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Tracking the slopes: A spatio-temporal prediction model for backcountry skiing activity in the Swiss Alps using UGC

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Abstract. Backcountry skiing is a popular form of recreation in Switzerland and worldwide, yet little is known about where and when people venture outside and methods to monitor skiing behaviour are limited by the vast and remote nature of backcountry terrain. With avalanche fatalities documented each year, there is a need for spatially and temporally explicit information on the persons exposed to avalanche danger for effective risk estimations. To do so, we explored over 6’800 user-generated GPS tracks and over 9 million clicks on a ski touring website to model backcountry skiing base rates on a daily scale in 126 regions in the Swiss Alps. We linked the data to weather, snow, temporal and environmental variables to train two different spatio-temporal prediction models based on the two data sources. We found that GPS and click data describe different types of behaviour (planning and real world behaviour), yet we could demonstrate that they correlate well with a 1-day time lag (ρ = 0.61), suggesting that online activity precedes actual skiing activity. Our results show that online and real-world behaviour are driven by similar underlying factors, with temporal aspects – such as weekends and the progression of the season – playing the most important role in both datasets. However, we found differences in how certain variables influenced behaviour: people tended to click on more routes in areas of high avalanche danger during more extreme weather conditions than they actually visited, and time spent on tour planning decreased as the season progressed. Our study demonstrates the potential of user-generated data sources to model skiing activity on regional and temporally fine scales, but also sheds light on specific limitations of the different data sources in approximating backcountry skiing activity.

1 Introduction

Winter sport activities that take place in mountainous terrain, e.g., skiing or snowshoeing, have increased in popularity in recent years. Simultaneously, the availability of better equipment and avalanche education has increased recreational activity in uncontrolled avalanche terrain. In Switzerland, the number of backcountry skiers – skiers who ascend under their own power and descend in uncontrolled avalanche terrain – has more than doubled in the last decade (Lamprecht et al., 2014, 2020), but it is unclear where and when these skiers are active in the terrain. Travelling in avalanche terrain comes with an inherent danger: accident statistics show that backcountry skiers are at risk of serious injuries or even death with an average of 23 people dying each winter in an avalanche in Switzerland, most of them triggering the avalanche themselves (Schweizer and Techel, 2017).

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Compared to research on the physical properties of avalanches and snowpack, research on the detailed spatio-temporal behaviour of skiers, and especially of those not involved in accidents, is much rarer. One reason for this disparity is that while fatal accidents and other incidents are reported comprehensively (e.g., Niemann et al., 2022; Pfeifer et al., 2018), accident-free backcountry trips, which are far more frequent, often go undocumented. As a result, we know when and where accidents occur, but we lack information on important context – such as how many other skiers were in the field – essential to calculating accident and fatality *rates* (Techel et al., 2015). Exposure, or the baseline backcountry skiing activity rate, is a crucial part of the avalanche risk equation. Moreover, knowing about daily backcountry skiing activities can be valuable for avalanche forecast verification, since it is impossible to determine whether a lack of reported avalanches stems from the fact that no avalanches happened or because no people were in the field to report a potential avalanche. Conditions where avalanches do not occur are important for avalanche forecasting, but remain difficult to interpret, and knowing whether skiers were active can shed light on such situations (Techel et al., 2015). Understanding when people engage in winter backcountry recreation is also one way to evaluate the effectiveness of avalanche forecasts and for targeting specific outreach efforts.

Although data is hard to come by, various approaches to include base rates when calculating the (relative) risk of accidentally triggering an avalanche have been used(e.g., Grímsdóttir and Mcclung, 2006; Pfeifer, 2009; Schmudlach and Köhler, 2016; Techel et al., 2015; Winkler et al., 2021; Degraeuwe et al., 2024; Toft et al., 2025).

For example, backcountry skiing activity base rates have been estimated by installing counters and voluntary registration boards in Switzerland (Zweifel et al., 2006) or by installing beacon checkers that detect and count signals from avalanche transceivers carried by skiers in Norway (Toft et al., 2025). While these methods provide accurate numbers at specific locations, they are expensive and not scalable to larger areas, especially when these are remote and inaccessible, as is often the case for backcountry skiing. To address this, recent studies have used mobile phone location data (Ahas et al., 2008) which is scalable to large areas, but so far the results have been inconsistent (Francisco et al., 2018; Toft et al., 2023).

With the emergence of new data collection and data sharing technologies, most importantly GPS and what was termed Web 2.0, in the early 2000s, user-generated content (UGC) arose as an easily accessible and inexpensive new data source for studying humans in nature (Wood et al., 2013). Following Goodchild (2007) and Santos (2022, p. 108), we define UGC as a collective term for “any kind of text, data or action that has been performed and produced by digital system users”, often with diverse and sometimes unknown motivations, accessible to the public through various online platforms. Spatially explicit UGC has proven to be efficient for visitor monitoring in protected areas and parks (Heikinheimo et al., 2017; Levin et al., 2017; Tenkanen et al., 2017) as well as in urban areas (Norman et al., 2019; Wartmann et al., 2021) but has rarely been used to analyze spatio-temporal backcountry skiing patterns (Techel et al., 2015). So far, only a handful of studies used UGC to explore backcountry skiing patterns (e.g., Sharp et al., 2018; Toft et al., 2024; Techel et al., 2014). In particular, different kinds of user-generated content have yet to be explored as a tool for estimating backcountry skiing base rates or identifying key drivers of activity fluctuations. Moreover, we are not aware of attempts to predict backcountry skiing activity for upcoming days.

We address this gap by leveraging two different types of user-generated data to model and predict backcountry skiing activity base rates in the Swiss Alps. Specifically, we used GPS data and online engagement data from a popular Swiss ski

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touring platform as proxies for actual and potential human presence in the backcountry. Our approach involved first comparing these two proxies and then linking them to a set of environmental, temporal and snow and weather condition-related variables using machine learning. We aimed to (a) find out if and how real-world behaviour corresponds to online engagement, (b) assess the suitability of each data source for modelling actual and potential activity and (c) identify the key drivers of spatio-temporal behaviour to predict daily variations in backcountry skiing activity at a regional scale, moving beyond the retrospective activity pattern analyzes found in the literature (e.g., Techel et al., 2015).

