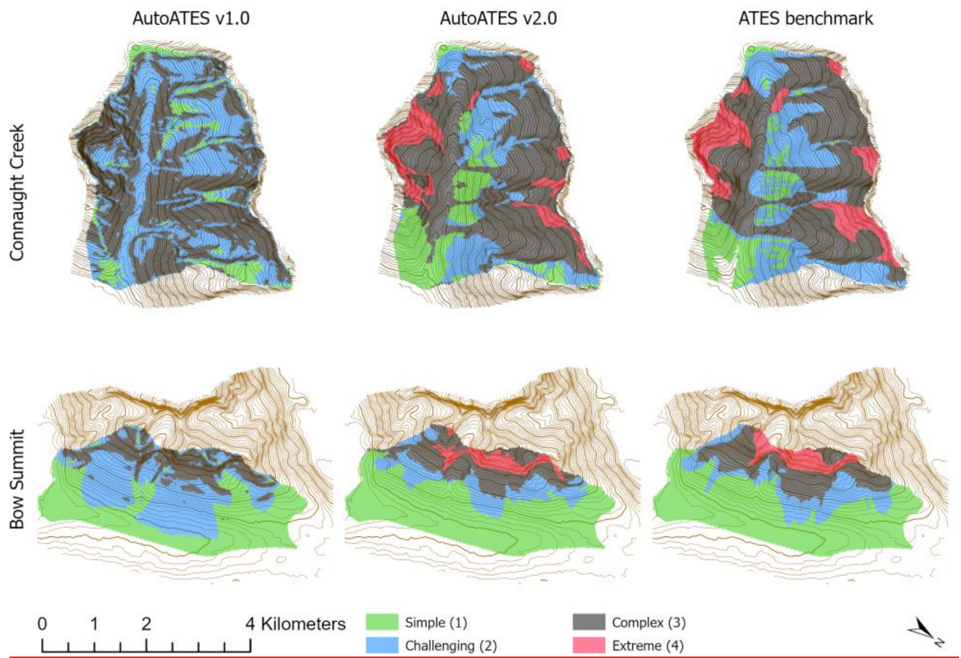


Figure 4: A visual comparison between AutoATES v1.0, v2.0 and the ATES benchmark maps for Connaught Creek and Bow Summit using the European ATES color scheme (Statham et al., 2023). AutoATES v1.0 does not use the extreme (4) class.

We use a confusion matrix for each study area to compare the ATES benchmark, which serves as the ground truth, against the results generated by the AutoATES v2.0 model (Table 4). The confusion matrices enable us to evaluate the performance of the AutoATES v2.0 model by calculating various metrics, such as accuracy, precision, recall, and F1-score. For Bow Summit, the ~~algorithm~~model performs ~~really well~~well for simple terrain with 91.97% accuracy, but the accuracy for challenging terrain is much lower at 65~~.34~~%. Complex and extreme terrain is closer to the average, ~~with~~ both with an accuracy of 79~~8.70~~% ~~and 78.97% respectively~~ (Table 4). The accuracy distribution between the four classes is slightly different for Connaught Creek. The v2.0 model performs the worst in simple terrain with an accuracy of 63~~3.31~~%. Challenging terrain has an accuracy of 71.0%, complex has an accuracy of 78.0% and extreme terrain has an accuracy of 83~~2.94~~% (Table 4).

Table 4: A confusion matrix is used to compare the ATES benchmark maps with AutoATES v2.0. Bow Summit is presented above, while Connaught Creek is presented below. The accuracy of each terrain class is marked out with grey shading (area or percent of pixels correctly identified).

	AutoATES v2.0				
Bow Summit	~~Simple (1)~~	Simple (1)~~Challenging (2)~~	Challenging (2)	Complex (3)	Extreme (4)
ATES benchmark	Simple (1)	4,527,848 m_2 (91.97%)	140,608 m_2 (10.78%)	16,900 m_2 (1.01%)	0 m_2 (0.00%)
	Challenging (2)	391,404 m_2 (7.95%)	852,436 m_2 (65.34%)	179,816 m_2 (10.75%)	0 m_2 (0.00%)
	Complex (3)	4,056 m_2 (0.08%)	310,960 m_2 (23.83%)	1,316,172 m_2 (78.70%)	110,188 m_2 (21.03%)
	Extreme (4)	0 m_2 (0.00%)	676 m_2 (0.05%)	159,536 m_2 (9.54%)	413,712 m_2 (78.97%)
Connaught Creek					

Formatert: Blokkjustert

Formatert: Blokkjustert

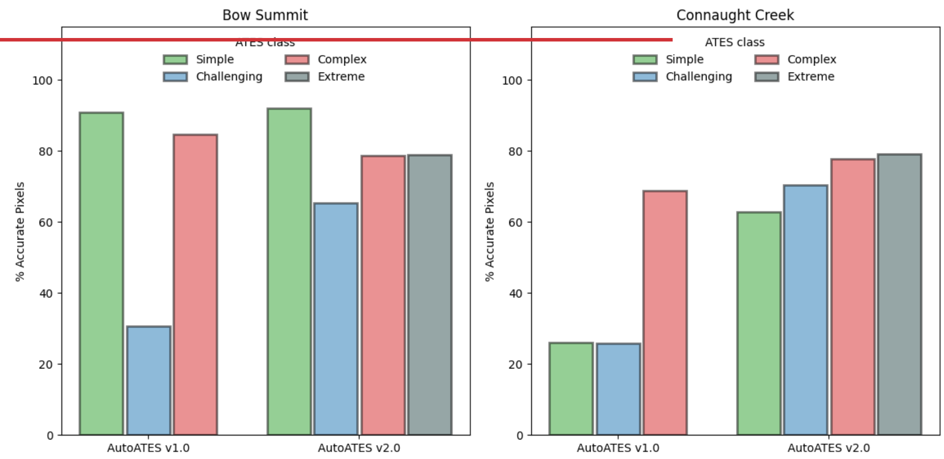
Formatert: Blokkjustert

	Simple (1)	1,364,844 m_2 (63.31%)	263,640 m_2 (10.64%)	76,388 m_2 (1.03%)	0 m_2 (0.00%)
ATES benchmark	**Challenging (2)**	683,436 m_2 (31.30%)	1,757,600 m_2 (70.96%)	884,208 m_2 (11.92%)	676 m_2 (0.05%)
	Complex (3)	102,752 m_2 (4.77%)	449,540 m_2 (18.15%)	5,787,236 m_2 (78.00%)	237,276 m_2 (17.01%)
	Extreme (4)	4732 m_2 (0.22%)	6084 m_2 (0.25%)	671,944 m_2 (9.06%)	1,156,636 m_2 (82.94%)

Formatert: Blokkjustert

Formatert: Blokkjustert

~~A visual presentation of the differences between the two models is shown in Figure 5 where a comparison shows how the models perform compared to the benchmark map for each ATES class, for Bow Summit and Connaught Creek. The bar sections show the absolute accuracy, which areis the percentage of pixels that areis identical between the benchmark and the automated map. In Bow Summit the v2.0 algorithm has greatly improved challenging terrain a lot with a cost of a small reduction in accuracy of complex terrain. In Connaught Creek, the v2.0 algorithm has improved in all terrain classes, but the improvement is especially clear for simple and challenging terrain.~~



