Decomposing risk - Using a continuous terrain exposure score to understand the impact of the avalanche forecast on ski tourers

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Abstract

In this paper, we present a novel terrain exposure score metric (the exposure score), which is continuous and can be applied to any GPS track in mountainous areas with sufficiently high-resolution map layers. We apply this metric to a large set of GPS tracks (N = 26,703 covering nearly 300,000 km) and use Bayesian analysis to answer our research question: do backcountry riders react to the information in the avalanche forecast as intended by the sender?

Our results indicate that backcountry riders in our sample choose to make fewer tours when forecasted the avalanche danger level is 4 - High in comparison to other forecasted danger levels, and that they make tours in less avalanche prone terrain when the forecasted danger level increases. We further find that our participants react relatively strongly to forecasted persistent weak layers. However, we do not find evidence that they choose to ride less avalanche prone terrain inside the core zone (where the main avalanche problem is forecast) than they do outside of this zone.

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1. Introduction

Preparedness authorities manage societal risk in part by communication the risk to the public (e.g., ISO 45001:2018, 2018). This paper revolves around the question of whether the public reacts to the communicated risk as intended by the sender and of how one can measure the behavioral reactions. More specifically, we analyze the correlation between risk information in regional avalanche forecasts and exposure to avalanche terrain among backcountry riders in Norway.

Each year, snow avalanches kill on average 100 people in Europe (EAWS, 2025a) and more than 30 people in North America (Avalanches.org, 2025a; BCCS, 2023). In Norway, 125 avalanche fatalities and over 760 avalanche accidents have been recorded over the past two decades. Most of the victims of fatal accidents were recreating in avalanche terrain at the time of the accidents (Techel and Zweifel, 2013; Techel et al., 2016; NAWS, 2025; NGI, 2022). In almost all accidents, the avalanche was triggered by someone in the victim's group (Schweizer and Lütschg, 2001).

Avalanche risk can be decomposed into the combination of the probability of avalanche release (hazard), an element's position in relation to the hazard (exposure), and the consequences of the element being hit by an avalanche (vulnerability). Avalanche hazard depends on a complex interaction between weather and the terrain resulting in a layered snowpack with typically high spatial and temporal variability (Statham, 2008). One of the main purposes of avalanche warning services (AWS) is to inform preparedness authorities and the public about this risk via avalanche forecasts. In North America and Europe, avalanche hazard is communicated via five avalanche danger levels (1 - Low, 2 - Moderate, 3 - Considerable, 4 - High, and 5 - Extreme) and five main types of avalanche problems (New snow - loose or slab, Wet snow - loose or slab, Wind-drifted snow, Persistent weak layer, and Gliding snow) (Avalanches.org, 2025b; EAWS, 2025b). The forecast typically also contain information about the elevation band and aspects where the avalanche problem(s) are expected to be present, the expected size of avalanches, and a text section that summarizes current and expected avalanche conditions.

During the past two decades, a relatively large number of studies have investigated the role of avalanche forecasts in recreational decison-making in the backcountry (e.g., Furman et al., 2010; Hallandvik et al., 2017; Marengo et al., 2017; Engeset et al., 2022; Saly et al., 2020; Sykes et al., 2020; St.Clair et al., 2021; Fischer et al., 2022; Hendrikx et al., 2022; Winkler et al., 2021; Morgan et al., 2023). A general picture emerging from this literature is that most riders to some extent include avalanche forecast information in their decisions, but also that there is a substantial variation in how people *use* (e.g., Hallandvik et al., 2017; St.Clair et al., 2021; Fischer et al., 2022) and to what extent they *understand* the content of the forecast (e.g., Engeset et al., 2022; Fischer et al., 2022; Morgan et al., 2023). In addition, there is still a limited understanding of how the information in avalanche bulletins affect riders' terrain choices. Furman et al. (2010) and Marengo et al. (2017) use the forecasted danger level as a factor in their hypothetical choice scenarios, and find that higher forecasted avalanche danger is associated with a significant reduction in the stated willingness to ski steep slopes. However, since there can be substantial differences between what people say and what they do (e.g., Loomis, 2011; Mooser et al., 2014), the inferences that can be drawn from these studies are limited.

During the past decade, the availability of technologies such as e.g., GPS trackers and time lapse cameras have made it possible to study people in the field (e.g., Hendrikx et al., 2016; Saly et al., 2020; Sykes et al., 2020, 2025; Hendrikx et al., 2022). However, the quantification of exposure to avalanche terrain has remained challenging. Ideally, such measures should consider both the terrain's ability to produce avalanches, and the likelihood that the location of the element (here a rider) is reached by the avalanche given release. Avalanche terrain is terrain where avalanches start (the potential release area or start zone) and the terrain where the avalanche runs, usually referred to the track and the run-out. Henceforth, we will refer to the latter as the run-out zone for brevity. Most slab avalanches start in terrain that is 30°or steeper (e.g., Perla, 1977; Schweizer and Lütschg, 2001; Schweizer and Jamieson, 2001). However, the terrain's ability to produce dangerous slab avalanches does not increase linearly (or even monotonically) with slope angle, and also depends on other terrain characteristics. Most previous research (e.g., Saly et al., 2020; Sykes et al., 2020; Hendrikx et al., 2022) therefore rely on the Avalanche Terrain Exposure Scale (ATES) (Statham et al., 2006). ATES classifies the terrain according to both the probability of avalanche release, and the exposure to avalanche paths. ATES was originally used to manually classify specific backcountry tours into one of three terrain classes: Simple, Challenging, or Complex. More recently, the scale has both been updated to include two extra terrain classes on each side of the spectrum (not avalanche terrain and extreme terrain, see Statham and Campbell (2024)), and automated so that it can be applied to vast areas of mountainous terrain (Sykes et al., 2020; Larsen et al., 2020; Toft et al., 2024). ATES is a tremendous improvement over simple measures of slope steepness, and potentially very valuable for communicating terrain exposure to backcountry travelers. However, it is challenging to use ATES to quantify avalanche terrain risk for at least two reasons. First, the different terrain classes in ATES are relatively broad. This makes it difficult to capture small, but potentially important, differences in terrain exposure. Second, the ordinal nature of the scale (different terrain classes) means that it is not straightforward to compare tours that crosses several terrain classes.

In this paper, we present a novel terrain exposure score metric (the exposure score), which is continuous and can be applied to any GPS track in mountainous areas for which map layers with 10 m DEM and forest density is available (see Toft et al. (2024) for details). We apply this metric to a large set of GPS tracks (N = 26,703 covering nearly 300,000 km) and use Bayesian analysis to answer our research question: do backcountry riders react to the information in the avalanche forecast as intended by the sender?

We know of only two studies that have done something similar. Winkler et al. (2021) combine 51,244 km of travel data and over 2.1 million movement points from GPS tracks with data on 784 avalanche accidents in Switzerland to derive a measure that can be used to quantify differences in avalanche risk between different conditions, where avalanche risk is defined as the probability of being involved in an avalanche accident given travel in avalanche terrain. To derive their measure of avalanche risk, Winkler et al. (2021) calculate the ratio of the share of avalanche accidents (e.g., number of accidents on danger level 2 - Moderate to total number of accidents) to the share of movement points (e.g., number of movement points on danger level 2 - Moderate over all movement points) under the assumption that reporting frequency is the same under all conditions. The authors find that their measure of avalanche risk increases by a factor of four as the forecasted avalanche danger level increases by one level, and that it is six times higher in areas where the avalanche problem is expected to be present (the critical zone) in comparison to areas outside of this zone. Winkler et al. (2021) analysis further suggests that backcountry riders choose to ride on lower elevation and avoid typical avalanche terrain (e.g., large steep slopes above treeline) at forecasted danger level 3 - Considerable. Degraeuwe et al. (2024) similarly combine a large dataset of GPS tracks (57,800 km) with accident data

(N = 1230) for Switzerland to derive a probabilistic method for reducing accident risk while maximizing freedom of movement. Their results confirm that slope angle is non-linearly related to accident risk, that the size of the relevant slope matters, and that the forecasted danger level is strongly correlated with their measure of avalanche risk. Their analysis further suggest that the critical elevation band is more important than the critical aspect.

The Winkler et al. (2021) and Degraeuwe et al. (2024) studies have contributed to a substantial improvement in our understanding of the link between terrain, forecasted avalanche conditions and avalanche risk. The present study builds on their important contributions. However, both our approach and the purpose of our analysis differ from those employed by Winkler et al. (2021) and Degraeuwe et al. (2024) in several important ways.

First, we use a different approach than Winkler et al. (2021) to identify exposed locations in the terrain. As mentioned above, it is important to consider the characteristics of the "relevant" avalanche slopes, and not only on the slope angle of the terrain at the location of the element to measure exposure (Winkler et al., 2021). The "relevant" avalanche slope can be identified via two approaches, which we will refer to as "bottom-up" and "top-down". The bottom-up approach starts at the location of the element (the rider) to identify the relevant slope area around a specific point (Schmudlach and Köhler, 2016; Winkler et al., 2021; Degraeuwe et al., 2024). The benefit of this approach is that it is centered around the element exposed to the hazard. However, an important drawback of the approach is that the cut-off distance from the element is static and set by the researcher (not the terrain). The top-down approach analyzes the terrain from the perspective of an avalanche (e.g., Harvey et al., 2018; Sykes et al., 2020; Larsen et al., 2020; Toft et al., 2024). This approach is based on terrain metrics and avalanche dynamics, and therefore identifies all points in an avalanche path, regardless of whether they are in the start zone or in the run-out zone. In contrast to Winkler et al. (2021), who rely on the bottom-up approach, we use the top-down approach to derive the exposure score presented in this paper.

Second, we calculate the cumulative exposure during a tour while Winkler et al. (2021) use the ten most exposed movement points to identify the level of exposure. Now, it may be argued that one can only die once, and that it is therefore important to focus on the highest level of exposure during a tour. However, people who frequently expose themselves to danger have more chances to die. We have therefore chosen to base our measure on the tour distance (in meters) in exposed areas.

Third, and perhaps most importantly, the main aim of the Winkler et al. (2021) and Degraeuwe et al. (2024) studies was to estimate and compare the avalanche risk at different levels of forecasted avalanche danger, elevation and aspects. Winkler et al. (2021) therefore include the avalanche forecast information in their risk measure, and only include tours in avalanche terrain in their analysis. Our main aim is to evaluate if backcountry riders react to forecast information by choosing safe(r) tours. This means that we want to evaluate to what degree the information in the forecast explains the terrain choices made by the riders. Our exposure score is therefore solely based on terrain, and not on forecast avalanche conditions. Furthermore, some riders may react by choosing tours outside of avalanche terrain, we therefore include these tours in our analysis in addition to tours in avalanche terrain.

Fourth, in contrast to Winkler et al. (2021) we move beyond bi-variate analyses and conduct multivariate analyses to evaluate the correlation between information in the regional avalanche forecast and unsupervised terrain choices. In other words, we evaluate the effects of different factors in the avalanche forecast given that all other factors are held constant. This is important, because the distribution of e.g., forecasted avalanche problems is not necessarily uniform across forecasted danger levels. The panel structure of our data enables us to control for unobserved individual heterogeneity. We use Bayesian analysis to estimate our models. This approach allows us to handle the unbalanced structure of our panel and the skewed distribution of the exposure score. The Bayesian approach further makes it possible to fit a model that follows our data closely, and to evaluate the degree of uncertainty in our predictions.

The rest of the paper is structured as follows: we provide a detailed description of our data sources and the derivation of the exposure score, including a small validation exercise, in section 2. This section also contain an explanation of the Bayesian analysis approach. Section 3 presents the results of our analysis. We discuss the implications of our findings and study limitations in section 4.

2. METHOD

2.1. GPS data

The analysis data stems from backcountry tours made by members of the CARE panel (a panel of backcountry riders, mainly from the Nordic countries, N = 3258), and a sample of 'anonymous' users recruited at avalanche awareness seminars and on social media in Norway 2023 - 2024. The latter sample is not strictly anonymous, but as we lack background information about them we will refer to them as the 'anonymous' sample. All participants, who either agreed to participate via the CARE panel (N = 2719) or agreed to share their tracks anonymously, were invited to share their GPS tracks via an application on Strava. The application, which was developed by two Master students in Data Science (Hofsøy Woie and Bårdsen) is linked to the Strava API. The application assigns a unique ID to each participant and allows us to access both new and historical activities.

Most tours in the data were made in mainland Norway. To limit the analysis work, we therefore exclude all tours that were made outside of mainland Norway. We further only include tracks in regions where there is a daily avalanche forecast issued by NAWS in the winter season (Dec 1st - May 31st). In Norway there are also regions where forecasts are only issued when 4 - High or 5 - Extreme avalanche danger is expected, tours in these areas are excluded. Finally, we only analyze tours made in the time period 2017 - 2024. The reason for excluding years prior to 2017 is that the boundaries of the forecasting regions changed in 2016.

We have manually gone through all GPS tracks to ensure that each track represents a backcountry tour, and trimmed off irrelevant parts (e.g., the drive home). If a GPS track went through several forecasting regions, we use the majority (mode) of the track to determine the region. We have tour observations in all forecasting regions, except one (Finnmarkskysten, see table 1). Finnmarkskysten is a sparsely populated area with low mountains, and with less frequent backcountry travel in avalanche terrain. The final sample consists of a panel of 26,703 tours made by 1086 individuals. Of these, N = 388 originate from the CARE panel and N = 698 belong to the anonymous sample.