2 State of the Art

There are three commonly acknowledged physical factors that contribute to avalanche release: weather, snowpack and terrain (McClung and Schaerer, 2006). While avalanche research has traditionally focused on these physical factors, the first decades of the 21st century have seen a paradigm shift, with growing attention paid to the role of the human factor (Furman et al., 2010). This reflects increasing acknowledgment that heuristic-based decision making is a key driver of behaviour in the backcountry, introducing unconscious biases that play a crucial role in avalanche accidents (Mccammon, 2004; Tversky and Kahneman, 1974). This has driven a wave of research into the human factor, including studies on decision making processes, risk taking behaviour, group dynamics, demographics, used equipment, or terrain use of backcountry skiers using mainly qualitative approaches like surveys, questionnaires or interviews (Furman et al., 2010; Happ et al., 2023; Mannberg et al., 2018; Marengo et al., 2017; Nichols et al., 2018; Silverton et al., 2009; Valle et al., 2022; Zweifel et al., 2006), which are sometimes combined with accident statistics (Gasser, 2020; Niemann et al., 2022; Pfeifer et al., 2018; Techel et al., 2015; Winkler et al., 2021, 2016).

In survey- and interview-based studies, participants are often questioned about their decisions in hypothetical scenarios, thus taking a stated preference approach (Furman et al., 2010; Haegeli et al., 2010; Marengo et al., 2017). While stated preferences can shed light on the thought processes and motivations behind a decision, people's stated preferences may differ from actual behaviour (Kroes and Sheldon, 1988; Wardman, 1988). This highlights the importance of using real-world observations, or revealed preference data, to analyze skiing behaviour. Compared to qualitative studies on decision-making that use stated preference methods, quantitative studies that analyze and monitor behaviour – and particularly detailed spatio-temporal behaviour – through real-world observations are less common. To date, studies of base rate have only analyzed temporally aggregated data at a small number of locations with no intent of predicting future activity rates. Zweifel et al. (2006) quantified backcountry recreation by using a registration board and automated measuring stations to count backcountry skiers at four different sites in Davos, Switzerland. A similar study was recently carried out in Norway by Toft et al. (2025), where automatic stations measuring the signal of emergency avalanche beacons carried by skiers were installed. Although results of such studies are promising and serve as potential ground truth data, they are only suitable for small-scale studies as they are resource intensive in terms of materials, personnel and budgets. Additionally, they typically only provide information about those accessing an area, but not about where they go. Exploring methods that can be employed on a larger scale, Toft et al. (2023) used telecom network signalling data to quantify backcountry recreation in Norway. However, they found that the positional accuracy of the data product provided by a Norwegian telecom company was insufficient, and distinguishing between backcountry recreation-

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ists and individuals on streets or in residential areas was impossible. Contrasting results were found by Francisco et al. (2018) in Andorra, where the authors successfully used telecom data to study backcountry skiing dynamics under different avalanche and weather conditions, claiming a positional accuracy of 150 m. Further research is needed to evaluate this data in different regional contexts. In another approach, Techel et al. (2015) used UGC in the form of written text reports of tours uploaded to two popular mountaineering platforms in Switzerland. They analyzed spatio-temporal patterns in the Swiss Alps and related them to avalanche accidents, showing that the risk of having an accident was strongly influenced by avalanche danger level and snow cover but was not congruent with the areas hosting most backcountry activity.

With growing public access to cheap GPS devices, mostly integrated in mobile phones, studies making use of recorded GPS data from backcountry skiers have become more popular (e.g., Bielański et al., 2018; Degraeuwe et al., 2024; Taczanowska et al., 2017). GPS data are often collected in traditional study settings, where researchers actively obtain data from voluntary participants, often alongside surveys (e.g., Hendrikx et al., 2018, 2022; Johnson and Hendrikx, 2021; Sykes et al., 2020; Toft et al., 2024; Ahonen et al., 2024). Participants are generally aware of, and potentially motivated by, the study's purpose. Such studies rely on resource-intensive recruitment processes and the willingness of volunteers to contribute their time and effort, resulting in a limited sample size. A less expensive way to gather GPS data is through social media or social fitness platforms such as Strava or Skitourenguru (Wood et al., 2013; Schmudlach and Eisenhut, 2024; Toft et al., 2024). If GPS data is acquired from such platforms, it can be considered as UGC, where individuals and their motivations, and therefore potential sampling biases, are largely unknown to researchers (Mashhadi et al., 2020). GPS data in backcountry skiing research can be used to shed light on decision-making processes related to different terrain, but also to estimate exposure or base rates of skiing activity. Toft et al. (2024) suggest that the forecast avalanche danger may not affect people's decision to *go* outdoors, but their decision on *where* to go. This is in line with Winkler et al. (2021), who showed that people ski on less serious terrain when the avalanche danger is heightened. However, there are other factors beyond the avalanche forecast that influence behaviour, most obviously in the form of the weather forecast, with Ahonen et al. (2024) finding that almost all skiers assess a weather forecast when preparing for a tour. This calls for further examination of different factors that influence skiing activity to eventually estimate activity base rates.

A further potential way of exploring behaviour is through the use of online engagement data, which has been widely used in marketing and search engine optimization (Joachims, 2002; Bucklin and Sismeiro, 2009; Akter and Wamba, 2016). Such data sources have more recently started to play a role in environmental science, leading to the development of *conservation culturomics* – where online data, such as Google Trends or Wikipedia data, are employed to study human-nature interactions (Ladle et al., 2016; Mittermeier et al., 2021).