Formatert: Blokkjustert

~~Figure 5: The figure shows how the new AutoATES v2.0 model performs compared to the benchmark maps for Bow Summit and Connaught Creek. The figure uses the European ATES color scheme (Statham and Campbell,et al., 2023). The bar sections show the absolute accuracy, which is the percentage of pixels that is identical between the benchmark and the automated map.~~

Formatert: Blokkjustert

3.2 Ablation study

The performance of the AutoATES v2.0 model has ~~is a dramatic~~ improved~~ment~~ ~~significantly~~dramatically~~as~~ compared to the AutoATES v1.0. The transition from v1.0 to v2.0 has been marked by numerous internal iterations, featuring improvements such as an optimized PRA ~~algorithm~~model accounting for forest data, incorporating the Flow-Py runout model, considering forest data in the final terrain class ~~algorithm~~model, and more. To fully understand the underlying factors behind the improvements of AutoATES v2.0, it is crucial to examine each of the components that have been modified.~~,~~ ~~which~~This will help clarify how each modification contributes to the overall performance of the ~~algorithm~~model.

To do this, we utilize the concept of an ablation study which is a common method used to evaluate the importance or contribution of individual components within a system, model, or ~~algorithm~~model. It is a type of sensitivity analysis that aims to understand the impact of removing or *ablating* specific components on the overall performance or output of the system. Ablation studies are commonly employed in machine learning, computational neuroscience, and other scientific disciplines to analyze and understand the roles and relationships of different elements in a complex system (Meyes et al., 2019)~~(Meyes et al., 2019)~~.

The general procedure for an ablation study involves the following steps:

1. Train or develop the full model or system with all its components and parameters intact~~,~~ and measure its performance on a given task or dataset.
2. Systematically remove or disable one component or parameter at a time, keeping the rest of the model unchanged.
3. Measure the performance of the modified model without the removed component or parameter.
4. Compare the performance of the modified model to the performance of the original, complete model.
5. Repeat steps 2-4 for each component or parameter of interest.

For AutoATES v2.0, we have identified six components of the ~~algorithm~~model that have been developed since ~~the~~ v1.0. Using the concepts of an ablation study approach, we have calculated the precision, recall and F1-score by removing different components of the ~~algorithm~~model (Table 5). The reference model is the final AutoATES v2.0. ~~The~~A lower F1-score for a model has compared to the reference, ~~the more~~indicates an important ~~is~~ the component ~~that~~ has been removed. In Bow Summit, the most important component is the inclusion of forest data in the PRA ~~algorithm~~model (dev4). In Connaught Creek, the most important factor is the post-forest-classification (dev6). In general, all new components in AutoATES v2.0 improve the model by several ~~percents~~percent, except the inclusion of the alpha angle threshold between challenging and simple terrain ~~AAT23~~ (dev2), which only improves by 0.08-0.14% for the two study areas.

Table 5: The results from the ablation study where different components are removed to measure the effect for Bow Summit. The term *dev1-6 defines the development model being evaluated, SAT34 is the slope angle threshold between complex and extreme terrain and AAT23 is the alpha angle threshold between challenging and complex terrain.*

	Version	Component removed	Pixel accuracy	Precision	Recall	F1-score	F1-score change
Bow Summit	v1.0*		67.40%	68.75%	66.07%	64.06%	-13.24 %
	dev1*	SAT34 threshold	87.63%	78.74%	76.05%	81.81%	4.51 %
	dev2	AAT23 threshold	84.20%	82.82%	80.97%	77.16%	-0.14 %
	dev3	Forest data from PRA v1.0	78.40%	78.6%	75.90%	70.21%	-7.09 %
	dev4	Forest data from PRA v2.0	76.80%	71.29%	70.61%	68.03%	-9.27 %
	dev5	Flow-Py (back to TauDEM)	79.10%	69.82%	68.99%	72.66%	-4.64 %
	dev6	Post-forest-classification	80.30%	73.38%	72.12%	75.49%	-1.81 %
	v2.0	Reference	84.40%	75.74%	76.19%	77.30%	0.00 %

	Version	Component removed	Pixel accuracy	Precision	Recall	F1-score	F1-score change
Connaught Creek	v1.0*		49.44%	40.21%	38.70%	38.70%	-32.68 %
	dev1*	SAT34 threshold	80.20%	72.43%	74.73%	72.79%	1.41 %
	dev2	AAT23 threshold	74.70%	73.65%	70.89%	71.30%	-0.08 %
	dev3	Forest data from PRA v1.0	71.80%	71.23%	64.12%	66.71%	-4.67 %
	dev4	Forest data from PRA v2.0	72.70%	73.33%	64.68%	67.73%	-3.65 %
	dev5	Flow-Py (back to TauDEM)	65.50%	66.78%	67.55%	65.87%	-5.51 %
	dev6	Post-forest-classification	59.90%	56.40%	48.20%	48.30%	-23.08 %
	v2.0	Reference	74.90%	73.80%	70.94%	71.38%	0.00 %

** AutoATES v1.0 and dev1 uses the old ATES v1.0 framework with three terrain classes, which could lead to higher F1-scores. See section 4.1.1 for an in-depth discussion.*

4. Discussion

One of the primary challenges when developing AutoATES v2.0 has been to create a robust process for validating the output. Initial attempts by Larsen et al., (2020) compared AutoATES v1.0 to available linear and spatial ATES ratings in Norway, however the validity of these ratings~~layers~~ was uncertain because they were developed ~~over multiple years by numerous experts with~~ limited review.~~Initial attempts by Larsen et al.,~~

Formatert: Blokkjustert

Formatert tabell

Formatert: Blokkjustert

Formatert: Blokkjustert

~~(2020) compared AutoATES v1.0 to available linear and spatial ATES ratings in Norway, but the validity of these layers was uncertain, given that multiple experts generated them, over a period of years, with limited review.~~

In contrast, the approach by Sykes et al.~~,~~ (2023), attempts to address these deficiencies~~,~~ and create benchmark maps for two regions in Canada. Their approach ~~-~~– which used three experts to map each study area and then create benchmark maps based on their individual output ~~-~~– is a more comprehensive methodology to address this issue. ~~Their approach, which used three human ATES mappers who independently mapped each study area, and then created benchmark maps based on their individual output through a detailed discussion of the terrain characteristics, is a more comprehensive methodology to address this issue.~~ For the purpose of our analysis, we consider these benchmark ATES maps as the standard to which we will measure any AutoATES models~~ to~~.