Due to the anonymity of a large share of our respondents, and the lack of knowledge of the characteristics of backcountry riders in general, it is unfortunately not possible to determine how representative our participants are of the general backcountry riding population in Norway or elsewhere. We have complete background information for a sub-sample of participants from the CARE panel (N = 368). Of these, 289 are male (78.5%). Median age in the sample is 34 (mean: 36, min: 18, max: 67). 28.3% of the participants have no avalanche training, 27.2% has a a short course (1 - 2 days), 19.3% has REC level 1, 12.8% has REC level 2, and 12.5% has some form of PRO training. About a quarter (25.8%) of the participants state that they have basic or moderate avalanche assessment skills (aware of the avalanche danger scale and that different avalanche problem exists), 56% say that they understand the difference between avalanche problems and know basic techniques to identify weak layers in the snow, and about 19% have advanced assessment skills. Median years of experience of backcountry travel in the sample is 14 years (mean = 16.7, min = 1, max = 62, SD = 11.4).

The lack of background information in the anonymous sample means that it is difficult to identify important differences between the two data sources. However, we note that the two samples differ slightly regarding geographic region (see table 1). The two data sources also differ regarding touring activity. While the median participant in the anonymous data logged four tours per season, the median CARE panelist made eight tours per season. The overall median number of tours per season is five. This is on par with the median number of backcountry tours per season in Switzerland in 2020 and lower than corresponding numbers for 2000 - 2014 (see Lamprecht and Stamm (2000); Lamprecht et al. (2008, 2014) and table 1 in Toft et al. (2024)).

Our data does not contain information about our participants' use of the avalanche forecast. However, a study on backcountry riders in the Tromsø area in Northern Norway found that over 90% of riders check the avalanche forecast before they head out on a tour (Ahonen et al., 2025). Due to the data collection strategy employed in Ahonen et al. (2025), the sample studied can be presumed to be relatively representative of backcountry skiers in the Tromsø area. Based on their finding, we find it reasonable to believe that the majority of our participants read at least parts of the forecast prior to their tours.

Table 1: Tour observations across forecasting regions

	Number of tours		Share of total tours (%)	
Region	Care panel	Anonymous	Care panel	Anonymous
West Finnmark	316	122	2	1
North Troms	140	79	1	1
Lyngen	1698	918	11	8
Tromsø	2543	1305	17	11
Inner Troms	280	115	2	1
Southern Troms	422	390	3	3
Ofoten	637	243	4	2
Lofoten and Vesterålen	948	609	6	5
Salten	199	167	1	1
Svartisen	411	315	3	3
Helgeland	22	60	0	1
Romsdal	1187	802	8	7
Sunnmøre	1135	1063	8	9
Trollheimen	871	1230	6	11
Jotunheimen	955	1507	6	13
Inner Sogn	1390	624	9	5
Inner Fjordane	753	326	5	3
Voss	376	652	3	6
Hardanger	140	280	1	2
Hallingdal	329	582	2	5
West Telemark	167	289	1	2
Heiane	106	0	1	0
Total	15025	11678	100	100

2.2. The terrain exposure score

The aim of the exposure score is to quantify accumulated exposure to avalanche terrain for any given tour. To achieve this, we derive the exposure score as a weighted measure of distance (in meters) in potential release areas and run-out areas. We provide a general overview of the different parts of the exposure score below.

2.2.1. Potential release areas and run-out zones for avalanches

To identify potential release areas (PRAs), we use a modified version of the PRA model from Veitinger et al. (2016) as described in the AutoATES v2.0 model (Toft et al., 2024). This model combines slope angle, forest density and wind shelter to identify the likelihood that a given raster cell is a PRA. The resulting measure is a function of the average of the three input parameters and takes into account that the minimum value of one parameter (e.g., a very low slope angle) dominates high values on other input parameters (e.g., low forest density) (see Veitinger et al., 2016).

To identify potential avalanche track and run-out (RO) zones, we use the forest detrainment module of the Flow-Py algorithm from D'Amboise et al. (2022). Flow-Py is a data driven approach to runout modelling and can be seen as a 3D extension of the simple α-angle approach. It takes a DEM (digital elevation model) as input to route avalanche flow through terrain features below the release area, taking both terrain shape and upstream direction of the flow into account. Flow is stopped when the given α-angle is reached or the flow has spread so wide that it's mass can be considered negligible. The forest detrainment model in addition accounts for stem density to limit spreading and rounout distances. We have modified this module to provide an extra output that gives the distance in meters from the release area (along the modeled run-out path).

The algorithm for PRA, followed by Flow-Py, is executed to create a layer for all of Norway that has values ranging from 0 to 1 in release areas, and values ranging from 0 to $\sim$ 5000 m for run outs as illustrated in Figure 1a. Areas outside the identified avalanche paths are given a no-data value .

While traveling in a runout zone, both the probability of remote triggering an avalanche and the probability of being hit by that avalanche (or a natural release) will naturally decrease with distance to the release area. This relationship is complex and to some extent unknown. To give us a reasonable proxy, we use the results from Harvey et al. (2018), where they kindly provided us with the explicit function in private communication. In their study a dataset of 75 remotely triggered avalanches with known distance to the release area was compiled. By fitting the frequency of avalanche as a function of distance they obtain the approximate form $f(x) = exp(-(\lambda \cdot x)^{\alpha_w})$, where x is the distance from the release area in meters, $\lambda \approx 0.016\text{m}^{-1}$ and $\alpha_w \approx 0.82$. When applying this to the exposure score, it approaches the corresponding PRA value in RO zones that are very close to PRA, and approaches zero at about 4250 meters from the PRA (see Figure 1b). The score is less than 0.004 at 500 meters from the PRA.

This approach does not take the likelihood that the triggered avalanche is large enough to reach and harm the party that triggers it, or the likelihood of natural avalanches being large enough to reach the party into account. These relative likelihoods will depend on how avalanche size (run-out and destructive potential) frequency is distributed, which have been shown to also be exponentially decreasing (Lied and Bakkehøi, 1980; Birkeland and Landry, 2002) with increasing distance from the PRA. Obtaining an exact exponential form that can be multiplied with our proxy above is however not straightforward, and is left for future refinement of the exposure score.

2.2.2. Accident-adjusted risk

After applying the above process, we now have values at the top of RO:s that are as high as the most avalanche prone PRA:s, and thus we need to adjust for the fact that it is clearly more likely to get caught in an avalanche when travelling in a release area than in a runout zone. To get a proxy for this effect, we combine information on the share of accidents and the share of tours in each zone type. Swiss accident statistics suggest that 75% of avalanches are triggered from the PRA and that 25% are caused by remotely triggering avalanches or natural release. This is approximately in line with Norwegian data. In our tour data, and excluding meters travelled outside of avalanche terrain, 18% of toured meters are in PRAs and 82% are in ROs. Based on this information, we calculate the relative risk of traveling a given distance in ROs as (see also Figure 1c):

$$RR_{RO} = \frac{\frac{P(accident|RO)}{P(tour|RO})}{\frac{P(accident|PRA)}{P(tour|PRA)}} \approx 0.072, \tag{1}$$

where $P(accident|RO)$ is the share of avalanche accidents triggered in run-out zones in the Swiss accident data, $P(tour|RO)$ is the share of tours in run-out zones in the Norwegian GPS data, $P(accident|PRA)$ is the share of accidents triggered from a PRA in the Swiss accident data, and $P(tour|RO)$ is the share of tours in PRAs in the Norwegian GPS data. Our approach thus acknowledges that travel in RO zones is not risk-free, but also that the risk decreases substantially with the distance from the start zone. Our chosen parameters and functional forms means that the bulk of the risk in RO zones ($\sim$ 70%) stems from first 100 meters from the end of the start zone. Our calculation of risk in run-out zones means that our instrument will take its highest value (0.072) in the area of the run-out zone adjacent to the PRA. Since all PRA:s in our data originally have a value between 0 and 1, we normalize them to a scale from 0.072 to 1 to avoid that our metric predicts that exposure is higher in the run-out zone than in the PRA.

2.2.3. The final exposure score

Finally, to calculate the exposure score, we first generate a point for every 10 m along the route in each GPS track. This enables us to extract values for every 10 m along the route. We thereafter sum of all values along the route in PRAs, and all values in runout zones (see Figure 1c). We also extract the region ID using a raster with IDs for each region, and the aspect for each point from an aspect layer.

The upper panel of Figure 2 depicts the distribution of the raw exposure score in our data (mean: 47.60, median: 25.02, SD: 63.39, Min: 0, Max: 989.93). As can be seen in the figure, the distribution is skewed towards zero with significant outliers. The lower panel of Figure 2 shows the log of the exposure score.

The exposure score thus increases with the distance traveled in avalanche terrain.

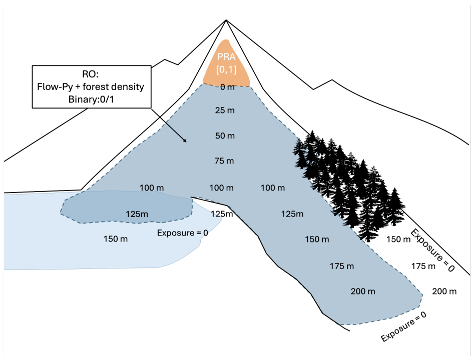
2.2.4. Validation of the exposure score

We have conducted a small validation exercise of the score. Specifically, we asked an avid and very experienced skier and guide, working as a snow observer for Norwegian Avalanche Warning Services (NAWS) to send us GPS tracks from three tours that he judged to have significantly different exposure to avalanche terrain (see figure 3). We thereafter calculated the exposure score for these tracks.

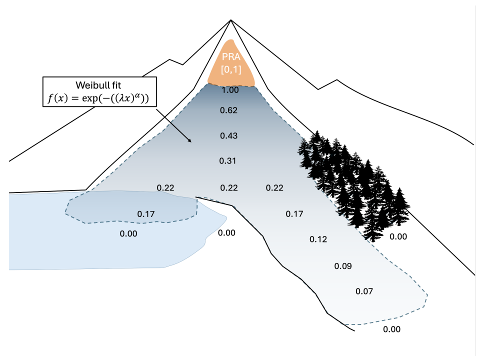
The resulting exposure score for the three tours were: 11.43 (low), 29.71 (medium), 195.07 (high). In other words, with the current calibration of the score, the cumulative terrain exposure on the blue route is estimated to be about three times that of the red route. The cumulative exposure on the turquoise route is estimated as 7 times higher than on the blue route. Part of the explanation behind the relatively small difference between the blue and red route is that parts of the red route go in runout zones, and that this tour is relatively longer.

2.3. Avalanche forecast information

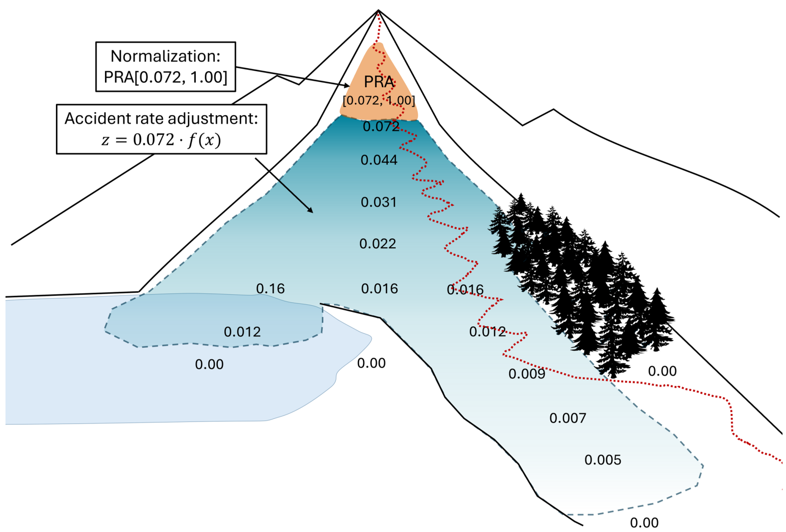
We use data on regional avalanche forecasts from the Norwegian AWS. The data includes all information in the forecast (forecasted danger, avalanche problem(s), elevation bands, aspect, etc.) for all regions in Norway during



(a) Identification of PRAs and RO zones



(b) Weibull-fit



(c) Exposure points

Figure 1: Illustration of the step-wise derivation of the exposure score. Panel (a) illustration the identification of RO areas using Flow-py. Panel (b) visualize the application of the Weibull-fit to derive the probability that the avalanche reaches a certain point given release, and panel (c) shows the accident adjustment. The final exposure score is the weighted sum of the value of all exposure points (measured every 10th meter) on the tour.