3 Material and Methods

Our study consists of the following steps (see Fig. 1):

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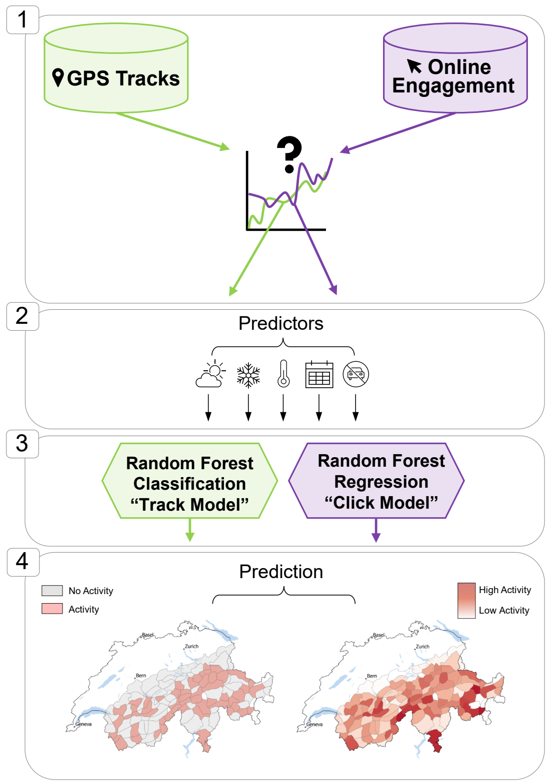

Figure 1. Methodology overview with (1) data, (2) predictors, (3) models and (4) predictions.

1. We use two different user-generated revealed preference datasets as a proxy for backcountry skiing activity: recorded GPS tracks and online engagement data from a ski touring web platform. Through correlation analysis, we assess if and how well both proxies align.

2. Based on a literature review, we identify suitable variables to predict backcountry skiing activity.

3. Using these variables, we train two models. One model performs a binary classification of absence and presence of activity, while the other model performs a regression estimating the level of potential activity

4. The two models are evaluated and discussed in terms of their performance and the importance of the predictor variables. Further, we assess how different variables impact skiing activity and predict activity for different scenarios.

3.1 Study Area

The study area covers the Swiss Alps with a total area of 26’371 km^2(Fig. 2a) and ranges in elevation from 192 m to 4’555 m a.s.l. (mean 1’822 m). It is mountainous, with 50% of the area above 1’500 m. Large parts of the Alps are prone to avalanche

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danger due to steep terrain in combination with substantial amounts of snow. The backcountry skiing season usually lasts from December until April or May.

The Swiss Alps are split into 128 warning regions to communicate avalanche conditions in the avalanche forecast published daily during winter by the WSL Institute for Snow and Avalanche Research SLF (Fig. 2a). These warning regions are the smallest spatial units for which avalanche danger forecasts are issued.

3.2 Data

3.2.1 Skitourenguru

Skitourenguru (www.skitourenguru.ch) is a popular web service that supports backcountry skiers in the selection and planning of suitable ski tours. It provides avalanche risk assessments for thousands of predefined backcountry ski routes across the Alpine region using an algorithm, which processes information from the avalanche forecast and terrain characteristics twice a day (Schmudlach and Köhler, 2016; Schmudlach and Eisenhut, 2024). Users can search for routes based on criteria such as the travel distance from their home location to the starting point of a tour, or on tour characteristics like elevation gain, route difficulty, or avalanche risk. Additionally, users can upload GPS tracks of their own tours (Schmudlach and Köhler, 2016). Both datasets used in this study were collected through the Skitourenguru website and are introduced in the subsequent sections.

3.2.2 GPS tracks (Track data)

Between 2013 and 2024, over 6’800 GPS tracks were uploaded by backcountry recreationists throughout all seasons except for seasons 21/22 and 22/23. This dataset has been used to study avalanche risk taken by backcountry skiers under different avalanche conditions (Winkler et al., 2021; Degraeuwe et al., 2024). These tracks were distributed across 126 of the 128 warning regions, though many warning regions only contained a few tracks over the whole study period. In this study, the dataset is used in an obfuscated form that safeguards the privacy of the contributing users. Figure 2b shows one example GPS track before obfuscation. To obfuscate, the coordinates of the GPS tracks were aggregated to the spatial granularity of the warning regions and timestamps to one day. After the obfuscation process, each trajectory is represented by a single data point, holding information about the warning region, the mean elevation of the trajectory and the date it was carried out.

3.2.3 Online engagement (Click data)

On Skitourenguru, engagement data is collected, where clicks on pre-defined ski routes (see Fig. 2b) are logged. This dataset contains over 8 million clicks on 2’666 unique ski routes covering 122 of the 128 warning regions and a time period of 9 years between 2015 to 2024. Every click can be related to exactly one geo-referenced route, from which terrain characteristics and the warning region can be inferred. Analogous to the GPS tracks, all clicks are aggregated to the spatial level of warning regions and to daily intervals. After the re-design of the website in 2021 and the related connection to other websites such as the website of the Swiss Alpine Club (SAC), the popularity of the website and the number of clicks has increased greatly. Due to this increase, data before and after 2021 are difficult to compare. Therefore, only data from 2021 onwards is included for modelling and prediction, which results in ≈5.3 million clicks and represents 65% of the initial dataset. However, all click data is used for the correlation analysis of GPS tracks and clicks to maximize temporal overlap between both data sets.

3.3 Correlation Analysis

Click data differ from track data in that we assume they reflect planning or potential behaviour rather than actual skiing behaviour. The baseline assumption linking click and track data is that a click on a specific tour is indicative of activity on the same tour in the days that follow. To test this hypothesis, we examined the correlation between clicks and tracks over seven different winter seasons, considering time lags ranging from 0 to 4 days. Given the obfuscated nature of the data and the sparsity of track data at the level of individual warning regions, we aggregated and counted both track and click data over the entire study area for each day. The relationship between daily track and click counts was quantified using Spearman's rank-order correlation coefficient (ρ) (Appendix B), a non-parametric measure of association. Correlations were calculated separately for winter seasons to account for inter-seasonal differences. Since the two data series differed in magnitude – click counts being much higher than track counts – they were normalized by their respective minimum and maximum count per season for visualization purposes.

3.4 Model Building

3.4.1 Variable Selection

The variables used to predict skiing activity are linked to the four factors that contribute to avalanche release as introduced in Section 2, as well as by a literature research in the domain of outdoor recreation and specifically backcountry skiing. A list of all variables, a short description and the data source they were derived from, can be found in Table 1.