~~When conducting making our confusiononsensus matrices, we combine non-avalanche and simple terrain to make a 4-class validation dataset to be used against the AutoATES v2.0. We have chosen to not include a non-avalanche terrain class due to the challenges of defining non-avalanche terrain using automated methods.~~

While the benchmark maps provide the best available validation dataset there are still fundamental differences in how terrain rating experts ~~human mappers~~ create ATES maps versus AutoATES. The scale of analysis for ~~human mappers~~terrain rating experts is generally focused on terrain features, classifying an entire ridgeline, bowl, or gulley as a single unit of analysis. In contrast, AutoATES is a raster-based model which operates on a pixel-by-pixel analysis scale. The size of the pixels depends on the DEM data available for a given study area. Variability in DEM resolution and quality is one of the biggest challenges of applying AutoATES in data sparse regions (e.g. ~~, like~~ Western Canada). The scale mismatch between terrain rating experts ~~human mapped ATES~~ and AutoATES is a persistent difference and an issue that needs to be thoroughly considered with further validation efforts. The optimal scale of use for AutoATES is outside the scope of this current work, but detailed analysis by Sykes et al., (2023) has considered the impact of DEM resolution on AutoATES and notes that there is no real difference in performance using DEM datasets with a spatial resolution ranging from 5-26 m. We therefore recommend that the spatial resolution of the DEM and forest data is between 5 to 30 meters.

4.1 Model performance

We investigated the performance of the AutoATES v2.0 ~~algorithm~~model compared to the v1.0 model~~,~~ both designed to identify potential release and runout areas. Although the underlying concept remains consistent between the two versions, numerous components have been altered or refined in the latest iteration.

4.1.1 Extreme terrain (dev1)

The first modification to the AutoATES v2.0 model was to include the extreme terrain class from ATES v2.0. We incorporated the new class by including another slope angle threshold (SAT). We measured the importance of this change by using the results from the ablation~~s~~ study (Table 5, dev1). The result is that the ablated model performs better with regards to F1-score (e~~i~~.g~~e~~., 4.51% improvement for Bow Summit, and 1.41% for Connaught Creek) than the reference model. This means that excluding the SAT34 threshold (e.~~i.~~g~~e~~., complex / extreme threshold) increases the accuracy of the model. However, without it, the ~~algorithm~~model would be using the old ATES v1.0 classification excluding extreme terrain. This implies that excluding the SAT34 threshold enhances the model~~'~~'s numerical accuracy. Nonetheless, its absence would cause the ~~algorithm~~model to employ the outdated ATES v1.0 classification, which does not account for extreme terrain, and therefore diminishing its value for ATES v2.0.

Formatert: Blokkjustert

When working with classification problems, decision boundaries are the borders or thresholds that separate different classes (Lee and Landgrebe, 1993)~~(Lee and Landgrebe, 1993)~~. The complexity of the decision boundaries often depends on the number of classes. When there are fewer classes, the decision boundaries tend to be simpler, as there are fewer regions to separate in the feature space. With simpler decision boundaries, the model may have an easier time making accurate predictions, as there is less chance of overfitting or incorrectly assigning data points to the wrong class. This could lead to higher precision, recall, and ultimately higher F1 scores. We believe the fewer classes in the ATES v1.0 is the reason why it performs better than the ATES v2.0 reference model.

4.1.2 Terrain traps (dev2)

To improve the ~~algorithm~~model's~~'~~ ability to identify~~ severe~~ terrain traps such as depressions and gullies, another alpha angle threshold (AAT) was added to be included in complex terrain. The previous model only had AAT thresholds which defaulted terrain into simple and challenging terrain. The extra component was added in the early stages of the development of AutoATES v2.0. The ablation analysis shows that this change has ~~a~~ very little effect on the overall performance of the model (Table 5, dev2)~~. (ei.ge.~~with a~~,~~ 0.14% decrease for Bow Summit~~,~~ and 0.08% for Connaught Creek~~)~~. This method would not help for modeling other common terrain traps such as cliffs, ~~crevasses~~crevasses and forest. We have not made any attempts to model other types of terrain traps because we believe it would have a very limited effect on the overall performance given our spatial resolution. ~~Rationale for why we did not try to model these? Is it a valid approach to model terrain traps using a 30 m DEM? We are probably not picking up this as Flow-Py is sensitive to DEM resolution.~~

4.1.3 Forest data in PRA (dev3 and dev4)

Forest density ~~is considered to be~~is one of the most important parameters for ATES classification. In the original PRA v1.0 from Veitinger et al. (2016) it was not possible to include forest density as one of the inputs. The modified PRA v2.0 used in the AutoATES v2.0 ~~algorithm~~model builds on the work from Sharp (2018).

~~The PRA was initially developed and optimized for a 2m DEM, while we utilize a 10m DEM as default. If roughness was calculated using a 10m DEM, it would measure the roughness at basin scale, instead of the roughness at the slope scale (Blöschl, 1999; Blöschl and Sivapalan, 1995). The roughness is also dependent of a snow depth value which is impossible to define without assessing the snowpack properties at a given time. We do not consider that there is value in running AutoATES v2.0 using high resolution DEMs (< 5 meter). Sykes et al., (2023) further illustrates the impact of DEM scale on ATES mapping. We have therefore chosen to remove the roughness parameter from our version of the PRA model.~~

When comparing the importance of PRA v1.0 (dev3) and PRA v2.0 (dev4) to the reference model, we see that the forest density into PRA is among one of the most important components (Table 5, dev3-4) (e~~i~~.ge., 7.09-9.27% decrease for Bow Summit, and 3.65-4.67% for Connaught Creek). Comparing the results between PRA v1.0 and PRA v2.0, we can measure the difference between the two models without forest input. We found that the PRA v1.0 performed better than v2.0 in Bow Summit, but the opposite is the case in Connaught Creek. However, given that Larsen et al. (2020) did not adapt the PRA v1.0 ~~algorithm~~model according to the recommendations of Veitinger et al. (2016), we believe the changes are conceptually still important even though there are no substantial differences between the two in the ablation validation.

4.1.4 Roughness in PRA

The PRA was initially developed and optimized for a 2 m DEM, while we utilize a 10 m DEM as default. If roughness was calculated using a 10 m DEM, it would measure the roughness at basin scale, instead of the roughness at the slope scale (Blöschl, 1999; Blöschl and Sivapalan, 1995). The roughness is also dependent of a snow depth value which is impossible to define without assessing the snowpack properties at a given time. ~~We do not consider that there is~~Sykes et al. (2023) demonstrate minimal value in running AutoATES v2.0 using high resolution DEM's (< 5 m). Sykes et al., (2023) further illustrates the impact of DEM scale on

formaterte: Skriftfarge: Tekst 1

formaterte: Skrift: Fet

formaterte: Skrift: Fet

formaterte: Brødtekst Tegn, Skrift: (Standard) Times, Skriftfarge: Svart, Norsk (bokmål)

ATES mapping. We have therefore chosen to remove the roughness parameter from our version of the PRA model.

formaterte: Skrift: (Standard) +Brødtekst (Calibri), Skriftfarge: Automatisk

4.1.5~~4~~ Flow-Py (dev5)

The previous iteration of AutoATES had some severe issues with the runout simulation of avalanches where avalanches ~~where~~were simulated using a flow model for water. The Flow-Py simulation works in a similar fashion where the flow is limited by an alpha angle threshold, but the flow model has been changed to give more realistic outputs in terms of snow avalanches. Some other advantages with the Flow-Py simulation suite are that there are additional outputs such as cell count and z_{delta} which makes it possible to account for the exposure of multiple overlapping paths and avalanche paths with high kinetic energy. When we compare the Flow-Py outputs compared to the TauDEM~~,~~ we see a substantial improvement when using the Flow-Py outputs (Table 5, dev5), with a~~(ei.ge.,~~ 4.64% decrease for Bow Summit, and 5.51% for Connaught Creek~~)~~.