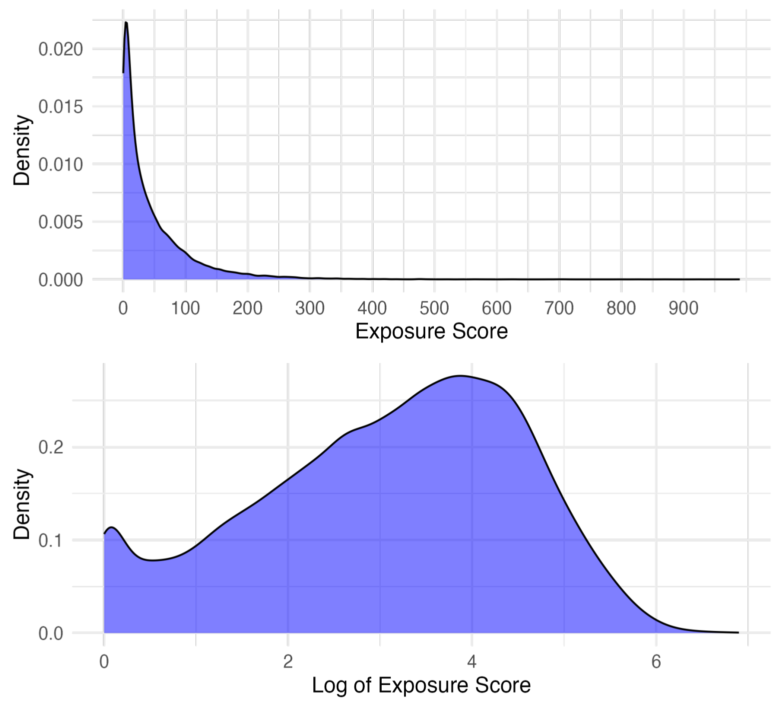


Figure 2: Density of tours across exposure scores. The upper panel shows the density of the raw exposure score. The lower panel shows the density of the log of the exposure score

the period 2017 – 2024 (N = 28,235 forecasting days). Table 2 shows the distribution of days with observations across forecasted danger levels in the AWS and GPS data, respectively. Column 2 and 4 show the number of days on which we observe at least one tour in the GPS data. As can be seen in the table, the distribution of days is relatively similar in the AWS and GPS data for forecasted danger levels 1 Low to 3 - Considerable. However, the share of days with forecasted avalanche danger 4 - High is lower in the GPS data than the share in the AWS data. Danger level 5 - Extreme, was only forecasted on one day in one region during the time period. No tours in our data were made in that region (Helgeland) on the day that danger level 5 - Extreme was forecast.

Table 3 shows the distribution of tour observations across danger levels and avalanche problems. For brevity and clarity, we will henceforth refer to 'New snow - loose' as 'Dry loose', 'New snow - slab' as Storm slab, and

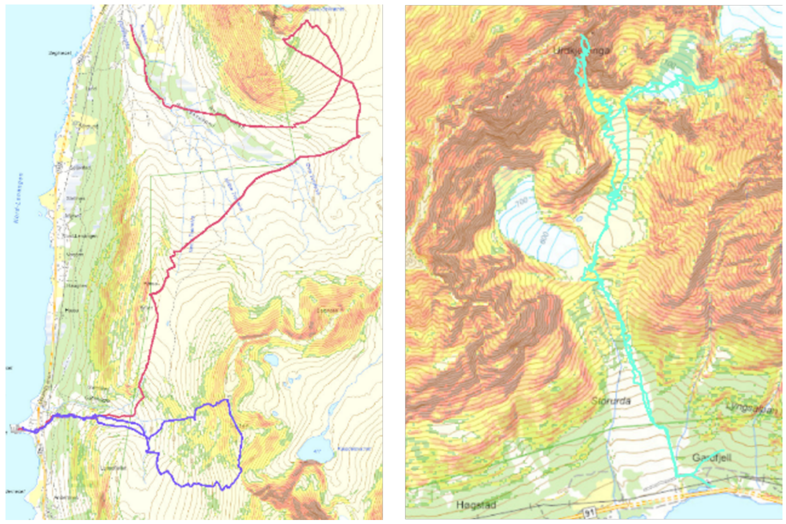


Figure 3: Validation tours: red (low exposure), blue (medium exposure), turquoise (high exposure). Inclination coloring: green (27°-30°), yellow (30°-35°), orange (35°-40°), dark orange (40°-45°), red (45°-50°), brown (>50°)

'Persistent weak layer' as 'PWL'. As can be seen in the table, we have very few (sometimes no) observations on some danger level - avalanche problem combinations. This is especially the case for danger level 4 - High.

2.4. Models

The aim of our empirical analysis is to evaluate if and to what extent backcountry riders react to information in the avalanche forecast. From an avalanche forecaster's perspective, it may be important to distinguish between terrain choices in terrain where the avalanche problem(s) is forecast to be present, i.e., the avalanche prone locations or the "core zone", and terrain choices elsewhere. In addition, and as noted in section 1, the analysis in Winkler et al. (2021) suggests that the risk of being involved in an avalanche accident is six times higher inside the core zone compared to outside of this zone. We therefore separate the exposure score into two: the exposure score in the core zone (es^{ap1}), and the exposure score outside of this zone (es^{nap1}). By construction, es^{ap1} thus takes the value zero if the tour did *not* go in avalanche terrain in the core zone for AP1. Similarly, es^{nap1} takes the value zero if the tour only went in the core zone. We focus on the main avalanche problem (AP1) for two reasons. First, it is usually the problem of greatest concern. Second, combining avalanche problem 1 and 2 creates issues of how

Table 2: Number of days with observations in AWS and GPS data

	Number of days with observations		Share of total days (%)	
Danger level	AWS data	GPS data	AWS data	GPS data
1 - Low	5227	1315	18	15
2 - Moderate	15057	5147	53	59
3 - Considerable	7371	2198	26	25
4 - High	602	62	2	1
5 - Extreme	1	0	0	0
Total	28258	8722	100	100

Table 3: Number of tours in GPS data over forecasted danger level and main avalanche problem (AP1)

Avalanche problem	1 - Low	2 - Moderate	3 - Considerable	4 - High	Total
Dry loose	26	109	51	0	186
Wet loose	2147	3311	1064	0	6522
Storm slab	123	1256	565	36	1980
Wind slab	1113	7093	2434	39	10679
PWL	279	3662	2432	20	6393
Wet slab	23	324	298	13	658
Gliding snow	42	66	28	0	136
No avalanche problem	148	0	1	0	149
Total	3901	15821	6873	108	26703

to weigh the different avalanche problems. Equation 2 describes our main estimation model.

$$\begin{aligned} es^k_{i,j,r} = \gamma_0 + \gamma_1 \cdot D_{j,r} + \gamma_2 \cdot AP1_{j,r} + \gamma_3 \cdot AP2_{j,r} \\ + \gamma_4 \cdot T_{i,j} + \gamma_5 \cdot N_{i,j,r} + \gamma_6 \cdot SAT_{j,r} + \vartheta_{i,j,r} \end{aligned} \tag{2}$$

$es^k_{i,j,r}$ represents the exposure score of tour j in region r by individual i in sector k (inside or outside the sector most exposed to the main avalanche problem).

To evaluate the correlation between the exposure score and the forecast avalanche conditions, we include factor variables for forecasted avalanche danger level (D), the first avalanche problem ($AP1$), and second avalanche problem ($AP2$). We include the second avalanche problem to account for the fact that some avalanche problems (perhaps most notably persistent weak layers) may have a significant impact on terrain choices. The reference level (i.e., to which we compare the effect of other forecasted danger levels) for D is "1 - Low". For the avalanche problem variables, we use a category consisting of loose snow dry snow, gliding snow and no avalanche problem, as the reference level. The motivation for including these different avalanche problems is both practical and based on the properties of different avalanche problems. The practical reason is that we have relatively few observations when $AP1$ is gliding snow or when there is no avalanche problem forecast. This is especially the case for higher forecasted danger levels (see table 3). The theoretical motivation is that avalanche risk is more easily managed when loose avalanches is the main concern. We therefore argue that it is reasonable to include these in the reference category. We maintain wet loose avalanches as a separate category to allow us to compare spring conditions with loose avalanches to spring conditions with wet slab avalanches.

The remaining variables in equation 2 are control variables included to better identify the effect of the main explanatory variables. $T_{i,j}$ is a factor variable that controls for the time of season. We use early season (November – January) as a reference. $N_{i,j,r}$ measures which tour of the season the exposure tour belongs to. We include this variable to account for that people may progressively seek out more serious terrain. The variable is raised by a factor of 0.5, which indicate that the contribution of increased tour days has a diminishing effect on terrain choices. The reason for using the square root of the tour number is based on our preliminary analysis, which showed that this functional form increased model fit. $SAT_{j,r}$ represents the share of avalanche terrain in region r that was included in the core zone for $AP1$ on the day that tour j was made. The motivation for including this variable is twofold. Both motivations are based on the relationship between the exposure scores inside and outside of the core zone. Since the exposure score depends on the distance traveled in terrain exposed to avalanches, the exposure score in the core zone for a random tour will, by construction, increase with the amount of terrain in this sector. Hence, if people do not react to the forecast at all, the exposure score will therefore increase with the size of the core zone. In addition, to evaluate differences in exposure scores inside and outside the core zone, it is important to account for the share of terrain that is affected. To evaluate the role of the share of avalanche terrain in the core zone, we estimate our models with and without the $SAT_{j,r}$ variable.

The severity of an avalanche problem is interlinked with the forecasted danger level. To allow for different effects of different avalanche problems at different forecasted danger levels, we also estimate a model where we interact $AP1$ with D. Due to a low number of observations on days with danger level 4 - High, we estimate this model on a sub-sample of days with forecasted avalanche danger level 1 - Low to 3 - Considerable. While this removes the opportunity to analyze the effect of forecasted avalanche danger 4 - High in this model, it avoids the potentially larger problems caused by combining avalanche danger level 3 - Considerable and 4 - High into one category. In addition, since most avalanche accidents occur on danger lever 2 - Moderate and 3- Considerable (Rainer et al., 2008) and since danger level 4 -High is relatively rarely forecasted, it may be argued that it constitute somewhat of an outlier.

2.5. Statistical analysis

Our panel of backcountry tours is heavily unbalanced. Some riders have submitted up to 100 tracks per season, while others have only submitted a single track. In addition, our dependent variable is severely skewed towards zero (see Figure 2). We first considered using standard (frequentist) regression techniques to estimate our models. However, these models were unable to produce an acceptable fit to the data. We therefore use Bayesian analyses to estimate our models.

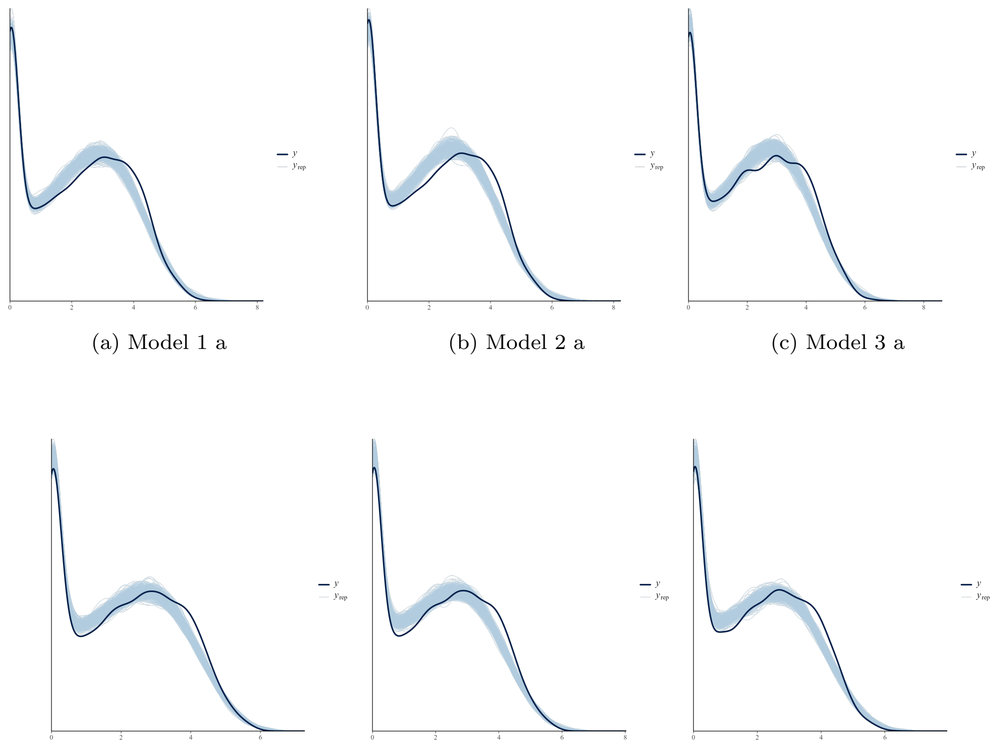
The upside of using Bayesian analysis is that it provides a framework for incorporating prior knowledge or beliefs, along with data, to gain insights and make predictions. Bayesian statistics offer several strengths for our analysis. First, these methods allow us to incorporate priors (which, if chosen correctly, will make our model converge at a faster rate) and handle unbalanced data (as presented in this paper) more effectively. Second, Bayesian analysis provides the posterior distribution for the exposure score. This gives us a more comprehensive understanding of the dataset and our parameters compared to more traditional methods from frequentist statistics.

We fit our models using the `brms()` library for Bayesian Multilevel Models Using Stan in R. The 'brms' package takes the power of the MCMC algorithms (Markov Chain Monte Carlo) to draw samples from the posterior distribution of the model parameters. All models were estimated using the standard priors as implemented in the mentioned R-package (Bürkner, 2017). The models were fitted to a training dataset (`df_train`, 75% of the data).