The selected variables can be divided into three temporally dynamic categories (weather, snow, temporality) and one static category (environment) (Table 1), which reflect the different sides of the avalanche triangle. Weather and snowpack are directly represented by weather variables and snow variables. The terrain aspect is not directly included in the variables, but suitability of the terrain is represented by environmental variables. Finally, the human factor is captured through temporal variables, reflecting human behaviour patterns related to preferences for weekdays, holidays, seasonality and accessibility.

There is rich literature on the importance of weather variables for outdoor activities (Verbos et al., 2018; Wegelin et al., 2022). For instance, Rutty and Andrey (2014) found that virtually all skiers access a weather forecast when planning a tour and that it can even deter them from ultimately going outside. Further, temporal variables relating to weekday, holiday and seasonality are often used for predicting behaviour in recreation and tourism and have shown to be an important driver for backcountry usage patterns (King et al., 2014; Madden et al., 2023; Techel et al., 2014). Snow conditions and the avalanche forecast are crucial for backcountry skiing and play an important role in the decision-making process. They can sometimes deter people from undertaking backcountry skiing trips, for instance when avalanche conditions are expected to be dangerous (Furman et al., 2013; Hendrikx et al., 2022; Marengo et al., 2017), while also enhancing activity due to the desire to ski an untracked slope of fresh snow, a common heuristic trap in backcountry skiing decision-making (Furman et al., 2010; Mccammon, 2004).

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Accessibility is a pre-requisite for recreation which is commonly used to predict recreational activity or recreation supply, and is a crucial factor for terrain-selection of backcountry skiers (Koppen et al., 2014; Olson et al., 2017; Schirpke et al., 2018; Willibald et al., 2019). Further, recreational activities can significantly disturb wildlife, posing a serious threat to wild animals and the existence of protected zones therefore influences the regions where backcountry activities are undertaken (Ingold, 2005; Lesmerises et al., 2018; Müllner et al., 2004).

3.4.2 Variable Calculation

The click data and the GPS tracks have the same spatial (warning regions) and temporal (daily) resolution. Both datasets were enriched with the predictor variables aggregated to these resolutions.

Meteorological variables were derived from gridded datasets interpolated from SwissMetNet Stations (MeteoSwiss, 2021b). For precipitation, we added hourly gridded precipitation values between 07:00 and 11:00, as backcountry ski tours typically start in the morning. Further, we used daily average temperature and the daily relative sunshine duration. Meteorological variables vary according to topographic elevation (Scherrer and Appenzeller, 2014; Spreafico and Weingartner, 2005). Since backcountry skiing usually takes place at higher elevations within a region, mean values were calculated based on the grid points that lie in an elevation band within ± 100 m of the mean track elevation (track data), respectively the mean route elevation in a given region (click data) (Fig. 2b). Daily measurements of new snow and absolute snow height were available for 226 automated (IMIS) and 126 manual measuring stations (BEOB) (WSL Institute for Snow and Avalanche Research SLF, 2023; Intercantonal Measurement and Information System IMIS, 2023). Most of the stations are concentrated in inner-Alpine regions, therefore some warning regions at the Alpine edge contain few or even no measuring stations. Further, some stations contain substantial measurement gaps. Due to the broad spatial resolution to which variables needed to be generalized, a spatial interpolation of the measurements would have been unnecessarily complex. Therefore, we opted to use the mean of the five nearest measuring stations for each warning region. If more than five stations lay within a region, those with the smallest elevation difference from the mean ski track elevation were selected. Further, we used the daily forecast avalanche danger communicated through the 5-level danger scale (1 = low, 2 = moderate, 3 = considerable, 4 = high, 5 = very high) as published by the WSL Institute for Snow and Avalanche Research SLF. For the remaining variables, we calculated ski route, GPS track and road densities by dividing total length by area, we calculated census density by dividing total number of inhabitants by area, we calculated accessibility by multiplying road density and census density and we used the proportion of protected wildlife area per warning region. The season start was determined using the first day of the season on which an avalanche forecast was issued and we used day of the season as the number of days since November 1, to allow comparison between seasons. Finally, for holidays we included all Swiss National holidays, as well as so-called bridge days (single days between a public holiday and a weekend), as well as the week between Christmas and New Year (see Appendix A for a complete list).

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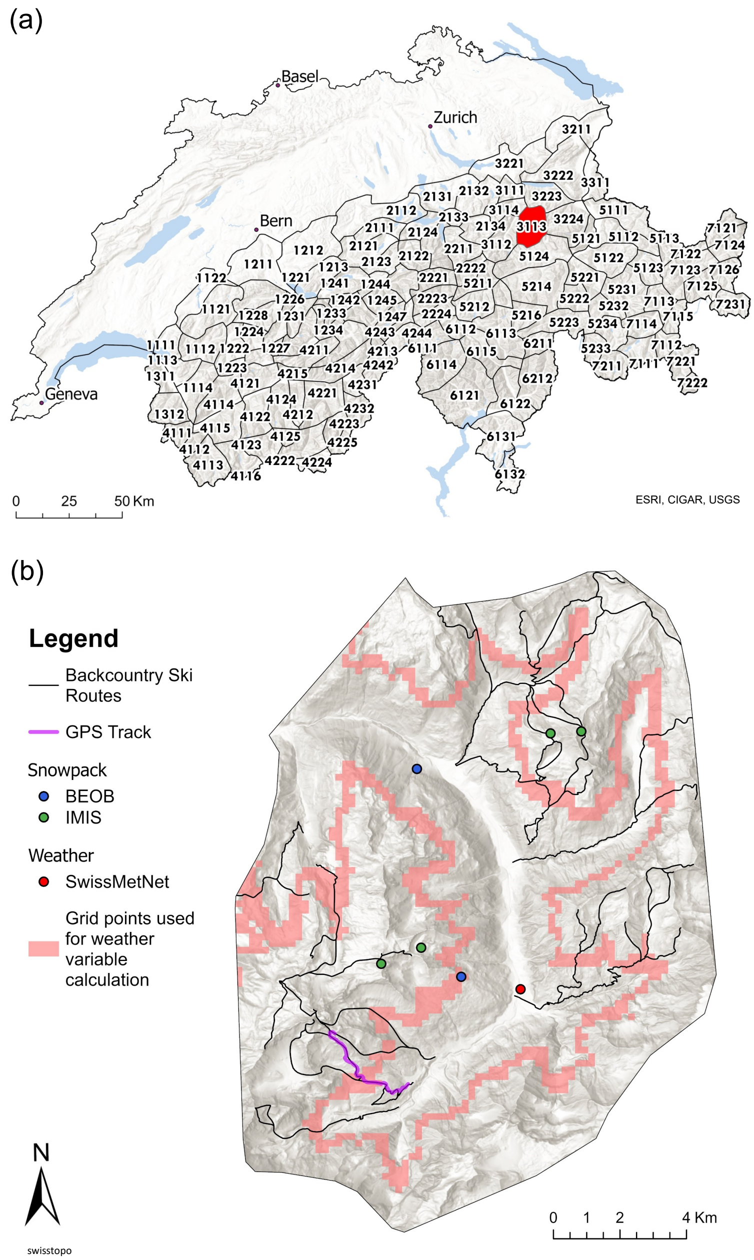