4.1.6~~5~~ Post-forest-classification (dev6)

Even though the inclusion of forest density in the PRA ~~algorithm~~model improved the performance of AutoATES, we found the need to reclassify sections that were obviously ~~where~~ densely forested and resulted in a higher ATES rating than needed. To improve this, we added a post-forest-classification criteria. This was ~~really efficient~~efficient for Connaught Creek, but less efficient for Bow Summit (Table 5, dev6) ~~(ei.ge.,~~ (1.81% decrease for Bow Summit, and 23.08% for Connaught Creek). The forest impact of dev6 is minimal at Bow Summit, but ~~really important~~important for Connaught Creek. We don't know why this is, but one hypothesis is that there is more steep forested terrain in Connaught Creek, and the ~~algorithm~~model therefore relies more on the post-forest-classification. Connaught Creek also has more large runouts and overhead hazard that rely on the post-forest-classification.

In the future, we hope to be less reliant on the post-forest-classification criteria by optimizing the forest detrainment module in Flow-Py. This module of Flow-Py makes it possible to reduce the runout length in areas with dense forest.

4.1.7~~6~~ Discrepancies

The discrepancy in accuracy scores between the two study areas is mainly attributed to the complex terrain of Connaught Creek with many smaller topographical features and the limitations of the ~~Vegetation Resources Inventory (~~BC VRI~~)~~ forest data resolution in capturing local forest characteristics (Sykes et al., 2023). This issue significantly affects the assessment of overhead hazards and boundaries delineation between ATES classes, with challenging (2) terrain showing the lowest accuracy and high rates of underprediction errors. Sykes et al. (2023) provides an extended discussion of the differences between the two study sites.

4.3 Application

AutoATES v2.0 is meant to be a stand-alone tool for mapping large-scale areas, but it should first be validated for a smaller area by experts to assess whether there is a need to make some changes to the input parameters. When the user is confident with their maps, the parameters could be used to generate ATES maps for a larger surrounding area.

Formatert: Brødtekst, Venstre

While it is possible to run the presented version of AutoATES v2.0 without making any changes, we recommend a workflow where the optimal parameters are first identified. The suggested parameters in this paper are valid for the two test areas in Western Canada.~~,~~ W~~so w~~hen applying AutoATES v2.0 for other areas, the parameters~~, there~~ will likely need to be ~~a~~ re-evaluated~~ the parameters for the area being mapped~~. Blindly applying the parameters presented in this document to other regions without site specific calibration risks inaccurate ATES mapping, and potential catastrophic outcomes. Users should apply ~~at~~this model at their own risk. We therefore urge all future users of our code to conduct~~, and document, their~~ a local validation before proceeding with the generation of large-scale ATES maps. This is~~,~~ especially important when the ~~intended~~ target group is the general public.

Begin with a relevant test area which should include a variety of terrain and all terrain classes. We recommend a workflow where the PRA model and Flow-Py is processed independent of the AutoATES classifier. The output from PRA and Flow-Py is easier to validate by local experts compared to the AutoATES output. It is more intuitive as avalanche experts have more tangible experience with identifying start and runout zones. In our experience, we complete approximately 1-3 iterations of PRA and Flow-Py before moving on to the AutoATES classifier. In general, we have experienced that the 'c' parameter in the Cauchy function for slope angle combined with the max alpha angle for Flow-Py are the most effective for customizing the output. We also recommend fine-tuning all parameters in the Cauchy function for PRA when using ~~new~~ ~~other~~ forest density data ~~than what's being~~ that is different than what we used in this validation.~~.~~ This could be done by using a local avalanche terrain expert to review the output from each Cauchy membership value and adjust until the output is appropriate.

When these steps are done in advance, our experience is that the output of the AutoATES classifier tends to be much more accurate. The final AutoATES could then be shared among local experts who~~ich~~ provide~~s~~ further feedback. Changes could then be made to the AutoATES classifier parameters and improved during an iterative process. When the final input parameters are set, they could be used to generate larger areas. A description of the input parameters used should be shared as meta~~-~~data with the resulting spatial maps.

4.3.1 Large scale application

We have used the DEM from ALOS at a spatial resolution of 26 m. This dataset is available worldwide and could enable large scale application of AutoATES v2.0 in the future. The main limitation right now is that to our knowledge, there is no global forest data available that have a suitable accuracy and resolution. In all countries we have tested AutoATES (Norway, Canada, USA) there has been a considerable testing period to determine the best available forest data and fine tuning of model parameters to work well with local forest data. This is the rationale for providing multiple 'default' settings for the input forest data including stem density, canopy cover, and basal area. The PRA parameters used for each of these are unique and need to be locally tested before large scale application of AutoATES v2.0.

formaterte: Skrift: Fet

formaterte: Skrift: Fet

Formatert: Brødtekst, Venstre

formaterte: Mønster: Klart

4.4 Limitations

Despite the notable improvements of the AutoATES v2.0 model, there are still some limitations that should be acknowledged.

- Flow-Py is computationally heavy, which may present challenges when processing large datasets or applying the model in real-time applications. This could potentially limit the scalability and accessibility of the model for certain use cases and users with limited computational resources.
- Determining the optimal input parameters for the AutoATES model is important to get the best performance possible. The suitability of these parameters across different snow climates and terrain types remains an open question. Further research and validation are needed to ensure that the chosen parameters provide accurate and reliable results in various contexts. Users should not blindly adopt the input parameters stated in this paper.
- The model does not account for changes in vegetation over time such as natural events like landslides or forest fires. Therefore, it is important to update the ATES mapping periodically to account for major changes in the landscape.

  Due to the limited sample size of mapped class 0 terrain in the validation data sets that we used to develop autoATESv2.0, we do not feel that there has been sufficient research on this topic to warrant publication at this time. AutoATES is a promising tool for estimating areas with no exposure to avalanche terrain, however there is significant liability associated with deeming an

formaterte: Skrift: (Standard) +Brødtekst (Calibri), Ikke Fet, Engelsk (USA) area safe from avalanche hazard. Further development of the autoATESv2.0 model and consultation with avalanche community stakeholders is necessary before delving into automated mapping of class 0 terrain.~~Class 0 – non-avalanche terrain – why is it not part of the model?~~

Addressing these limitations in future work could enhance the performance, applicability, and reliability of the AutoATES model, ensuring its effectiveness across a wide range climates and terrain characteristics.