Due to the zero-inflated nature of our outcome variable (17.1% of the tours have an exposure score equal to zero), we analyze our data with a hurdle-gamma model. Hurdle models model the zeros and the positive continuous values as two separate processes. Our use of a gamma distribution is motivated by the similarity between the distribution of non-zero exposure scores and a gamma distribution with $\alpha = 0.1$ (shape) and $\beta = 0.01$ (rate). A Q-Q plot of the positive exposure scores against the Gamma distribution further indicate a reasonably good fit, supporting the suggestion of this distributional assumption for the continuous component of the exposure score. Our model thus first estimates the likelihood of the exposure score being zero or not (hurdle part) and then the distribution of the continuous positive exposure scores using the gamma distribution. We use a log link function for the mean (`mu`) of the gamma distribution, an identity link for the shape parameter, and a logit link for the hurdle component (`hu`). The logit link for `hu` models the probability of observing a zero on a logistic scale. All models were *successfully* sampled using a version of the MCMC-technique called Hamiltonian Monte Carlo (HMC) (Neal, 2011), specifically via the No-U-Turn Sampler (NUTS) (Hoffman and Gelman, 2014), which is the standard sampling technique of `brms()`. As noted by Bürkner (2017), using NUTS sampling can be very effective, especially for high-dimensional models and without the necessity of the priors to be conjugate (i.e. for Gibbs sampling) (Hoffman and Gelman, 2014).

We evaluate our models using convergence indicators ($\hat{R}$), the effective sample size (ESS), the credible intervals (CrI), and posterior predictive checks. In frequentist statistics, we discuss p-values, significance levels, and confidence intervals. In a Bayesian framework, these terms do not make sense. $\hat{R}$ quantifies the degree of convergence of the MCMC-algorithm. If $\hat{R}$ is close to 1, it indicates that the chain has converged to the same posterior distribution. The ESS describes how much information that is lost due to correlation between the samples from the posterior distribution of parameters. A high ESS indicates efficient sampling and more precise and stable posterior summaries (e.g., means, intervals). The ESS should ideally be above 1000 for reliable mean estimates and tail quantiles (95% CrI). All models produce effective sample sizes (Bulk_ESS and Tail_ESS) and $\hat{R}$-values that are satisfactory (at convergence, $\hat{R} = 1$, Bulk_ESS > 1000).

We evaluate the posterior predictive distribution of our models using various `pp_check()` plots from the `bayesplot` package (Gabry and Mahr, 2025). Figure 4 shows 100 draws from the predicted posterior distributions of the estimated exposure scores (y_{pred}) on log scale, along with the distribution of the exposure scores in our data (y). The upper (lower) panel shows the distributions inside (outside) the core zone for models 1, 2 and 3, respectively (A-models are estimated on exposure scores inside the core zone, while b-models are estimated on exposure scores outside of this zone). As can be seen in the figures, although the fit is not perfect, our models predict the data well. This means that we can be relatively confident that the estimates from our models describe our sample of exposure scores well.



(a) Model 1 a (b) Model 2 a (c) Model 3 a

(d) Model 1 b (e) Model 2 b (f) Model 3 b

Figure 4: Predicted and actual density distribution of exposure scores (log scale). N draws = 100.

Although the models show a good fit to the data in terms of density overlays and other diagnostic plots (see e.g., MCMC trace plots in Figure A.11), we would like to highlight a few issues that should be considered when interpreting the results. First, the models consistently underestimate the median exposure (see Figure A.12). Second, scatter plots of the average prediction errors (residuals) against the observed exposure scores show a linear dependency(i.e., increased variance in the residuals at higher exposure scores, see Figure A.11 in the appendix). This indicates that our models are unable to fully capture the complexity of the true underlying density function. Specifically, it is possible that the hurdle gamma model is not perfect. In particular, there could be issues with 17.1% of the data being 0, and 11% of our exposure scores being in the interval [0, 1], with some extremely high outliers. In addition, our explanatory variables are likely unable to fully explain the variance in exposure scores. For example, our model lacks important individual characteristics such as risk preferences and tour specific characteristics such as weather and the motivation for making the tour (e.g., a short tour to get exercise or a 'big project').

We have explored a number of methods to remedy the problems, including removing extreme outliers, different scalings of the outcome variable, and alternative distributional assumptions for the models. We also tried to remove the hurdle part by adding a small ϵ to all exposure scores (thereby removing all zeros from the data). Neither of these approaches improved the median predictions or changed the structure of the residuals. We contemplated adding controls for personal and tour characteristics. However, we only have access to this information for a relatively small sub-sample of participants (CARE panelists active in the 2023 - 2024 season). Conducting the analysis on this sample would substantially reduce the representativeness of the data, and we have therefore chosen to not include these characteristics in our model.

While heteroscedasticity should be taken seriously, especially in non-linear models, and while the models should ideally be able to predict the data, the noted issues are of less importance for our analysis. One reason for this is that the main purpose of our analysis is to evaluate the effect of our explanatory variables on the exposure score (e.g., the effect of forecasted avanche danger level), the absolute value of the predicted score is not very important. Hence, under-predicting the absolute value of the exposure score does not affect the inference from the model. In addition, the differences between the median predictions and the observed median are relatively small when considering that the exposure score goes from 0 up to 900. For example, the posterior median exposure score in Model 2a is approximately 7.3 compared to a true median of 8, i.e., a difference of 0.7 "exposure score points" (about 9%). We also note that the all other convergence diagnostics and overall distributional checks were satisfactory, and that the bayesian hurdle-gamma model makes a substantially better job at predicting the data compared to standard frequentistic models (e.g., Tobit). The heteroscedastic residuals means that the model is poorer at predicting very high exposure scores (over 250). However, as can be seen in e.g., Figure 9 our models predict much lower exposure scores (range 5 - 30).

3. RESULTS

3.1. Effects of forecasted danger level on the decision to make a backcountry tour

Most tours in our sample take place on days when danger level 2 - Moderate (60%) or danger level 3 - Considerable (26%) are forecasted. Less than 1% of the tours are on days when danger level 4 - High is forecasted (see Figure 5). However, we cannot infer that the forecasted avalanche danger has an impact on the decision to make a tour based on these numbers. The relatively high share of tours on days with e.g., danger level 2 - Moderate may merely be because this danger level is often forecasted (see Table 2).

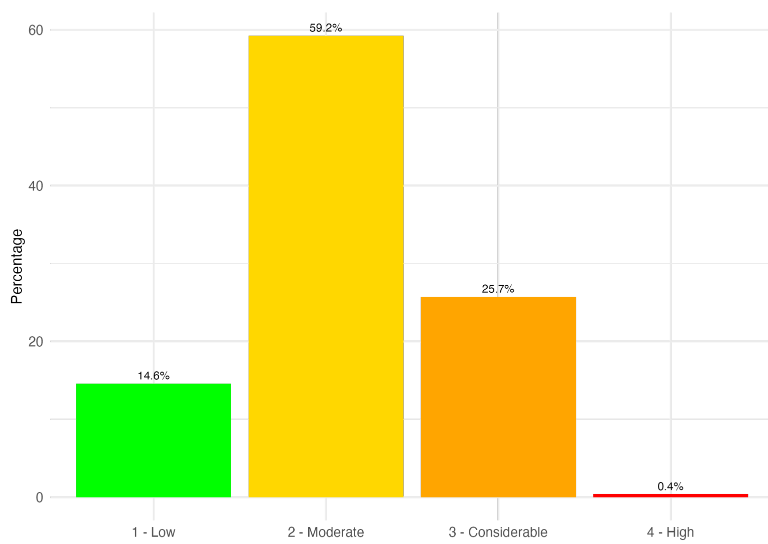


Figure 5: Share of tours across forecasted danger levels

To get a correct picture of the distribution of tours across forecasted danger levels, one must adjust the number of tours on each danger level to the number of days that the danger level was forecasted. Since both frequency of tours and forecasted danger level may vary between regions and seasons, we calculate the adjusted number of tours separately per region and season. Figure 6 shows violin plots of the resulting distribution of number of tours per forecasted danger level day.

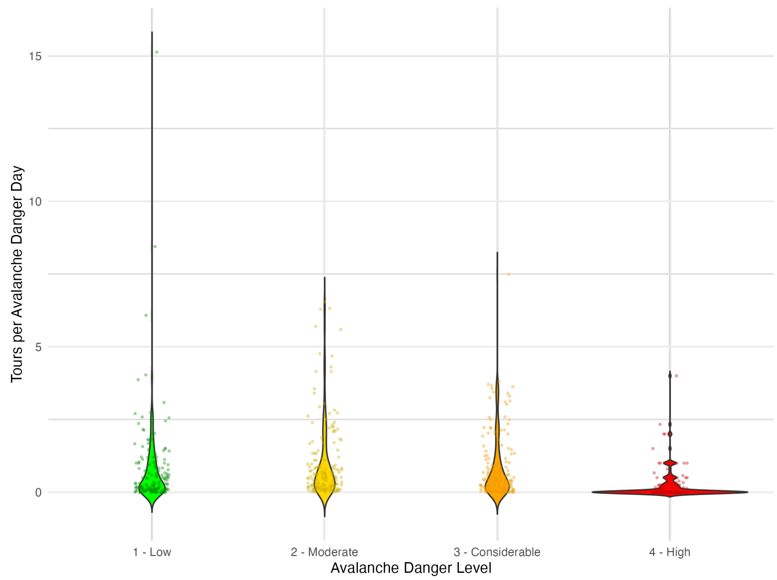


Figure 6: Violin plots of tours per forecasted danger level day. Jittered dots show individual observations for each region and season combination

The most striking difference between danger levels in Figure 6 is that there is much greater spread in the number of tours at lower danger levels as compared to danger level 4 - High. The median number of tours per forecasted danger level day is 0.38 at danger level 1 - Low , 0.62 at danger level 2 - Moderate, 0.41 at 3 - Considerable, and 0.00 at 4 - High. Table 4 presents results of Wilcoxon-signed rank tests of differences in the number of tours per danger level day. The last column presents p-values adjusted with Bonferroni correction for multiple testing. As can be seen in the table, our data indicate that the number of tours per forecasted danger level day is significantly lower on days with danger level 4 - High in comparison to all other forecasted danger levels. However, none of the other differences are significant at 5 percent level after correction for multiple testing. In other words, our findings suggest that people are more likely to choose to stay home on days with danger level 4 - High, as compared to other forecasted danger levels.

Table 4: Comparison of number of tours per danger level day

Comparison	p-value	Bonferroni p-value
Low vs Moderate	0.0115	0.0688
Low vs Considerable	0.4936	1.0000
Low vs High	0.0000	0.0000
Moderate vs Considerable	0.0642	0.3853
Moderate vs High	0.0000	0.0000
Considerable vs High	0.0000	0.0000

Whether or not people choose to go on a backcountry tour says very little about the level of risk they expose themselves to in the backcountry as tours can take place outside of avalanche terrain. In addition, and as mentioned in section 2, people may choose to tour outside of the core zone. We therefore now turn to the analysis of how our participants' exposure scores co-vary with the forecasted avalanche danger level and main avalanche problem.

3.2. Effects of avalanche forecast information on terrain exposure

3.2.1. Descriptive analysis

Figures 7 and 8 show the distribution of exposure scores inside (orange) and outside (blue) of the core zone (i.e., where the main avalanche problem is expected to be most pronounced) over forecasted avalanche danger level and main avalanche problems, respectively.

As can be seen in Figure 7, the share of tours with zero exposure score appears to increase as the danger level increases from 1 - Low to 3 - Considerable. However, on danger level 4 - High, the exposure scores are more uniformly distributed. Figure 7 further suggests that our participants make tours with slightly higher exposure scores inside the core zone on days with danger levels 2 - Moderate and 3 - Considerable, while the opposite pattern is observed on days when danger level 4 - High is forecasted.

Figure 8 shows relatively large differences in exposure scores inside and outside the core zone. Our participants appear to make less exposed tours inside the core zone as compared to outside this zone on days when glide and dry loose avalanches are the main concern, or when storm - or wind slabs are forecast. By contrast, the distributions suggest that the riders make more exposed tours inside than outside the core zone on days when wet loose avalanches, wet slabs, and persistent weak layers are the main concern.

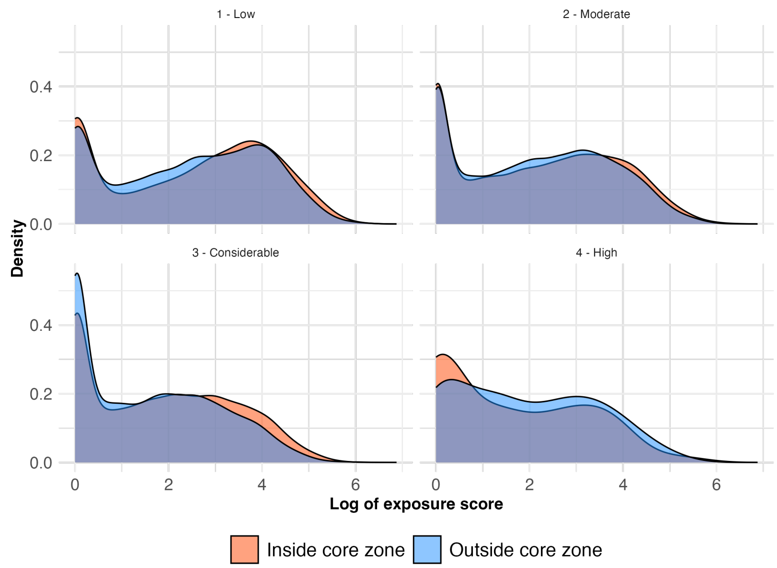


Figure 7: Density of exposure scores inside and outside of the core zone, over forecasted danger level.