Figure 2. (a) Map of Switzerland showing 128 Alpine warning regions, the smallest spatial units used to communicate avalanche danger in the avalanche forecasts in Switzerland. Each region is labelled with its respective warning region code (WRC). **(b)** Example region 3113, highlighted in **(a)**, showing weather stations (SwissMetNet), snow measurement stations from automatic measuring stations (IMIS) and from manual measuring stations (BEOB), backcountry ski routes featured on www.skitourenguru.ch, one example GPS track, and the elevation belt used to calculate meteorological variables by averaging all grid points that lie within. To obfuscate exact GPS locations, each GPS track has only the warning region code (3113 in this example) as spatial reference.

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3.4.3 Model Building

Different models can be used for prediction tasks, such as fully explainable, linear models (e.g., GLM/GAM: Willibald et al., 2019), partially explainable machine learning models (e.g., random forests: Minehart et al., 2024) and deep learning models (e.g., neural networks: Loumiotis et al., 2018). Choosing the right model involves trade-offs: while more complex models like machine learning or deep learning models can better capture non-linear relationships, they are harder or even impossible to interpret. More simple models on the other hand offer a high level of interpretability but have limited power with non-linear and potentially correlated data. Considering the characteristics of our training data, which is noisy, non-linear, inter-correlated and relatively small in size (GPS track data), we chose to use random forests.

Random forests have proven to be an efficient and effective tool to predict visits to outdoor recreation areas (Madden et al., 2023) or map recreational ecosystem services (Manley and Egoh, 2022; Nyelele et al., 2023). They have a number of advantages in that they are well suited to non-linear and correlated data and agnostic with respect to data types such as numerical and categorial data (Marsland, 2011). Compared to deep learning architectures like neural networks, random forests are however relatively easy to interpret as the algorithm consists of a set of decision trees that make the prediction based on majority voting (Breiman, 2001). Moreover, they provide an estimate of the variable importance as well as of how different values of a variable influence the outcome. In other words, random forests provide a level of interpretability that most other machine learning algorithms fail to provide (Gilpin et al., 2018; Liaw et al., 2002). Additionally, they work well for relatively small and noisy data sets because they are not prone to overfitting due to the large number of trees that are grown (Breiman, 2001).

We used the track data and the click data to train two separate random forests using the 'randomForest' library in R (Liaw et al., 2002). Because the track data was far less abundant than the click data – many regions only contained a few tracks over an entire season – it was used to train a binary classifier, with 'presence' (when at least one track was recorded) and 'absence' (when no track was recorded). The click data was used to train a regression model, where the response variable was the daily click count per warning region. Both models had identical spatial (warning regions) and temporal (1 day) resolution. For the remainder of this article we use the terminology 'track model' for the binary classification model derived from the GPS track data and 'click model' for the regression model derived from the click data.

While correlated variables do not impact the predictive power of a random forest, they can hinder the accurate estimation of variable importance as measured by variable permutation (Darst et al., 2018). Moreover, they may lead to increased computation time without contributing significant additional information. Therefore, a correlation analysis was carried out to exclude strongly correlated variables ($r > 0.4$). Additionally, variables with near zero importance values were excluded to speed up computation. Further, data points were excluded when they were recorded outside the winter season (May - October), or when no weather or snow data was available for the given day, since random forests do not accept NA values as input. Accordingly, 2.5% of click data and 1% of track data was filtered out.

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Since both datasets included only presence data, we inferred absence by adding data points for days and regions without clicks or tracks, assuming absence of evidence implies evidence of absence – on the premise that no record signals fewer people in the field. For modelling, we assigned a click count of 0 or a track label 'absence' to these generated points.

For the track data, the resulting absence points outnumbered the presence points by a ratio of 30:1. Class imbalance is a frequent problem when working with real life data and can be challenging for machine learning algorithms. When fed with imbalanced data, most algorithms fail to yield equally good performances in both the minority and the majority class since, depending on the performance measure chosen, the algorithm prioritizes accuracy of the bigger class (Guo et al., 2008; Krawczyk, 2016). To address this, the two classes were artificially balanced by downsampling the absence class to train the track model. This in turn meant that we expected our model to overpredict presence, since presence counts were artificially inflated. We return to this issue in the discussion.

In typical machine learning applications, training and testing data are created by randomly partitioning the dataset. However, if temporally autocorrelated processes are present, a random split violates the assumption of independence between training and test sets (Otis and White, 1999). Since temporal autocorrelation was clearly present in our data, we used an entire season as the test set while training the model on data from all other seasons. This approach resulted in four (nine) training runs, each cross-validated using four (nine) different seasons for the click (track) data.

Hyperparameters were fine-tuned using a grid search to find the best possible parameter values for *mtry* (the number of variables randomly selected at each node of a tree) and *sampsize* (the number of data points sampled for each tree), which are the most common parameters used for tuning random forests (Fig. S7-S8 in the Supplement). As the generalization error generally decreases with a higher number of trees and consequently more trees lead to a more stable prediction, we opted for a forest of 500 trees for each model (Liaw et al., 2002).