5. Conclusion

In conclusion, the development of AutoATES v2.0 has focused on creating a more robust and accurate ~~algorithm~~model for mapping avalanche terrain into ATES ratings by incorporating new components to improve the ~~algorithm~~model. This has been achieved by integrating new components that enhance the ~~algorithm~~model's performance, including the addition of an extreme terrain class, improved PRA with support for multiple forest density types, Flow-Py, and a post-forest-classification criteria. Moreover, a significant portion of the code has been rewritten to increase efficiency and eliminate dependency on proprietary software.

However, limitations related to the determination of optimal input parameters for different regions and climates need to be considered for future model development. By addressing these limitations and continuing to refine the model through iterative testing and expert feedback, AutoATES v2.0 can serve as a valuable tool for avalanche risk assessment and decision-making in a wide range of snow climates and terrain types. Ultimately, our goal is for AutoATES v2.0 to enable efficient, large-scale, and potentially global ATES mapping in a standardized manner.

6. Code and data availability

To reproduce the results from this study, please find the AutoATES v2.0 ~~algorithm~~model and validation data from the ablation study in the OSF repository. For future application of AutoATES v2.0, a GitHub repository will be maintained with future iterations of the ~~algorithm~~model available (Toft et al. 2023).

7. Author contribution

Håvard Toft~~T~~ was the developer of the first version of automated ATES. The ~~new ve~~model improvement~~rsions improvements~~ have been led by Håvard Toft~~HT~~ with substantial~~ignificant~~ contributions from John Sykes~~S~~ and Andrew Schauer~~S~~. The ablation study has been carried out by Håvard Toft~~HT~~ with inputs from John Sykes~~JS~~. Håvard Toft~~T~~ prepared the final manuscript with input from Andrew Schauer and John Sykes. Jordy Hendrikx~~H~~ and Audun Hetland~~H~~ has~~ve~~ contributed with review and edits as their role as supervisors~~as editors~~. All ~~co-~~authors contributed to the final manuscript.

8. Competing interests

The authors declare that they have no conflict of interest.

9. References

Andres, J. and Chueca Cia, J.: Mapping of avalanche start zones susceptibility: Arazas basin, Ordesa and Monte Perdido National Park (Spanish Pyrenees), J Maps, 8, 14–21, 2012.

Barbolini, M., Pagliardi, M., Ferro, F., and Corradeghini, P.: Avalanche hazard mapping over large undocumented areas, Natural Hazards, 56, 451–464, https://doi.org/10.1007/S11069-009-9434-8, 2011.

BFF and SLF: Richtlinien zur Berücksichtigung der Lawinengefahr bei raumwirksamen Tätigkeiten, Eidgenössische Drucksachen- und Materialzentrale, 42, 1984.

formaterte: Skriftfarge: Mørk rød

Formatert: Venstre

Feltkode endret

Feltkode endret

Formatert: Blokkjustert

formaterte: Engelsk (USA)

Formatert: Blokkjustert

formaterte: Skrift: (Standard) +Brødtekst (Calibri), Engelsk (USA)

Formatert: Innrykk: Venstre: 0 cm, Hengende: 1,27 cm

formaterte: Skrift: (Standard) +Brødtekst (Calibri), 11 pkt, Engelsk (USA)

formaterte: Skrift: (Standard) +Brødtekst (Calibri), Engelsk (USA)

Birkeland, K. W., Greene, E. M., and Logan, S.: In Response to Avalanche Fatalities in the United States by Jekich et al, Wilderness Environ Med, 28, 380–382, https://doi.org/10.1016/j.wem.2017.06.009, 2017.

Blöschl, G.: Scaling issues in snow hydrology, Hydrol Process, 13, 2149–2175, https://doi.org/10.1002/(SICI)1099-1085(199910)13:14/15<2149::AID-HYP847>3.0.CO;2-8, 1999.

Blöschl, G. and Sivapalan, M.: Scale issues in hydrological modelling: A review, Hydrol Process, 9, 251–290, https://doi.org/10.1002/hyp.3360090305, 1995.

Bühler, Y., Kumar, S., Veitinger, J., Christen, M., and Stoffel, A.: Automated identification of potential snow avalanche release areas based on digital elevation models, Natural Hazards and Earth System Sciences, 13, 1321–1335, https://doi.org/10.5194/nhess-13-1321-2013, 2013.

Bühler, Y., von Rickenbach, D., Stoffel, A., Margreth, S., Stoffel, L., and Christen, M.: Automated snow avalanche release area delineation – validation of existing ~~algorithm~~models and proposition of a new object-based approach for large-scale hazard indication mapping, Natural Hazards and Earth System Sciences, 18, 3235–3251, https://doi.org/10.5194/nhess-18-3235-2018, 2018.

CAA: Technical Aspects of Snow Avalanche Risk Management – Resources and Guidelines for Avalanche Practitioners in Canada (C. Campbell, S. Conger, B. Gould, P. Haegeli, B. Jamieson, & G. Statham Eds.), Canadian Avalanche Association, 2016.

Campbell, C. and Gould, B.: A proposed practical model for zoning with the Avalanche Terrain Exposure Scale, in: International Snow Science Workshop Proceedings, Grenoble – Chamonix Mont-Blanc, 385–391, 2013.

Christen, M., Kowalski, J., and Bartelt, P.: RAMMS: Numerical simulation of dense snow avalanches in three-dimensional terrain, Cold Reg Sci Technol, 63, 1–14, https://doi.org/10.1016/j.coldregions.2010.04.005, 2010.

Chueca Cía, J., Andrés, A. J., and Montañés Magallón, A.: A proposal for avalanche susceptibility mapping in the Pyrenees using GIS: the Formigal-Peyreget area (Sheet 145-I; scale 1:25.000), J Maps, 10, 203–210, https://doi.org/10.1080/17445647.2013.870501, 2014.

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

Delparte, D. M.: Avalanche terrain modeling in Glacier National Park, Canada, PhD thesis, 1–195, https://doi.org/10.1007/s13398-014-0173-7.2, 2008.

DIBK: Byggteknisk forskrift (TEK17), Kommunal- og distriktsdepartementet, 2017.

Engeset, R. V., Pfuhl, G., Landrø, M., Mannberg, A., and Hetland, A.: Communicating public avalanche warnings – what works ?, Natural Hazards and Earth System Science, 18, 2537–2559, https://doi.org/https://doi.org/10.5194/nhess-18-2537-2018, 2018.

Fisher, K. C., Haegeli, P., and Mair, P.: Exploring the avalanche bulletin as an avenue for continuing education by including learning interventions, Journal of Outdoor Recreation and Tourism, 37, 100472, https://doi.org/10.1016/J.JORT.2021.100472, 2022.

Ghinoi, A. and Chung, C.-J.: STARTER: a statistical GIS-based model for the prediction of snow avalanche susceptibility using terrain features—application to Alta Val Badia, Italian Dolomites, Geomorphology, 66, 305–325, https://doi.org/10.1016/j.geomorph.2004.09.018, 2005.