Figures 7 and 8 provide an idea of the tours our participants make under various avalanche conditions. However, the above analyses do not test if the observed differences are statistically significant. The avalanche problems are furthermore not evenly distributed across danger levels. Simple bi-variate analyses cannot tell us if people e.g., choose more exposed terrain because the forecasted avalanche danger is 1 -Low as compared to 2 - Moderate, or if they do so because wet loose avalanches are more likely forecast on danger level 1 - Low and persistent weak layers are more often forecast on days when danger level 2 - Moderate is forecasted. Let us therefore now turn to the results of our statistical analyses.

3.2.2. Bayesian analysis

The full set of results from the Bayesian analyses are available in Tables A.7 - A.12 in the appendix. Table 5 shows the Bayesian R^2, and credible intervals for the R^2 values for six models. In comparison to Model 1, Model 2 adds a control for the share of avalanche terrain in the core zone in the region, and Model 3 adds interaction effects between forecasted avalanche danger and AP1. When evaluating Bayesian R^2 values model comparisons, it is most relevant to evaluate the overlap in the credible intervals.

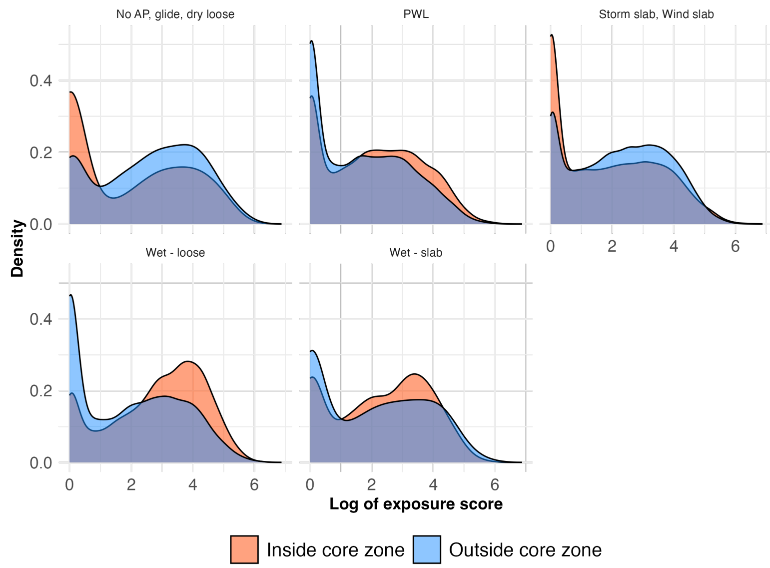


Figure 8: Density of exposure scores inside and outside of the core zone, over forecast main avalanche problems.

As can be seen in Table 5, there is very little overlap between Models 1 and 2. This is a strong indication that Models 2a and 2b explain a higher proportion of the variance in the data than Models 1a and 1b. In other words, including the share of avalanche terrain in the core zone is important. There is more overlap between Models 3 and 2, which is an indication that Models 3a and 3b don't do a substantially better job than Models 2a and 2b in explaining the data. As can be seen in Table A.11 and A.12, we do not find any indication that the effect of an increase in the forecasted danger level depends on the type of avalanche problem. This is an indication that interaction effects should not be included in the model. Based on this, we focus on the results from Models 2a and 2b here.

Table 6 presents the estimated coefficients and credible intervals emanating from our analysis. The table shows the effects of the variables on a log scale. They should in other words be interpreted as the effect on the log-transformed version of the exposure score. Column 1 and 2 show results for exposure scores inside the core zone and columns 3 and 4 contain the corresponding results for exposure scores outside of this zone.

As can be seen in the table, all estimates related to forecasted avalanche danger level are negative and the credible intervals are all below zero. In other

Table 5: Bayesian R^2 values with 95% credible intervals

	Model	R^2	95% CrI
1	Model 1a	0.19	[0.175, 0.214]
2	Model 2a	0.24	[0.221, 0.268]
3	Model 3a	0.25	[0.230, 0.279]
4	Model 1b	0.14	[0.127, 0.156]
5	Model 2b	0.17	[0.152, 0.184]
6	Model 3b	0.19	[0.170, 0.208]

words, our results show that our participants accumulate lower exposure scores at higher forecasted danger levels. This is true both inside and outside the core zone.

To visualize the estimated effects of forecasted avalanche danger, we present posterior distributions of mean predicted exposure scores across forecasted avalanche danger levels in Figure 9. The predictions stem from the same models as those presented in Table 6 and thus include controls for variations in e.g., AP1 across danger levels. The dots on the horizontal axis show the median of the predicted mean exposure scores, and the line shows the 95% credible interval. The width of the distributions increases with the uncertainty in the predictions. The degree of uncertainty depends both on the amount of data (number of tours) available for each forecasted danger level, and the variability in this data (spread in exposure scores).

The upper panel depicts predicted mean exposure scores inside the core zone, and the lower panel shows exposure scores outside of the core zone.

As expected from the results in Table 6, Figure 9 shows that our participants tour in less serious terrain during heightened forecasted avalanche danger. The mean predicted exposure scores inside the core zone is 22.6 for Low avalanche danger, 18.7 for Moderate, 12 for Considerable, and 10.3 for High. The corresponding numbers outside the core zone are 19.8 (low), 16.9 (Moderate), 11.3 (Considerable), and 12.6 (High).

While absolute values of the exposure scores are difficult to interpret the differences in mean exposure score between forecasted danger levels are more informative. Our models suggest that our participants on average choose to tour in terrain inside the core zone that is 17% less exposed when the forecasted danger level is 2 - Moderate compared to 1 - Low, and that they reduce their exposure by an additional 36% when the forecasted danger increases from 2 - Moderate to 3 - Considerable (47% between 3 - Considerable

Table 6: Bayesian regression results with 95% credible intervals: Models 2a and 2b

	Inside Core Zone		Outside Core Zone	
Variable	Estimate	95% CrI	Estimate	95% CrI
(Intercept)	2.49	[2.28, 2.71]	2.87	[2.68, 3.08]
DL: Moderate	-0.19	[-0.25, -0.12]	-0.16	[-0.23, -0.09]
DL: Considerable	-0.63	[-0.70, -0.55]	-0.56	[-0.64, -0.48]
DL: High	-0.78	[-1.13, -0.42]	-0.45	[-0.78, -0.11]
AP1: PWL	-0.33	[-0.52, -0.14]	-0.33	[-0.51, -0.15]
AP1: Storm slab/Wind slab	-0.35	[-0.54, -0.16]	-0.01	[-0.19, 0.16]
AP1: Wet loose	-0.07	[-0.26, 0.11]	0.08	[-0.09, 0.25]
AP1: Wet slab	-0.28	[-0.51, -0.06]	-0.13	[-0.35, 0.09]
AP2: PWL	-0.10	[-0.16, -0.05]	0.05	[-0.01, 0.10]
AP2: Storm slab/Wind slab	-0.17	[-0.24, -0.10]	0.13	[0.05, 0.20]
AP2: Wet loose	0.02	[-0.05, 0.09]	0.19	[0.13, 0.26]
AP2: Wet slab	0.06	[-0.06, 0.18]	-0.13	[-0.27, 0.01]
Time of season: Feb or March	0.22	[0.15, 0.29]	0.16	[0.09, 0.22]
Time of season: April	0.33	[0.25, 0.41]	0.28	[0.19, 0.37]
Time of season: May or later	0.33	[0.23, 0.43]	0.23	[0.13, 0.34]
Tour number	0.12	[0.10, 0.15]	0.13	[0.10, 0.16]
Source: Care panel	0.14	[0.04, 0.24]	0.22	[0.12, 0.32]
Share AT affected by AP1	2.69	[2.46, 2.93]	-2.72	[-2.98, -2.46]

and 1 - low). In other words, our model predicts that the reduction in terrain exposure is greater when the avalanche danger increases from 2 - Moderate to 3 - Considerable, than from 1- Low to 2 - Moderate. The difference in exposure between forecasted danger level 4 - High and 1 - Low is 54% inside the core zone. Outside the core zone, the difference in mean predicted terrain exposure is about 37% between 4 - High and 1 - Low forecasted avalanche danger.

The difference in predicted exposure scores between forecasted avalanche danger 3 - Considerable and 4 - High avalanche danger is relatively small inside the core zone (about 15%) and negative outside the core zone. However, we are reluctant to interpret this as evidence that people do *not* adjust their terrain choices to increased avalanche risk at forecasted danger level 4 - High. The reason for this is that we have relatively few observations of

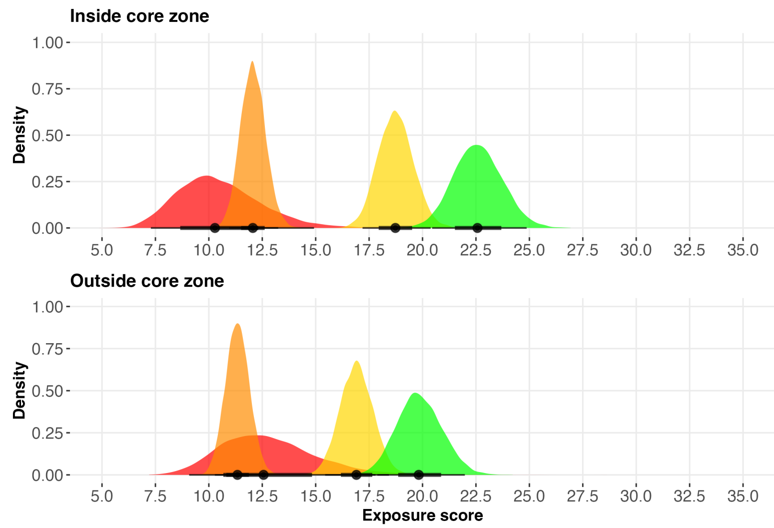


Figure 9: Predicted exposure scores (estimated at means) across avalanche forecasted danger levels after Bayesian analysis

tours made on days when danger level 4 - High was forecasted (N = 145) and that one reason for this is that people choose to not go out at all under these conditions. Since we do not have data on tours that were never made and since our descriptive statistics indicate that people make fewer tours on days when danger level 4 - High is forecasted (see table 4), our model will underestimate the difference in exposure between 4 - High avalanche danger and other danger levels. Note also that the distribution of predicted exposure scores for danger level 4 - High is very wide. As mentioned above, this indicates a high degree of uncertainty in our model's predictions. The uncertainty is a result the large spread in terrain exposure combined with a low number of tours and a lack of variables (e.g., risk preferences and purpose of the tour) that explains the spread.

Since we estimate models separately for exposure inside and outside of the core zone, we cannot test for an effect of 'being in the core zone' on terrain choices. However, as is clear from Figure 9, there is no indication that predicted exposure scores inside the core zone are lower than exposure scores outside this zone. The main difference that can be observed is that our models predict that people have more similar terrain exposure across danger levels outside the core zone than they do inside this zone.

Let us now turn to how the forecasted main avalanche problem affect terrain exposure. Figure 10 visualizes the posterior distributions across AP1 inside and outside the core zone. As in Figure 9, a general result is that the exposure scores are higher inside than outside the core zone. Another general result is that our participants make tours with relatively similar terrain exposure on days when wet loose avalanches are forecasted and on days when 'No avalanche problem, dry loose, or glide avalanches' are forecasted. However, Figure 10 also shows that the differences in exposure scores between some AP1:s depend on whether the model is estimated on scores inside or outside the core zone. In particular, while our model predicts minor differences in exposure scores between PWL or storm slab/wind slab inside the core zone (2.3% difference in median predicted exposure scores), the difference outside the core zone is relatively large (34%). Similarly, the percentage differences in median exposure scores between PWL and wet loose (50.0%) and wet slab (38.6%) avalanches are more than twice as large outside the core zone than inside this zone (wet loose = 22.3%, wet slab = 4.7%). By contrast, the difference between wet loose and storm slab/wind slab is *greater* inside the core zone (24.1% difference) than outside this zone (15.9% difference).