3.4.4 Performance Evaluation

After training on the training data, the model was applied to unseen test data, repeating for each cross-validation run. Classification performance was assessed using Sensitivity, Specificity, Balanced Accuracy and the Hanssen-Kuipers Skill Score (KSS). Sensitivity and Specificity were calculated according to Swets (1988). Balanced Accuracy is the geometric mean of Sensitivity and Specificity and is frequently used when classes are imbalanced (Marsland, 2011). To account for class imbalance, we additionally used KSS, a measure developed in meteorology and suitable for imbalanced prediction problems where the minority class is the focus (Hanssen and Kuipers, 1965; Peirce, 1884; Ebert and Milne, 2022). R^2 and RMSE were used to assess performance of the regression model (e.g., Montgomery et al., 2006). Further, we calculated the prediction delta for both models, which we defined as the absolute difference between predicted and observed tracks, respectively clicks to assess the spatial and temporal distribution of errors. Equations of performance metrics can be found in Appendix B.

To assess how different variables impact the prediction, variable importance values were calculated using the built-in function for variable importance in the 'randomForest' R library (Liaw et al., 2002). Variable importance was calculated using a permutation-based method, measuring the average decrease in model accuracy and therefore predictive power, when a specific variable was excluded. To examine how each variable influenced activity, we calculated permutation-based partial dependency

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(PD) using the R package ‘pdp’ (Greenwell, 2017). PD isolates a variable’s effect by holding all other variables constant and thereby assessing its impact on the probability for a given outcome of the response variable (Breiman, 2001).

PD plots were computed separately for the two data sources clicks and tracks. Since PD values typically differ in scales for regression and classification models, we applied min-max normalization to each PD curve independently to allow for visual comparison between click and track PD. A normalized value of 1 in the click model thus corresponds to the maximum PD effect of a given variable within the click task, and likewise for the track model. Consequently, normalized values are not directly comparable across tasks in terms of absolute magnitude. Furthermore, min-max normalization masks differences in the strength of variable effect. Variables with lower importance typically yield flatter PD curves, but this relative flatness is lost after normalization. Thus, while normalization enables qualitative comparison of the effect *shapes* (e.g., increase or decrease of activity likelihood), it does not reflect differences in effect *magnitude* or *importance*.

To demonstrate how the models are spatially influenced by altering one variable, we created idealized scenarios where all but one variable was held constant. For each scenario, a reference value was defined, and the variable of interest was systematically altered, while all other variables were fixed at reference values. The resulting differences in model predictions were visualized to highlight the spatial heterogeneity in variable influence. This approach allowed us to map the response of model predictions to changes in individual variables in a spatial context on an exemplary basis.

4 Results and Interpretation

We structure the results according to the research objectives outlined in Section 1. This section presents: (4.1) the characteristics of the training datasets used as proxies for backcountry skiing activity, (4.2) the predictive performance of both models, (4.3) the spatial and temporal distribution of errors, and (4.4) the importance of different variables for the prediction.

4.1 Correspondence between click and track data

Correlation analysis revealed that a 1-day lag between clicks and tracks exhibits the strongest correlation in all seasons ($\rho_{\text{mean}} = 0.61$, $p < 0.001$), therefore the click dates were shifted by one day for the entire analysis (Fig. 3, Table 2). Notably, correlation generally increased over time and peaks in season 23/24. This is likely due to the increasing number of clicks over the years and specifically after 2021.

On average, 765 GPS tracks were recorded each season in the whole study area. However, there were substantial variations between seasons, e.g., in season 2016/17, relatively few tracks were recorded (524), which can be attributed to an extreme lack of snow in this season (Zweifel et al., 2017). More tracks were recorded on weekends (57%) and in the second half of the season (61%), compared to weekdays and the beginning of the season. The tracks were spatially autocorrelated, with 50% of all tracks recorded in only 21 of the 128 warning regions. Although the click data was denser in both spatial and temporal distribution, it showed similar patterns to the track data. On average, 890’000 clicks were recorded per season, but lower click counts were recorded in years with below-average snow conditions (e.g., 2021/22) (Pielmeier et al., 2023). Overall, 38% of all clicks were recorded for weekends (i.e., on Friday and Saturday considering a 1-day time lag) and 50% of all clicks were

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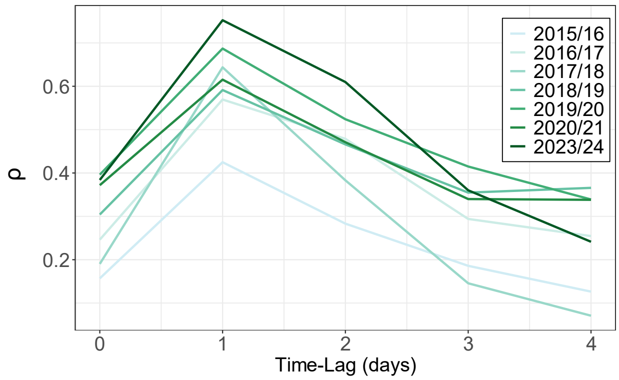

Figure 3. Spearman rank correlation (ρ) of daily sums of tracks and clicks with different time lag between both datasets. The time lag represents the number of days by which the click data is shifted, so that date(click) becomes date(click) + time lag.

recorded in the second half of the season, indicating that click data was more uniformly distributed over time than the track data. However, similarly to the tracks, clicks were spatially autocorrelated, with 50% of the clicks recorded in 23 warning regions.

In Fig. 4, normalized daily aggregates of clicks and tracks over the whole study region are shown for two exemplary seasons, where 1 represents the highest value measured in this season for each series. Correlation analysis of both time series exhibited correlation coefficients ρ ranging from 0.46 - 0.72 ($\rho_{\mathrm{mean}} = 0.62$) in different seasons (Table 2). Visually, the time series aligned relatively well, but the track data, unlike the click data, included many days with zero counts producing noisy time series. Peaks in both datasets coincided, but they often differed in magnitude. Further, tracks were more concentrated on the weekends, while clicks were distributed more evenly throughout the week, and peaks on the weekends were relatively less pronounced in click than track data.