Harvey, S., Schmudlach, G., Bühler, Y., Dürr, L., Stoffel, A., and Christen, M.: Avalanche Terrain Maps For Backcountry Skiing in Switzerland, in: International Snow Science Workshop Proceedings, Innsbruck, Austria, 1625–1631, 2018.

Heim, A.: Bergsturz und Menschenleben, Zürich, Fretz und Wasmuth, 1932.

Hendrikx, J., Johnson, J., and Mannberg, A.: Tracking decision-making of backcountry users using GPS tracks and participant surveys, Applied Geography, 144, 102729, https://doi.org/10.1016/J.APGEOG.2022.102729, 2022.

formaterte: Skrift: (Standard) +Brødtekst (Calibri)

formaterte: Skrift: (Standard) +Brødtekst (Calibri), Engelsk (USA)

formaterte: Skrift: (Standard) +Brødtekst (Calibri), Norsk (nynorsk)

formaterte: Skrift: (Standard) +Brødtekst (Calibri), Engelsk (USA)

Johnson, J. and Hendrikx, J.: Using Citizen Science to Document Terrain Use and Decision-Making of Backcountry Users, Citiz Sci, 6, https://doi.org/10.5334/cstp.333, 2021.
Keskinen, Z., Hendrikx, J., Eckerstorfer, M., and Birkeland, K.: Satellite detection of snow avalanches using Sentinel-1 in a transitional snow climate, Cold Reg Sci Technol, 199, 103558, https://doi.org/10.1016/j.coldregions.2022.103558, 2022.
Landrø, M., Hetland, A., Engeset, R. V., and Pfuhl, G.: Avalanche decision-making frameworks: Factors and methods used by experts, Cold Reg Sci Technol, 170, 102897, https://doi.org/10.1016/j.coldregions.2019.102897, 2020.
Larsen, H. T., Hendrikx, J., Slåtten, M. S., and Engeset, R. V.: Developing nationwide avalanche terrain maps for Norway, Natural Hazards, 103, https://doi.org/10.1007/s11069-020-04104-7, 2020.
Lee, C. and Landgrebe, D. A.: Decision boundary feature extraction for nonparametric classification, IEEE Trans Syst Man Cybern, 23, 433–444, https://doi.org/10.1109/21.229456, 1993.
Lied, K. and Bakkehøi, S.: Empirical calculations of snow avalanche run-out distances based on topographic parameters, Journal of Glaciology, 26, 165–177, 1980.
Maggioni, M. and Gruber, U.: The influence of topographic parameters on avalanche release dimension and frequency, Cold Reg Sci Technol, 37, 407–419, https://doi.org/10.1016/S0165-232X(03)00080-6, 2003.
Meyes, R., Lu, M., de Puiseau, C. W., and Meisen, T.: Ablation studies in artificial neural networks, arXiv preprint, 2019.
Pistocchi, A. and Notarnicola, C.: Data-driven mapping of avalanche release areas: a case study in South Tyrol, Italy, Natural Hazards, 65, 1313–1330, https://doi.org/10.1007/s11069-012-0410-3, 2013.
Plattner, C., Braun, L., and Brenning, A.: The spatial variability of snow accumulation at Vernagtferner, Austrian Alps, in winter 2003/2004, Z. Gletscherk., Glazialgeol., 39, 43–57, 2006.
Sampl, P. and Zwinger, T.: Avalanche simulation with SAMOS, Ann Glaciol, 38, 393–398, https://doi.org/10.3189/172756404781814780, 2004.
Sandvoss, M., McClymont, B., and Farnden, C.: A user's guide to the vegetation resources inventory, Tolko Industries, Ltd.: Williams Lake, BC, Canada., 2005.
Schläppy, R., Jomelli, V., Grancher, D., Stoffel, M., Corona, C., Brunstein, D., Eckert, N., and Deschatres, M.: A New Tree-Ring-Based, Semi-Quantitative Approach for the Determination of Snow Avalanche Events: use of Classification Trees for Validation, Arct Antarct Alp Res, 45, 383–395, https://doi.org/10.1657/1938-4246-45.3.383, 2013.
Schmudlach, G. and Köhler, J.: Method for an automatized avalanche terrain classification, in: Proceedings, International Snow Science Workshop - Breckenridge, Colorado, 729–736, 2016.
Schumacher, J., Toft, H., McLean, J. P., Hauglin, M., Astrup, R., and Breidenbach, J.: The utility of forest attribute maps for automated Avalanche Terrain Exposure Scale (ATES) modelling, Scand J For Res, 37, 264–275, https://doi.org/10.1080/02827581.2022.2096921, 2022.
Schweizer, J. and Lütschg, M.: Characteristics of human-triggered avalanches, Cold Reg Sci Technol, 33, 147–162, https://doi.org/10.1016/S0165-232X(01)00037-4, 2001.
Sharp, E.: Evaluating the exposure of heliskiing ski guides to avalanche terrain using a fuzzy logic avalanche susceptibility model, University of Leeds, Leeds, 2018.
Statham, G. and Campbell, C.: The Avalanche Terrain Exposure Scale v2.0, [Manuscript in preparations], 2023.
Statham, G., McMahon, B., and Tomm, I.: The Avalanche Terrain Exposure Scale, International Snow Science Workshop Proceedings, Telluride, Colorado, 491–497, 2006.
Sykes, J., Hendrikx, J., Johnson, J., and Birkeland, K. W.: Combining GPS tracking and survey data to better understand travel behavior of out-of-bounds skiers, Applied Geography, 122, https://doi.org/10.1016/j.apgeog.2020.102261, 2020.
Sykes, J., Haegeli, P., and Bühler, Y.: Automated snow avalanche release area delineation in data-sparse, remote, and forested regions, Natural Hazards and Earth System Sciences, 22, 3247–3270, https://doi.org/10.5194/nhess-22-3247-2022, 2022.

Sykes, J., Toft, H., Haegeli, P., and Statham, G.: Automated Avalanche Terrain Exposure Scale (ATES) mapping - Local validation and optimization in Western Canada, [Manuscript submitted for publication], 2023.

Tarboton, D. G.: A new method for the determination of flow directions and upslope areas in grid digital elevation models, Water Resour Res, 33, 309–319, https://doi.org/10.1029/96WR03137, 1997.

Tarboton, D. G.: Terrain analysis using digital elevation models (TauDEM), Utah State University, Logan, 2005.

Techel, F. and Zweifel, B.: Recreational avalanche accidents in Switzerland: Trends and patterns with an emphasis on burial, rescue methods and avalanche danger, in: International Snow Science Workshop Proceedings, Grenoble-Chamonix, 1106–1112, 2013.

Techel, F., Jarry, F., Kronthaler, G., Mitterer, S., Nairz, P., Pavšek, M., Valt, M., and Darms, G.: Avalanche fatalities in the European Alps: long-term trends and statistics, Geogr Helv, 71, https://doi.org/10.5194/gh-71-147-2016, 2016.