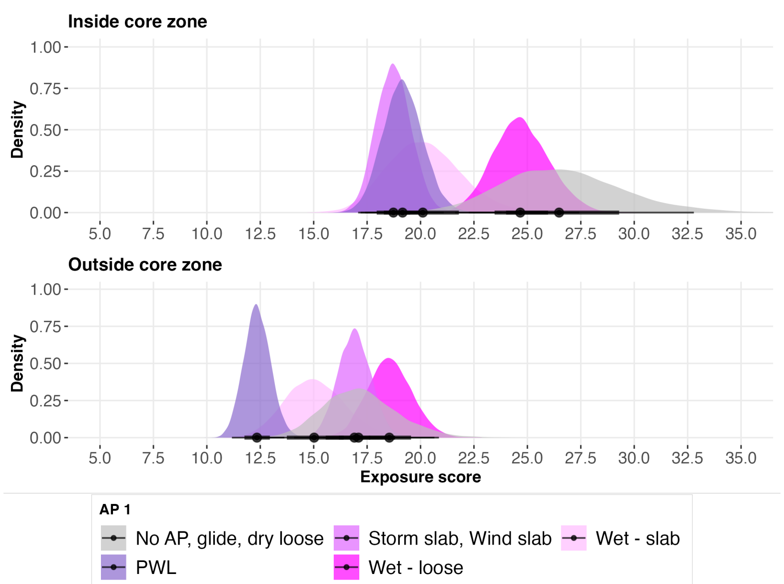


Figure 10: Predicted exposure scores (estimated at means) across main avalanche problems (AP1) after Bayesian analysis

Concerning our control variables, our results suggest that people choose to travel in less exposed terrain inside the core zone of AP1 when AP2 is persistent weak layer or wind slabs, but not when AP2 is a wet loose or wet slab problem (see table 6). Outside of the core zone, we find a *positive* correlation between exposure and wind slabs being forecast as AP2, but no effect of other problems. However, we refrain from drawing inference from these results since the core zone for AP1 and AP2 will sometimes overlap, and at other times be completely different. Perhaps unsurprisingly, we find that our participants travel in more exposed terrain later in the season and that terrain exposure depends on the number of tours made previously during the season, i.e., that people advance into more serious terrain.

Finally, the estimated effect of the share of avalanche terrain affected by AP1 (SAT) is positive inside the most affected sector and negative outside of this sector. This is to some extent expected, as the share of avalanche terrain inside the core zone affects the amount of terrain available to 'collect exposure points'. Indeed, if our participants did not react to avalanche conditions at all, the effect of information in the forecast would be zero, and the correlation between SAT and the exposure score would be close to perfect. The estimate for this variable may appear large compared to the efffects of other explanatory variables. However, SAT is on a scale from 0 to 1. Mean SAT for all exposure scores is 0.16. The mean predicted exposure score inside the core zone at mean SAT (and mean of all other explanatory variables) is 18.7. An increase in SAT with one standard deviation (0.101) is associated with a predicted mean increase in the exposure score to 19.3. This corresponds to an increase of about 3 %, which is relatively small compared to the other observed effects. In other words, while the share of avalanche terrain affected by AP1 is an important factor to consider, one should not conclude that the relative size of the estimate in Table 6 indicates that it is the main driver of terrain exposure.

4. DISCUSSION

In this paper, we describe the development of an instrument (the exposure score) that quantifies the terrain exposure that backcountry riders accumulate during backcountry tours. The instrument considers both the exposure in start and run-out zones. It is based on terrain models that consider a range of terrain characteristics and rely on accident data to calibrate the difference in relative exposure between start and run-out zones. Our small validation exercise indicates that the exposure score manages to distinguish between tours with low, medium, and high terrain exposure.

We apply the exposure score to a large data set of GPS tracks (N = 26,703) to evaluate if backcountry riders adjust their terrain choices depending on information in the avalanche forecast (danger level and main avalanche problem) using Bayesian regression. Since avalanche forecasts only describe the avalanche hazard and avalanche problems inside the core zone, we analyze exposure scores inside and outside the core zone separately.

Concerning the effects of the forecasted avalanche danger level, our results indicate that higher danger levels are associated with lower terrain exposure both inside and outside the core zone. The relationship between forecasted avalanche danger and terrain exposure appears to be non-linear, such that the reduction in terrain exposure is greater between danger level 2 - Moderate and 3 - Considerable than it is between 1 - Low and 2 - Moderate.

It may be tempting to evaluate if the predicted reduction in terrain exposure is sufficient to keep total avalanche risk constant. Jamieson et al. (2009) and Winkler et al. (2021) find an approximately exponential increase in risk as a function of regional danger level. The definition of risk and the size of the exponent differ between the two studies. Jamieson et al. (2009) uses risk of death and finds that this risk increases by a factor 10 with each step of the danger level, while Winkler et al. (2021) use risk of getting caught, injured or killed by an avalanche and find that this risk increases by a factor four. If one assumes that total exposure to avalanche risk is the product of terrain exposure and avalanche hazard, then the terrain exposure at a given danger level must be around one quarter to one tenth of the exposure score at the danger level below to keep risk of injury or death constant. This is a much larger reduction than our model predicts. However, this simple calculation relies on several very strong assumptions, and it may not be an adequate tool for interpreting our results. First, while forecasted avalanche danger level is a proxy for general avalanche hazard in a region, it lacks resolution on the slope scale. It is known that hazard has a large spatial variability over small distances (e.g., McClung, 2023) and the regional danger level can thus not be expected to give the correct risk for a given track. Furthermore, since the tracks cannot be assumed to be randomly placed in the region (individuals make some kind of decisions), the danger level cannot be assumed to give the correct *average* risk for a given day and region. All this is assuming the forecast is correct, which is not known. Second, the terrain exposure score captures the large scale traits of a tour, but lacks nuance when it comes to individual terrain features, giving it limited resolution. Third, our model predictions do not adjust for tours that were not made. If the likelihood of refraining from going on a tour increases with the danger level, our model will underestimate the reduction in terrain exposure. Our data does not indicate significant differences in the number of tours per forecast danger level day for danger levels 1 - Low to 3 - Considerable. However, it does indicate a significant reduction in tours on days when danger level 4 - High is forecasted. In addition, we cannot be sure that our participants log all their tours and if there are structural differences between tours that are logged and not logged. It is possible that people are more prone to log more advanced tours than simpler tours, e.g., for safety reasons or because they want to remember or showcase these tours, but it is also possible that batteries run out on long tours. We therefore refrain from drawing any conclusions regarding the 'sufficiency' of the reduction in terrain exposure predicted by our models. Instead, we settle with noting that our models predict that people to some degree adjust their terrain choices in accordance with the forecasted avalanche danger, and are more likely to stay home on days when danger level 4 - High is forecasted.

It may also be tempting to compare exposure inside and outside the core zone at a given avalanche danger level. Winkler et al. (2021) find that, on days with danger level 2 - Moderate and danger level 3 - Considerable, the probability of having an accident is six times higher inside the core zone. Similar caveats as for evaluating the effect of forecast avalanche danger apply for using these numbers to compare exposure inside and outside the core zone in our data, and we have not done any such comparison in our statistical analysis. Nevertheless, we note that descriptively we find absolutely no indication that our participants make more conservative route choices inside the core zone. Indeed, if anything they make tours with higher terrain exposure inside the core zone. Unless the avalanche forecasted core zone is systematically incorrect, this finding is troubling. Unfortunately, our data does not allow us to dig deeper into the underlying mechanisms.

Turning to the effects of the forecasted main avalanche problem (AP1), we find that the exposure scores are substantially lower both inside and outside the core zone when AP1 is a PWL as compared to wet loose and 'No avalanche problem, dry loose, or glide avalanches' for a given avalanche danger. This finding may reflect that PWL is associated with higher uncertainty and that our participants increase their safety margin everywhere. Inside the core zone, we find a very similar distribution of exposure scores on days when

AP1 is storm/wind slabs as when AP1 is a PWL. Outside the core zone, however, we find that the exposure scores on days with storm/wind slabs are more similar to days when wet loose avalanches or 'No avalanche problem, dry loose, or glide avalanches' are forecasted. This finding may indicate that our participants avoid leeward terrain to reduce their exposure to the avalanche problem. Both results are encouraging.

4.1. Limitations and implications

Our data and analysis have several limitations that should be noted. First, the exposure score needs further validation to ensure that it measures terrain exposure correctly. There are also further refinements that can be made to better model how the exposure varies in run-out zones at various distances to release areas. Second, our model treats AP1 as the avalanche problem of main concern and defines the core zone based on this assumption. In reality, AP2 can sometimes be equally important as AP1 and can have a different, sometimes non-overlapping core zone. This is not taken into account by our model. Third, people's terrain choices naturally depend on a much wider range of factors than just avalanche conditions. As such, our model can only explain a small part of the terrain choices of our participants. Fourth, as previously noted, our data consists of tours made. To model decisions related to avalanche exposure, data on tours that our participants chose to *abstain from doing* is required. Fifth, as noted in section 3.2.2 and not unexpected given the the limitations listed above, our models produced residuals that correlated with the exposure score, with a cluster at lower values. This indicates that the data generating process is more complex than our current model and explanatory variables are able to handle. Finally, it should be kept in mind that our predictions are for our data. While the median number of tours appear to be on par with representative samples in Switzerland (see Toft et al. (2024)) there is likely some selection bias in the CARE panel data.

Keeping these limitations in mind, we still argue that our results have several important implications that are of interest to researchers, avalanche forecasters and avalanche educators. The development of the exposure score means that a new quantitative measure of exposure to avalanche terrain, that can be applied to any GPS track in areas where sufficiently high-resolution map layers are available. While further validation and calibration is needed, the score can be used to evaluate how a wide range of factors correlate with terrain exposure. Our analysis of terrain exposure among Norwegian backcountry riders shows that people's terrain choices correlate with both forecasted avalanche danger and with important avalanche problems inside the core zone.

Our results thus indicate that people use their knowledge and available information (forecasts and/or observations) to mitigate avalanche risk. This is very good news and suggests that risk communication has an impact. However, our results also indicate that there is potentially room for improvement. Most importantly, the lack of evidence for lower terrain exposure inside the core zone indicates that our participants may not read or understand avalanche forecast information as intended by the sender. There are several possible explanations for this and we would like to linger around a few of them. First, the avalanche forecast at Varsom.no follows an information pyramid with a summary of the avalanche conditions (including the forecasted avalanche danger level) on the top and detailed information (including type of forecasted avalanche problems and the core zone) further down. The danger level, avalanche problem(s) and the core zone are presented using both symbols and text. However, while the symbol is sufficient in itself to communicate the danger level, users need to read text to know the vertical extension of the core zone. It may therefore be more difficult to notice and remember the extension of the core zone than the danger level. Second, although the exact meaning of any given avalanche danger level is complex and previous research suggest that backcountry riders perceive the danger scale as linear rather than concave (Fischer et al., 2022; Ebert et al., 2025), avalanche forecast users may still have a stronger gut feeling for differences in danger between avalanche danger levels than they do for the difference in danger between terrain inside and outside of the core zone. Our results thus point to a need to define the difference in danger inside and outside the core zone more precisely, and to communicate both this and the extension of the zone in the avalanche bulletin. In avalanche education, our results indicate an analogous need to teach students how to use this information.

We hope that our study will spur more research on the topic. Methodologically, we would like to see that the exposure score algorithm is validated on a larger dataset of tours with a known distribution of terrain exposure, and calibrated if needed. We also hope to see alternative approaches to analyzing the score statistically, e.g., using other distributions and/or machine learning techniques. We also look forward to more elaborate model specifications that can answer related research questions. For example, including participants' own observations during the tour in the model may be important since these likely affect slope scale assessments as much as or more than the information in the avalanche forecast. We also see a need to include personal characteristics such as risk preference and ski skills, and tour specific characteristics such as motivation of the tour. The latter is important because it is not always the case that people ride as 'steep as they dare'. We suspect that motivation is an important factor for explaining the large share of tours with very low exposure scores in our data. Finally, it would be interesting to see how factors related to group dynamics affect terrain choices.

ACKNOWLEDGEMENT

We are very grateful to all riders who have generously shared their data with us, to Hofsøy Woie and Bårdsen for making it possible to collect it, and to Eline Nemeth Lunde for cleaning the data. We also thank Finn Hovem for helping out with the validation of the exposure score, Finally, we acknowledge that this research would not have been possible without the financial support from the Norwegian Research Council (RCN 262626), and the GUESSED research project (NordForsk project number 105061).