From a spatial perspective, track and click counts aligned relatively well, especially in the central and northeastern part of the Alps ($\rho = 0.3 - 0.66$, $p < 0.05$) (Fig. 5). Discrepancies could be found at the southern edge of the Alps ($\rho < 0.3$, $p > 0.05$) (Ticino, southern Valais and southern Grisons), where tracks were more abundant than clicks, as well as in some regions of the central Alps, where clicks were slightly more abundant than tracks. Overall, regions with higher click counts also exhibited higher track counts and vice versa, confirming the relationship between both datasets. Lowest correlation coefficients were found in regions with low click and track counts.

4.2 Model Performance

An overview of the skill scores obtained from different test seasons used for cross-validation is shown in Table 3. The track model predicting presence or absence of activity yielded a mean balanced accuracy of 0.74 ±0.01, while specificity (0.75 ±0.05) was slightly higher than sensitivity (0.74 ±0.05). Towards the end of the study period, sensitivity increased, while specificity decreased and in season 2020/21, sensitivity was higher than specificity (0.80 vs. 0.69). Similarly, KSS increased

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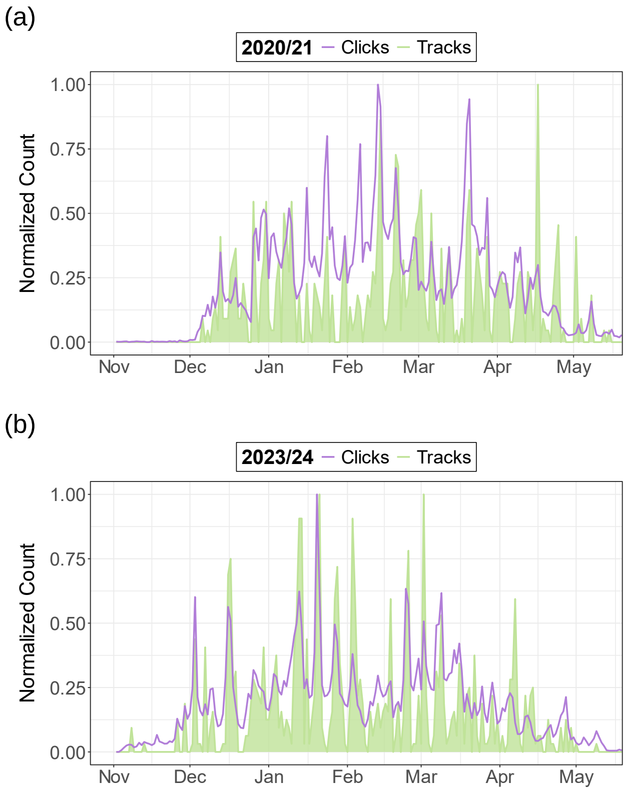

Figure 4. Normalized click and track counts. **(a)** Season 2020/21, correlation coefficient $\rho = 0.67$ ($p < 0.001$) **(b)** Season 2023/24, correlation coefficient $\rho = 0.75$ ($p < 0.001$). Counts are aggregated daily across the entire study area. For comparability, both time series were normalized separately with the maximum count per season. A value of 1 represents the highest count of tracks or clicks for that season. Click counts were shifted by one day.

during the study period, though overall variation between seasons was low (0.49 ±0.02). Balanced accuracy had the smallest variation across different seasons (0.75 ±0.01) and showed an overall decreasing trend over the study period. Although the relative rates of false negatives and false positives were similar, the absolute number of false positives was much higher. The underlying driver for the systematic overprediction of the track model lay in the modelling process itself, as artificially balanced numbers of presence and absence points were used for training. When verified with real-life and therefore unbalanced data, the model predicted more presence than was observed.

The click model predicting absolute click counts yielded an average R^2 of 0.64 ±0.04, and an average $RMSE$ of 86 ±15. This means that on average 64% of the variability in potential behaviour could be explained by the model, and the predicted clicks deviated by an average of 86 clicks from the true value. The predictive power varied slightly by season, with R^2 ranging from 0.71 in season 2021/22 to 0.61 in season 2022/23. The RMSE was in line with R^2, except for season 2022/23, which

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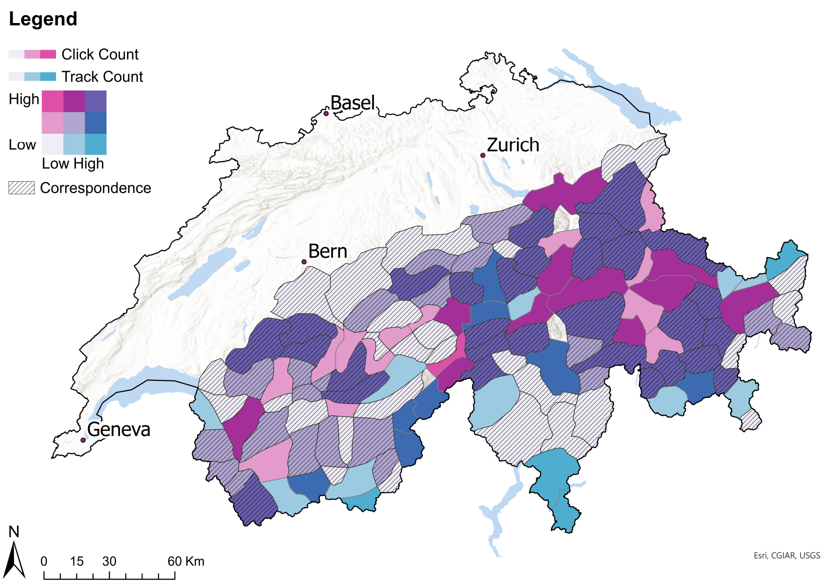

Figure 5. Bi-variate map showing click and track counts per warning regions. Blue indicates tracks > clicks, pink indicates tracks < clicks, purple and dashed indicates correspondence between clicks and counts, where light purple indicates low counts and dark purple indicates high counts in both datasets. Note that the datasets are only compared relatively, since the click dataset is much larger than the track dataset. Classes (Low-High) were generated using quantiles.

exhibited the lowest RMSE (68) but also the lowest R^2 (0.61). The low RMSE can be explained by overall low click counts in this season, due to mild temperatures and a lack of snow (MeteoSwiss, 2023).