Techel, F., Mitterer, C., Ceaglio, E., Coléou, C., Morin, S., Rastelli, F., and Purves, R. S.: Spatial consistency and bias in avalanche forecasts -a case study in the European Alps, Natural Hazards and Earth System Sciences, 18, 2697–2716, https://doi.org/10.5194/nhess-18-2697-2018, 2018.

Thumlert, S. and Haegeli, P.: Describing the severity of avalanche terrain numerically using the observed terrain selection practices of professional guides, Natural Hazards, 1–27, https://doi.org/10.1007/s11069-017-3113-y, 2017.

Toft, H. B., Sykes, J. M., and Schauer, A.: AutoATES v2.0, https://github.com/AutoATES, 2023a.

Toft, H. B., Müller, K., Hendrikx, J., Jaedicke, C., and Bühler, Y.: Can big data and random forests improve avalanche runout estimation compared to simple linear regression?, Cold Reg Sci Technol, 211, 103844, https://doi.org/10.1016/j.coldregions.2023.103844, 2023b.

Veitinger, J., Purves, R. S., and Sovilla, B.: Potential slab avalanche release area identification from estimated winter terrain: a multi-scale, fuzzy logic approach, Natural Hazards and Earth System Sciences, 16, 2211–2225, https://doi.org/10.5194/nhess-16-2211-2016, 2016.

Werners, B.: Aggregation models in mathematical programming, Mathematical Models for Decision Support, 48, 295–305, 1988.

~~Andres, J. and Chueca Cia, J.: Mapping of avalanche start zones susceptibility: Arazas basin, Ordesa and Monte Perdido National Park (Spanish Pyrenees), J Maps, 8, 14–21, 2012.~~

~~Barbolini, M., Pagliardi, M., Ferro, F., and Corradeghini, P.: Avalanche hazard mapping over large undocumented areas, Natural Hazards, 56, 451–464, https://doi.org/10.1007/S11069-009-9434-8, 2011.~~

~~BFF and SLF: Richtlinien zur Berücksichtigung der Lawinengefahr bei raumwirksamen Tätigkeiten, Eidgenössische Drucksachen- und Materialzentrale, 42, 1984.~~

~~Birkeland, K. W., Greene, E. M., and Logan, S.: In Response to Avalanche Fatalities in the United States by Jekich et al, Wilderness Environ Med, 28, 380–382, https://doi.org/10.1016/j.wem.2017.06.009, 2017.~~

~~Blöschl, G.: Scaling issues in snow hydrology, Hydrol Process, 13, 2149–2175, https://doi.org/10.1002/(SICI)1099-1085(199910)13:14/15<2149::AID-HYP847>3.0.CO;2-8, 1999.~~

~~Blöschl, G. and Sivapalan, M.: Scale issues in hydrological modelling: A review, Hydrol Process, 9, 251–290, https://doi.org/10.1002/hyp.3360090305, 1995.~~

~~Bühler, Y., Kumar, S., Veitinger, J., Christen, M., and Stoffel, A.: Automated identification of potential snow avalanche release areas based on digital elevation models, Natural Hazards and Earth System Sciences, 13, 1321–1335, https://doi.org/10.5194/nhess-13-1321-2013, 2013.~~

~~Bühler, Y., von Rickenbach, D., Stoffel, A., Margreth, S., Stoffel, L., and Christen, M.: Automated snow avalanche release area delineation – validation of existing algorithms and proposition of a new object-based approach for large-scale hazard indication mapping, Natural Hazards and Earth System Sciences, 18, 3235–3251, https://doi.org/10.5194/nhess-18-3235-2018, 2018.~~

~~CAA: Technical Aspects of Snow Avalanche Risk Management – Resources and Guidelines for Avalanche Practitioners in Canada (C. Campbell, S. Conger, B. Gould, P. Haegeli, B. Jamieson, & G. Statham Eds.), Canadian Avalanche Association, 2016.~~

Formatert: Blokkjustert

~~Campbell, C. and Gould, B.: A proposed practical model for zoning with the Avalanche Terrain Exposure Scale, in: International Snow Science Workshop Proceedings, Grenoble – Chamonix Mont-Blanc, 385–391, 2013.~~

~~Christen, M., Kowalski, J., and Bartelt, P.: RAMMS: Numerical simulation of dense snow avalanches in three-dimensional terrain, Cold Reg Sci Technol, 63, 1–14, https://doi.org/10.1016/j.coldregions.2010.04.005, 2010.~~

~~Chueca Cía, J., Andrés, A. J., and Montañés Magallón, A.: A proposal for avalanche susceptibility mapping in the Pyrenees using GIS: the Formigal-Peyreget area (Sheet 145-I; scale 1:25.000), J Maps, 10, 203–210, https://doi.org/10.1080/17445647.2013.870501, 2014.~~

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

~~Delparte, D. M.: Avalanche terrain modeling in Glacier National Park, Canada, PhD thesis, 1–195, https://doi.org/10.1007/s13398-014-0173-7.2, 2008.~~

~~DIBK: Byggteknisk forskrift (TEK17), Kommunal- og distriktsdepartementet, 2017.~~

~~Engeset, R. V., Pfuhl, G., Landrø, M., Mannberg, A., and Hetland, A.: Communicating public avalanche warnings – what works ?, Natural Hazards and Earth System Science, 18, 2537–2559, https://doi.org/https://doi.org/10.5194/nhess-18-2537-2018, 2018.~~

~~Fisher, K. C., Haegeli, P., and Mair, P.: Exploring the avalanche bulletin as an avenue for continuing education by including learning interventions, Journal of Outdoor Recreation and Tourism, 37, 100472, https://doi.org/10.1016/J.JORT.2021.100472, 2022.~~

~~Ghinoi, A. and Chung, C.-J.: STARTER: a statistical GIS-based model for the prediction of snow avalanche susceptibility using terrain features—application to Alta Val Badia, Italian Dolomites, Geomorphology, 66, 305–325, https://doi.org/10.1016/j.geomorph.2004.09.018, 2005.~~

~~Harvey, S., Schmudlach, G., Bühler, Y., Dürr, L., Stoffel, A., and Christen, M.: Avalanche Terrain Maps For Backcountry Skiing in Switzerland, in: International Snow Science Workshop Proceedings, Innsbruck, Austria, 1625–1631, 2018.~~

~~Heim, A.: Bergsturz und Menschenleben, Zürich, Fretz und Wasmuth, 1932.~~

~~Hendrikx, J., Johnson, J., and Mannberg, A.: Tracking decision-making of backcountry users using GPS tracks and participant surveys, Applied Geography, 144, 102729, https://doi.org/10.1016/J.APGEOG.2022.102729, 2022.~~

~~Johnson, J. and Hendrikx, J.: Using Citizen Science to Document Terrain Use and Decision-Making of Backcountry Users, Citiz Sci, 6, https://doi.org/10.5334/cstp.333, 2021.~~