Appendix A. Tables

Table A.7: Predictions from Bayesian analysis: Model 1 - Exposure INSIDE the most affected sector

Effect	$\hat{\beta}$	SE	95% CrI	$\hat{R}$
(Intercept)	2.90	0.11	[2.69, 3.12]	1.00
DL: Moderate	-0.10	0.03	[-0.17, -0.04]	1.00
DL: Considerable	-0.46	0.04	[-0.53, -0.38]	1.00
DL: High	-0.65	0.19	[-1.00, -0.27]	1.00
AP1: PWL	-0.34	0.10	[-0.54, -0.15]	1.00
AP1: Storm slab/Wind slab	-0.47	0.10	[-0.67, -0.28]	1.00
AP1: Wet loose	-0.03	0.10	[-0.22, 0.16]	1.00
AP1: Wet slab	-0.27	0.12	[-0.51, -0.05]	1.00
AP2: PWL	-0.09	0.03	[-0.15, -0.04]	1.00
AP2: Storm slab/Wind slab	-0.19	0.03	[-0.26, -0.13]	1.00
AP2: Wet loose	-0.06	0.04	[-0.13, 0.01]	1.00
AP2: Wet slab	0.09	0.06	[-0.03, 0.22]	1.00
Time of season: May or later	0.38	0.05	[0.28, 0.48]	1.00
Time of season: April	0.34	0.04	[0.25, 0.42]	1.00
Time of season: Feb or March	0.23	0.04	[0.16, 0.30]	1.00
Tour number	0.12	0.01	[0.10, 0.15]	1.00
Source: Care panel	0.17	0.05	[0.07, 0.28]	1.00

Table A.8: Predictions from Bayesian analysis: Model 1 - Exposure OUTSIDE the most affected sector

Effect	$\hat{\beta}$	SE	95% CrI	$\hat{R}$
(Intercept)	2.74	0.10	[2.54, 2.94]	1.00
DL: Moderate	-0.25	0.04	[-0.32, -0.18]	1.00
DL: Considerable	-0.73	0.04	[-0.81, -0.66]	1.00
DL: High	-0.59	0.17	[-0.92, -0.25]	1.00
AP1: PWL	-0.46	0.09	[-0.64, -0.28]	1.00
AP1: Storm slab/Wind slab	-0.11	0.09	[-0.29, 0.07]	1.00
AP1: Wet loose	-0.16	0.09	[-0.33, 0.01]	1.00
AP1: Wet slab	-0.15	0.12	[-0.38, 0.07]	1.00
AP2: PWL	0.00	0.03	[-0.06, 0.06]	1.00
AP2: Storm slab/Wind slab	0.11	0.04	[0.04, 0.19]	1.00
AP2: Wet loose	0.23	0.04	[0.16, 0.30]	1.00
AP2: Wet slab	-0.18	0.07	[-0.32, -0.04]	1.00
Time of season: May or later	0.25	0.05	[0.15, 0.35]	1.00
Time of season: April	0.31	0.04	[0.22, 0.39]	1.00
Time of season: Feb or March	0.18	0.04	[0.11, 0.25]	1.00
Tour number	0.12	0.01	[0.09, 0.15]	1.00
Source: Care panel	0.18	0.05	[0.08, 0.28]	1.00

Table A.9: Predictions from Bayesian analysis: Model 2 (added control for share of terrain that is avalanche terrain in region) - Exposure INSIDE the most affected sector

Effect	$\hat{\beta}$	SE	95% CrI	$\hat{R}$
(Intercept)	2.49	0.11	[2.28, 2.71]	1.00
DL: Moderate	-0.19	0.03	[-0.25, -0.12]	1.00
DL: Considerable	-0.63	0.04	[-0.70, -0.55]	1.00
DL: High	-0.78	0.18	[-1.13, -0.42]	1.00
AP1: PWL	-0.33	0.10	[-0.52, -0.14]	1.00
AP1: Storm slab/Wind slab	-0.35	0.10	[-0.54, -0.16]	1.00
AP1: Wet loose	-0.07	0.09	[-0.26, 0.11]	1.00
AP1: Wet slab	-0.28	0.11	[-0.51, -0.06]	1.00
AP2: PWL	-0.10	0.03	[-0.16, -0.05]	1.00
AP2: Storm slab/Wind slab	-0.17	0.03	[-0.24, -0.10]	1.00
AP2: Wet loose	0.02	0.04	[-0.05, 0.09]	1.00
AP2: Wet slab	0.06	0.06	[-0.06, 0.18]	1.00
Time of season: May or later	0.33	0.05	[0.23, 0.43]	1.00
Time of season: April	0.33	0.04	[0.25, 0.41]	1.00
Time of season: Feb or March	0.22	0.03	[0.15, 0.29]	1.00
Tour number	0.12	0.01	[0.10, 0.15]	1.00
Source: Care panel	0.14	0.05	[0.04, 0.24]	1.00
Share AT affected by AP1	2.69	0.12	[2.46, 2.93]	1.00

Table A.10: Predictions from Bayesian analysis: Model 2 (added control for share of terrain that is avalanche terrain in region) - Exposure OUTSIDE the most affected sector

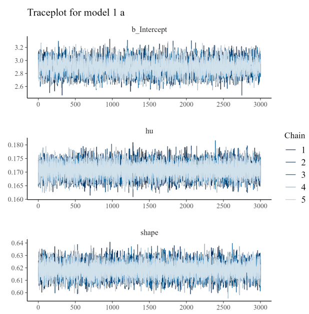
Effect	$\hat{\beta}$	SE	95% CrI	$\hat{R}$
(Intercept)	2.87	0.10	[2.68, 3.08]	1.00
DL: Moderate	-0.16	0.04	[-0.23, -0.09]	1.00
DL: Considerable	-0.56	0.04	[-0.64, -0.48]	1.00
DL: High	-0.45	0.17	[-0.78, -0.11]	1.00
AP1: PWL	-0.33	0.09	[-0.51, -0.15]	1.00
AP1: Storm slab/Wind slab	-0.01	0.09	[-0.19, 0.16]	1.00
AP1: Wet loose	0.08	0.09	[-0.09, 0.25]	1.00
AP1: Wet slab	-0.13	0.11	[-0.35, 0.09]	1.00
AP2: PWL	0.05	0.03	[-0.01, 0.10]	1.00
AP2: Storm slab/Wind slab	0.13	0.04	[0.05, 0.20]	1.00
AP2: Wet loose	0.19	0.04	[0.13, 0.26]	1.00
AP2: Wet slab	-0.13	0.07	[-0.27, 0.01]	1.00
Time of season: May or later	0.23	0.05	[0.13, 0.34]	1.00
Time of season: April	0.28	0.04	[0.19, 0.37]	1.00
Time of season: Feb or March	0.16	0.04	[0.09, 0.22]	1.00
Tour number	0.13	0.02	[0.10, 0.16]	1.00
Source: Care panel	0.22	0.05	[0.12, 0.32]	1.00
Share AT affected by AP1	-2.72	0.13	[-2.98, -2.46]	1.00

Table A.11: Predictions from Bayesian analysis: Model 3 (Interactions) - Exposure INSIDE the most affected sector

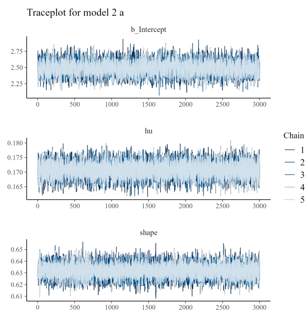
Effect	$\hat{\beta}$	SE	95% CrI	$\hat{R}$
(Intercept)	2.52	0.19	[2.16, 2.91]	1.00
DL: Moderate	-0.29	0.22	[-0.74, 0.15]	1.00
DL: Considerable	-0.31	0.27	[-0.84, 0.22]	1.00
AP1: PWL	-0.18	0.21	[-0.61, 0.22]	1.00
AP1: Storm slab/Wind slab	-0.32	0.19	[-0.72, 0.05]	1.00
AP1: Wet loose	-0.18	0.19	[-0.57, 0.19]	1.00
AP1: Wet slab	-0.12	0.43	[-0.92, 0.75]	1.00
AP2: PWL	-0.09	0.03	[-0.14, -0.03]	1.00
AP2: Storm slab/Wind slab	-0.20	0.03	[-0.27, -0.13]	1.00
AP2: Wet loose	0.06	0.04	[-0.01, 0.13]	1.00
AP2: Wet slab	0.05	0.06	[-0.08, 0.17]	1.00
Time of season: May or later	0.37	0.05	[0.27, 0.47]	1.00
Time of season: April	0.33	0.04	[0.25, 0.41]	1.00
Time of season: Feb or March	0.22	0.03	[0.15, 0.29]	1.00
Tour number	0.11	0.01	[0.09, 0.14]	1.00
Source: Care panel	0.16	0.05	[0.06, 0.26]	1.00
Share AT affected by AP1	2.66	0.12	[2.42, 2.89]	1.00
DL(Moderate) x AP1(PWL)	-0.04	0.25	[-0.53, 0.44]	1.00
DL(Considerable) x AP1(PWL)	-0.50	0.29	[-1.07, 0.07]	1.00
DL(Moderate) x AP1(Storm/wind slab)	0.05	0.23	[-0.40, 0.50]	1.00
DL(Considerable) x AP1(Storm/wind slab)	-0.41	0.28	[-0.96, 0.13]	1.00
DL(Moderate) x AP1(Wet loose)	0.20	0.23	[-0.25, 0.65]	1.00
DL(Considerable) x AP1(Wet loose)	-0.10	0.28	[-0.65, 0.45]	1.00
DL(Moderate) x AP1(Wet slab)	-0.19	0.45	[-1.11, 0.66]	1.00
DL(Considerable) x AP1(Wet slab)	-0.26	0.48	[-1.24, 0.64]	1.00

Table A.12: Predictions from Bayesian analysis: Model 3 (Interactions) - Exposure OUTSIDE the most affected sector

Effect	$\hat{\beta}$	SE	95% CrI	$\hat{R}$
(Intercept)	2.52	0.19	[2.16, 2.91]	1.00
DL: Moderate	-0.29	0.22	[-0.74, 0.15]	1.00
DL: Considerable	-0.31	0.27	[-0.84, 0.22]	1.00
AP1: PWL	-0.18	0.21	[-0.61, 0.22]	1.00
AP1: Storm slab/Wind slab	-0.32	0.19	[-0.72, 0.05]	1.00
AP1: Wet loose	-0.18	0.19	[-0.57, 0.19]	1.00
AP1: Wet slab	-0.12	0.43	[-0.92, 0.75]	1.00
AP2: PWL	-0.09	0.03	[-0.14, -0.03]	1.00
AP2: Storm slab/Wind slab	-0.20	0.03	[-0.27, -0.13]	1.00
AP2: Wet loose	0.06	0.04	[-0.01, 0.13]	1.00
AP2: Wet slab	0.05	0.06	[-0.08, 0.17]	1.00
Time of season: May or later	0.37	0.05	[0.27, 0.47]	1.00
Time of season: April	0.33	0.04	[0.25, 0.41]	1.00
Time of season: Feb or March	0.22	0.03	[0.15, 0.29]	1.00
Tour number	0.11	0.01	[0.09, 0.14]	1.00
Source: Care panel	0.16	0.05	[0.06, 0.26]	1.00
Share AT affected by AP1	2.66	0.12	[2.42, 2.89]	1.00
DL(Moderate) x AP1(PWL)	-0.04	0.25	[-0.53, 0.44]	1.00
DL(Considerable) x AP1(PWL)	-0.50	0.29	[-1.07, 0.07]	1.00
DL(Moderate) x AP1(Storm/wind slab)	0.05	0.23	[-0.40, 0.50]	1.00
DL(Considerable) x AP1(Storm/wind slab)	-0.41	0.28	[-0.96, 0.13]	1.00
DL(Moderate) x AP1(Wet loose)	0.20	0.23	[-0.25, 0.65]	1.00
DL(Considerable) x AP1(Wet loose)	-0.10	0.28	[-0.65, 0.45]	1.00
DL(Moderate) x AP1(Wet slab)	-0.19	0.45	[-1.11, 0.66]	1.00
DL(Considerable) x AP1(Wet slab)	-0.26	0.48	[-1.24, 0.64]	1.00



(a) Model 1 a



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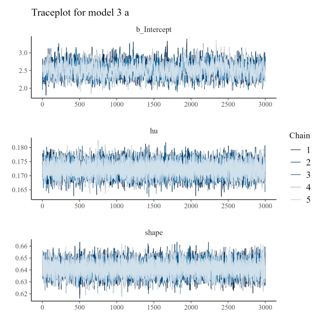

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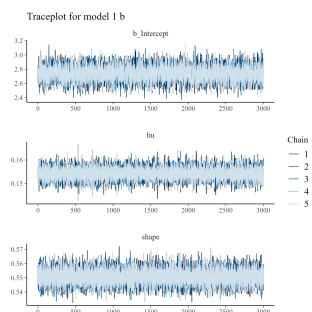

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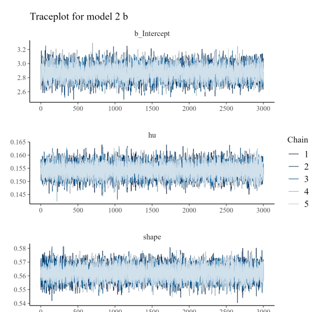

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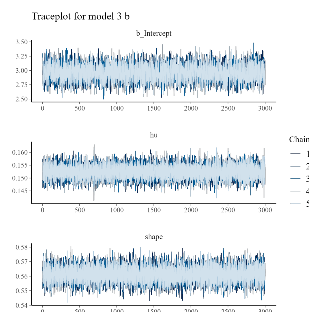
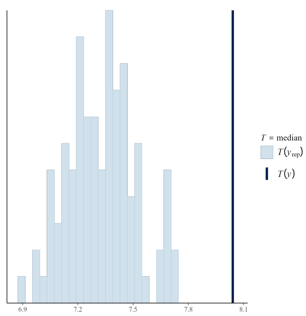


(f) Model 3 b

Figure A.11: MCMC trace plots

Appendix A.1. Figures



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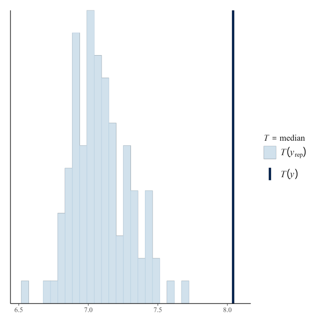

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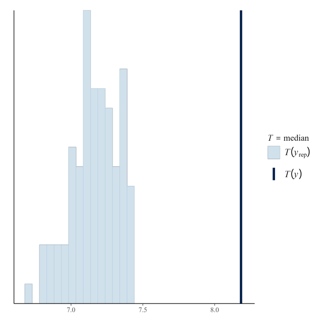

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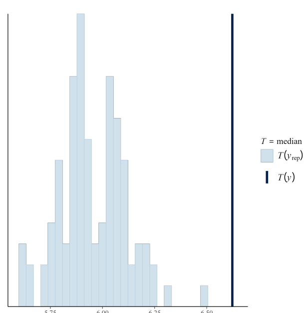

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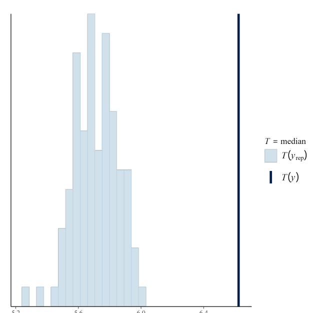

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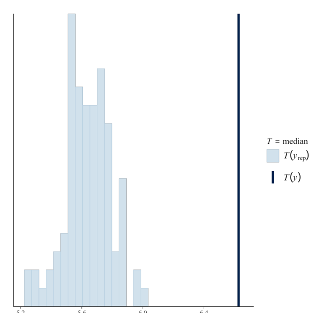
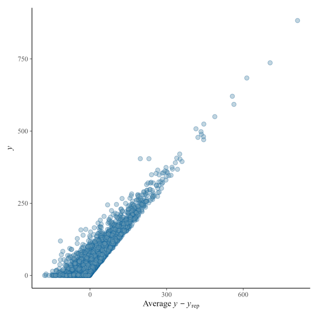


(f) Model 3 b

Figure A.12: Predicted and actual median exposure scores. N draws = 100.



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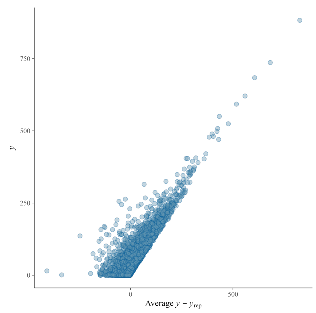

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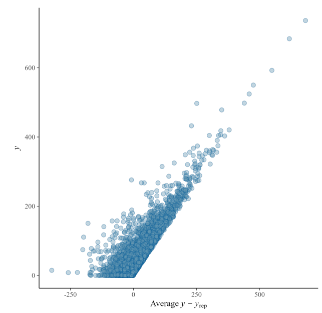
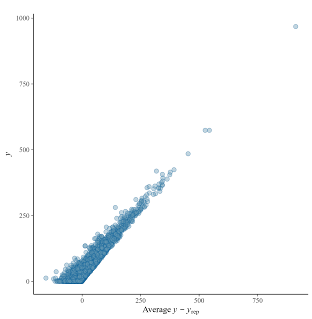
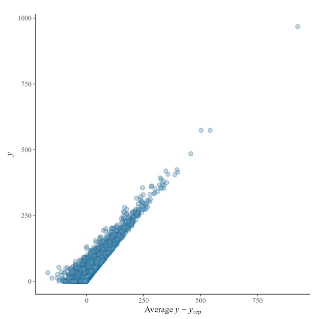


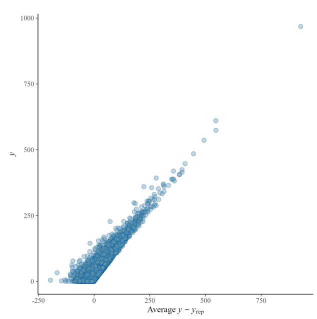
(c) Model 3 a



(d) Model 1 b



(e) Model 2 b



(f) Model 3 b

Figure A.13: Correlation between residuals and exposure scores

References

Ahonen, L., Landrø, M., Rong, G., Pfuhl, G., Mannberg, A., Hetland, A., and Cowley, B. U.: Searching for avalanche clues—An exploratory comparison of professional and recreational use of snow, terrain, and group factors, Journal of Outdoor Recreation and Tourism, 49, 2025.

Avalanches.org: Accidents, https://avalanche.org/avalanche-accidents/#/, 2025a.

Avalanches.org: Accidents, https://avalanche.org/avalanche-encyclopedia/human/resources/north-american-public-avalanche-danger-scale/, 2025b.

BCCS: BCCS Avalanche Web Report 2011-2022, Tech. rep., Government of Brittish Columbia, 2023.

Birkeland, K. W. and Landry, C. C.: Power-laws and snow avalanches, Geophysical Research Letters, 9, 49–1–49–3, https://doi.org/10.1029/2001GL014623, 2002.

Bürkner, P.-C.: brms: An R Package for Bayesian Multilevel Models Using Stan, Journal of Statistical Software, 80, 1–28, https://doi.org/10.18637/jss.v080.i01, 2017.

D'Amboise, C. J., Neuhauser, M., Teich, M., Huber, A., Kofler, Perzl, F., Fromm, R., Kleemayr, K., and Fischer, J.: Flow-Py v1. 0: a customizable, open-source simulation tool to estimate runout and intensity of gravitational mass flows, Geoscientific Model Development, 15, 2423–2439, 2022.

Degraeuwe, B., Schmudlach, G., Winkle, K., and Köhler, J.: SLABS: An improved probabilistic method to assess the avalanche risk on backcountry ski tours, Cold Regions Science and Technology, 221, https://doi.org/10.1016/j.coldregions.2024.104169, 2024.

EAWS: Fatalities, https://www.avalanches.org/fatalities/fatalities-2024-25/, 2025a.

EAWS: Fatalities, https://www.avalanches.org/standards/avalanche-danger-scale/, 2025b.

Ebert, P. A., Miller, D. L., Comerford, D. A., and Diggins, M.: End user and forecaster interpretations of the European Avalanche Danger Scale: A study of avalanche probability judgments in Scotland, Risk Analysis, 2025.

Engeset, R. V., Pfuhl, G., Landrø, M., Mannberg, A., and Hetland, A.: Communicating public avalanche warnings – what works?, Natural Hazards and Earth System Sciences, 18, 2537–2559, 2022.

Fischer, K., Haegeli, P., and Mair, P.: Travel and terrain advice statements in public avalanche bulletins: a quantitative analysis of who uses this information, what makes it useful, and how it can be improved for users., Nat. Hazards Earth Syst. Sci., 22, 1973–2000, 2022.

Furman, N., Shooter, W., and Schurman, S.: The Roles of Heuristics, Avalanche Forecast, and Risk Propensity in the Decision Making of Backcountry Skiers., Leisure Sciences, 32, 453–469, 2010.

Gabry, J. and Mahr, T.: bayesplot: Plotting for Bayesian Models, `https://mc-stan.org/bayesplot/`, r package version 1.12.0, 2025.

Hallandvik, L., Svarstad-Andresen, M., and Aadland, E.: Decision-making in avalanche terrain – How does assessment of terrain, reading of avalanche forecast and environmental observations differ by skiers' skill level., Journal of Outdoor Recreation and Tourism, 20, 45–51, 2017.

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

Hendrikx, J., Johnson, J., and Shelly, C.: Using GPS tracking to explore terrain preferences of heli-ski guides., Journal of Outdoor Recreation and Tourism, 13, 45–51, 2016.

Hendrikx, J., Johnson, J., and Mannberg, A.: Tracking decision-making of backcountry users us-ing GPS tracks and participant surveys., Applied Geography, 144, 2022.

Hoffman, M. D. and Gelman, A.: The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo, Journal of Machine Learning Research, 15, 1593–1623, 2014.

ISO 45001:2018: Occupational health and safety management systems — Requirements with guidance for use, https://www.iso.org/standard/63787.html, 2018.

Jamieson, B., Schweizer, J., and Shea, C.: Simple calculations of avalanche risk for backcountry skiing, Proceedings of the International Snow Science Workshop, Davos, Switzerland, 2009.

Lamprecht, M. and Stamm, H.: Sport schweiz 2000, Tech. rep., Sportaktivität und Sportkonsum der Schweizer Bevölkerung, https://www.assa-asss.ch/wp-content/uploads/2021/06/ASSA_2021-DE-2.pdf, 2000.

Lamprecht, M., Fischer, A., and Stamm, H.: Das sportverhalten der schweizer bevölkerung, Tech. rep., Observatorium Sport und Bewegung Schweiz c/o Lamprecht Stamm Sozialforschung und Beratung AG, 2008.

Lamprecht, M., Fischer, A., and Stamm, H.: Sport Schweiz 2014 Sportaktivität und Sportinteresse der Schweizer Bevölkerung, Tech. rep., Bundesamt für Sport BASPO, 2014.

Larsen, H., Hendrikx, J., Slåtten, M. S., and Engeset, R. V.: Developing nationwide avalanche terrain maps for Norway, Natural Hazards, 103, 2829–2847, 2020.

Lied, K. and Bakkehøi, S.: Empirical calculations of snow-avalanche run-out distance based on topographic parameters, Journal of glaciology, 26, 1980.

Loomis, J.: What's to know about hypothetical bias in stated preference valuation studies?, Journal of Economic Surveys, 25, 2011.

Marengo, D., Monaci, M. G., and Miceli, R.: Winter recreationists' self-reported likelihood of skiing backcountry slopes: Investigating the role of situational factors, personal experiences with avalanches and sensation-seeking, Journal of Environmental Psychology, 49, 2017.

McClung, D.: The Avalanche Handbook, Mountaineers Books, 2023.

Mooser, R., Raffaelli, R., and Notaro, S.: Testing hypothetical bias with a real choice experiment using respondents' own money, European Review of Agricultural Economics, 41, 2014.

Morgan, A., Haegeli, P., Finn, H., and Mair, P.: A user perspective on the avalanche danger scale – insights from North America., Natural Hazards and Earth System Sciences, 23, 2023.

NAWS: Snøskredulykker- og hendelser, https://www.varsom.no/snoskred/snoskredulykker/, 2025.

Neal, R. M.: MCMC Using Hamiltonian Dynamics, in: Handbook of Markov Chain Monte Carlo, edited by Brooks, S., Gelman, A., Jones, G. L., and Meng, X. L., pp. 113–162, Chapman & Hall/CRC, 2011.

NGI: Snøskredulykker med død, https://www.ngi.no/forskning-og-radgivning/naturfare-container/skred-og-ras/snoskred-og-sorpeskred/snoskredulykker-med-dod/, 2022.

Perla, P.: Slab avalanche measurements, Canadian Geotechnical Journal, 1977.

Rainer, B., Frimmel, C., Sumann, G., Brugger, H., Kinzl, J., and Lederer, W.: Correlation between avalanche emergencies and avalanche danger forecast in the alpine region of Tyrol, European Journal of Emergency Medicine, 15, https://doi.org/10.1097/MEJ.0b013e3282b974bd, 2008.

Saly, D., Hendrikx, J., Birkeland, K. W., Challender, S., and Johnson, J.: Using time lapse photography to document terrain preferences of backcountry skiers., Cold Regions Science and Technology, 122, 2020.

Schmudlach, G. and Köhler, J.: Automated Avalanche risk rating of backcountry ski routes, Proceedings, International Snow Science Workshop, Breckenridge, Colorado, 2016, https://arc.lib.montana.edu/snow-science/objects/ISSW16_O19.04.pdf, 2016.

Schweizer, J. and Jamieson, J.: Snow cover properties for skier triggering of avalanches, Cold Regions Science and Technology, 33, https://doi.org/10.1016/S0165-232X(01)00039-8, 2001.

Schweizer, J. and Lütschg, M.: Characteristics of human-triggered avalanches, Cold Regions Science and Technology, 33, https://doi.org/10.1016/S0165-232X(01)00037-4, 2001.

Statham, G.: AVALANCHE HAZARD, DANGER AND RISK – A PRACTICAL EXPLANATION, Proceedings of the International Snow Science Workshop, Whistler, CA, pp. 424–427, 2008.

Statham, G. and Campbell, C.: The Avalanche Exposure Scale (ATES) v.2, Natural Hazards and Earth System Sciences, 2024.

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

St.Clair, A., Finn, H., and Haegeli, P.: A user perspective on the avalanche danger scale – insights from North America., International Journal of Disaster Reduction, 66, 2021.

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, 2020.

Sykes, J., Haegeli, P., Atkins, R., Mair, P., and Bühler, Y.: Development of operational decision support tools for mechanized ski guiding using avalanche terrain modeling, GPS tracking, and machine learning, Natural Hazards and Earth System Sciences, 25, 2025.

Techel, F. and Zweifel, B.: Recreational avalanche accidents in Switzerland:Trends and patterns with an emphasis on burial, rescue methods and avalanche danger, International snow science workshop proceedings, https://www.wsl.ch/fileadmin/user_upload/SLF/Lawinen/Unfaelle_Schadenlawinen/Unfallberichte_Publikationen/Englisch/Techel_Zweifel_Unfaelle_ISSW_2013_Paper.pdf, 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, Geographica Helvetica, 71, 147–159, https://doi.org/10.5194/gh-71-147-2016, 2016.

Toft, H. B., Sykes, J., Schauer, A., Hendrikx, J., and Hetland, A.: AutoATES v2.0: Automated Avalanche Terrain Exposure Scale mapping, Natural Hazards and Earth System Sciences, 24, 1779–1793, https://nhess.copernicus.org/articles/24/1779/2024/, 2024.

Veitinger, J., Purves, R. S., and Sovilla, N.: 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, 2016.

Winkler, K., Schmudlach, G., Degraeuwe, B., and Techel, F.: On the correlation between the forecast avalanche danger and avalanche risk taken by backcountry skiers in Switzerland., Cold Regions Science and Technology, 188, 2021.