~~Keskinen, Z., Hendrikx, J., Eckerstorfer, M., and Birkeland, K.: Satellite detection of snow avalanches using Sentinel-1 in a transitional snow climate, Cold Reg Sci Technol, 199, 103558, https://doi.org/10.1016/j.coldregions.2022.103558, 2022.~~

~~Landrø, M., Hetland, A., Engeset, R. V., and Pfuhl, G.: Avalanche decision-making frameworks: Factors and methods used by experts, Cold Reg Sci Technol, 170, 102897, https://doi.org/10.1016/j.coldregions.2019.102897, 2020.~~

~~Larsen, H. T., Hendrikx, J., Slåtten, M. S., and Engeset, R. V.: Developing nationwide avalanche terrain maps for Norway, Natural Hazards, 103, https://doi.org/10.1007/s11069-020-04104-7, 2020.~~

~~Lee, C. and Landgrebe, D. A.: Decision boundary feature extraction for nonparametric classification, IEEE Trans Syst Man Cybern, 23, 433–444, https://doi.org/10.1109/21.229456, 1993.~~

~~Lied, K. and Bakkehøi, S.: Empirical calculations of snow avalanche run-out distances based on topographic parameters, Journal of Glaciology, 26, 165–177, 1980.~~

~~Maggioni, M. and Gruber, U.: The influence of topographic parameters on avalanche release dimension and frequency, Cold Reg Sci Technol, 37, 407–419, https://doi.org/10.1016/S0165-232X(03)00080-6, 2003.~~

~~Meyes, R., Lu, M., de Puiseau, C. W., and Meisen, T.: Ablation studies in artificial neural networks, arXiv preprint, 2019.~~

Pistocchi, A. and Notarnicola, C.: Data-driven mapping of avalanche release areas: a case study in South Tyrol, Italy, Natural Hazards, 65, 1313–1330, https://doi.org/10.1007/s11069-012-0410-3, 2013.

Plattner, C., Braun, L., and Brenning, A.: The spatial variability of snow accumulation at Vernagtferner, Austrian Alps, in winter 2003/2004, Z. Gletscherk., Glazialgeol., 39, 43–57, 2006.

Sampl, P. and Zwinger, T.: Avalanche simulation with SAMOS, Ann Glaciol, 38, 393–398, https://doi.org/10.3189/172756404781814780, 2004.

Sandvoss, M., McClymont, B., and Farnden, C.: A user's guide to the vegetation resources inventory, Tolko Industries, Ltd.: Williams Lake, BC, Canada., 2005.

Schläppy, R., Jomelli, V., Grancher, D., Stoffel, M., Corona, C., Brunstein, D., Eckert, N., and Deschatres, M.: A New Tree-Ring-Based, Semi-Quantitative Approach for the Determination of Snow Avalanche Events: use of Classification Trees for Validation, Arct Antarct Alp Res, 45, 383–395, https://doi.org/10.1657/1938-4246-45.3.383, 2013.

Schmudlach, G. and Köhler, J.: Method for an automatized avalanche terrain classification, in: Proceedings, International Snow Science Workshop - Breckenridge, Colorado, 729–736, 2016.

Schumacher, J., Toft, H., McLean, J. P., Hauglin, M., Astrup, R., and Breidenbach, J.: The utility of forest attribute maps for automated Avalanche Terrain Exposure Scale (ATES) modelling, Scand J For Res, 37, 264–275, https://doi.org/10.1080/02827581.2022.2096921, 2022.

Schweizer, J. and Lütschg, M.: Characteristics of human-triggered avalanches, Cold Reg Sci Technol, 33, 147–162, https://doi.org/10.1016/S0165-232X(01)00037-4, 2001.

Sharp, E.: Evaluating the exposure of heliskiing ski guides to avalanche terrain using a fuzzy logic avalanche susceptibility model, University of Leeds, Leeds, 2018.

Statham, G. and Campbell, C.: The Avalanche Terrain Exposure Scale v2.0, [Manuscript in preparations], 2023.

Statham, G., McMahon, B., and Tomm, I.: The Avalanche Terrain Exposure Scale, International Snow Science Workshop Proceedings, Telluride, Colorado, 491–497, 2006.

Sykes, J., Hendrikx, J., Johnson, J., and Birkeland, K. W.: Combining GPS tracking and survey data to better understand travel behavior of out-of-bounds skiers, Applied Geography, 122, https://doi.org/10.1016/j.apgeog.2020.102261, 2020.

Sykes, J., Haegeli, P., and Bühler, Y.: Automated snow avalanche release area delineation in data-sparse, remote, and forested regions, Natural Hazards and Earth System Sciences, 22, 3247–3270, https://doi.org/10.5194/nhess-22-3247-2022, 2022.

Sykes, J., Toft, H., Haegeli, P., and Statham, G.: Automated Avalanche Terrain Exposure Scale (ATES) mapping - Local validation and optimization in Western Canada, [Manuscript submitted for publication], 2023.

Tarboton, D. G.: A new method for the determination of flow directions and upslope areas in grid digital elevation models, Water Resour Res, 33, 309–319, https://doi.org/10.1029/96WR03137, 1997.

Tarboton, D. G.: Terrain analysis using digital elevation models (TauDEM), Utah State University, Logan, 2005.

Techel, F., Jarry, F., Kronthaler, G., Mitterer, S., Nairz, P., Pavšek, M., Valt, M., and Darms, G.: Avalanche fatalities in the European Alps: long-term trends and statistics, Geogr Helv, 71, https://doi.org/10.5194/gh-71-147-2016, 2016.

Techel, F., Mitterer, C., Ceaglio, E., Coléou, C., Morin, S., Rastelli, F., and Purves, R. S.: Spatial consistency and bias in avalanche forecasts -a case study in the European Alps, Natural Hazards and Earth System Sciences, 18, 2697–2716, https://doi.org/10.5194/nhess-18-2697-2018, 2018.

Thumlert, S. and Haegeli, P.: Describing the severity of avalanche terrain numerically using the observed terrain selection practices of professional guides, Natural Hazards, 1–27, https://doi.org/10.1007/s11069-017-3113-y, 2017.

Toft, H. B., Sykes, J. M., and Schauer, A.: AutoATES v2.0, https://github.com/AutoATES, 2023.

Toft, H. B., Müller, K., Hendrikx, J., Jaedicke, C., and Bühler, Y.: Can big data and random forests improve avalanche runout estimation compared to simple linear regression?, Cold Reg Sci Technol, 211, 103844, https://doi.org/10.1016/j.coldregions.2023.103844, 2023.

~~Veitinger, J., Purves, R. S., and Sovilla, B.: Potential slab avalanche release area identification from estimated winter terrain: a multi-scale, fuzzy logic approach, Natural Hazards and Earth System Sciences, 16, 2211–2225, https://doi.org/10.5194/nhess-16-2211-2016, 2016.~~

~~Werners, B.: Aggregation models in mathematical programming, Mathematical Models for Decision Support, 48, 295–305, 1988.~~