4.3 Prediction Errors

4.3.1 Spatial Distribution

Residuals show that the track model consistently overpredicted activity across all regions, while the click model both over- and underpredicted depending on the region (Fig. 7). This is also visible in Fig. 6, where the track model predictions poorly matched observations due to systematic overprediction. Contrastingly, the click model closely follows a 1:1 relationship between predicted and observed values, indicating strong predictive accuracy.

For the track model, errors were autocorrelated within regions and largely followed the distribution of the initial training data, with larger absolute errors in regions with more recorded tracks and smaller absolute errors in regions with very few recorded tracks. Contrastingly, the errors of the click model were neither autocorrelated, nor did they follow the underlying distribution of the training data. Generally, residuals approached zero in most regions, with larger absolute errors dispersed across the

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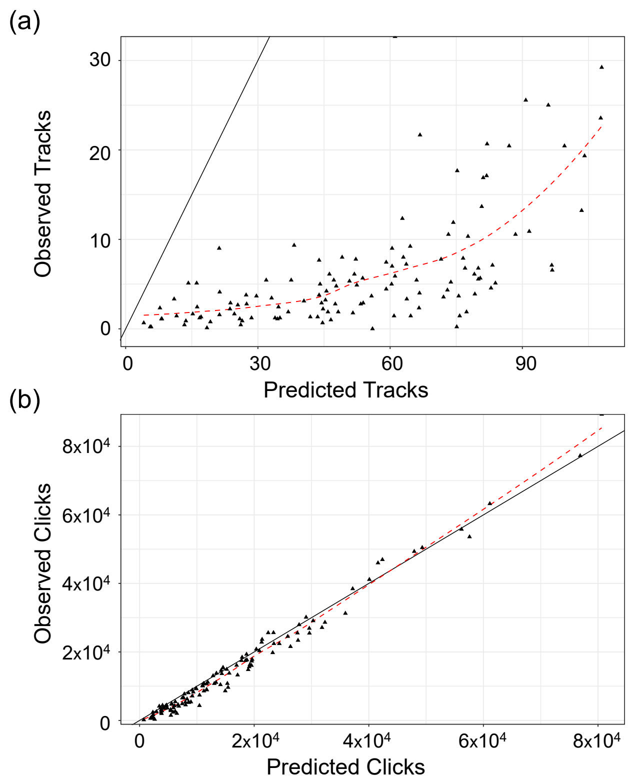

Figure 6. (a) Predicted vs. observed tracks and **(b)** clicks. Each plot compares model predictions to actual counts, aggregated by warning region and averaged across all winter seasons. The red dashed line indicates the trend, and the black line marks the 1:1 line representing perfect agreement.

whole study area. Visually, the only slight spatial trend was that the click model underpredicted activity slightly more often in the northeastern and eastern part of the study area, which coincides with regions that received more clicks overall.

4.3.2 Temporal Distribution

Figure 8 shows the predicted and observed track and click counts aggregated over the whole study area for one example season. The click model captured weekly and seasonal cycles, with higher predicted activities on the weekends and in the middle of the season, coinciding well with observations. The magnitudes of peaks were often underpredicted, while periods of lower activity were overpredicted. Overall, the predicted clicks reflected a smoothed version of the observed clicks. The track model on the other hand produced a very noisy prediction and systematically overpredicted activity. Nonetheless, track predictions correlated fairly well with click predictions ($\rho = 0.7$, $p < 0.001$, for season 2023/24). Most predicted click peaks and some predicted track peaks visibly aligned in their temporal locations with the observed peaks. However, the predicted magnitude, especially for tracks, frequently did not match observations well. This was also reflected in the prediction delta (i.e., difference between model predictions and actual counts) (Fig. 8b and d), which was continuously positive for the track model while

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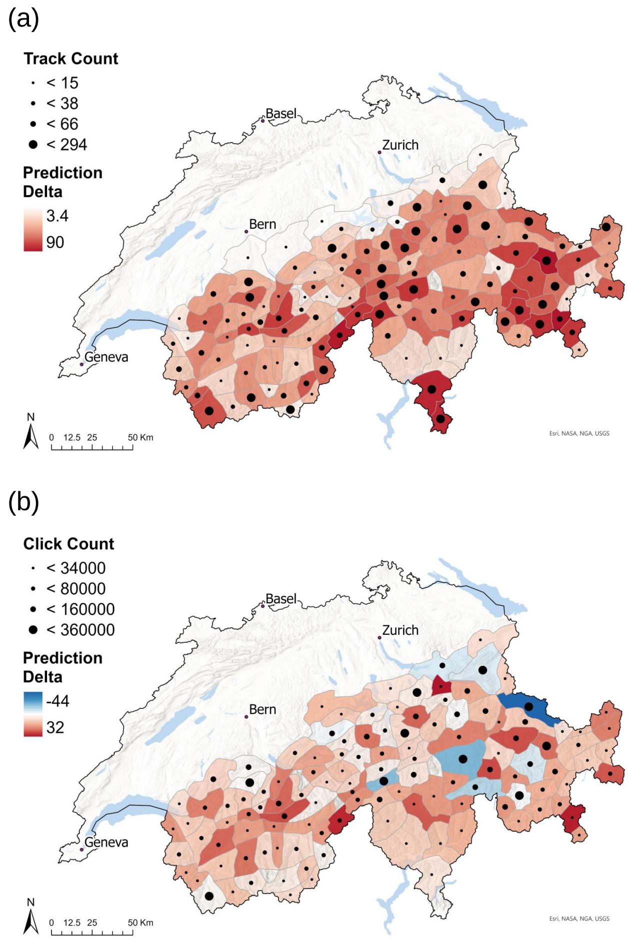

Figure 7. Mean prediction error for **(a)** track model and **(b)** click model across all seasons, where red indicates that the model overpredicted and blue indicates that the model underpredicted activity. **(a)** The prediction error was calculated as **(a)** the mean number of days per season with a false positive prediction and **(b)** the mean daily difference between predicted and observed clicks. Black circles indicate the total number of tracks **(a)** or clicks **(b)** per region.

alternating between positive and negative for the click model. Track prediction delta was almost zero in the early stages of the season (November), which coincides with almost zero recorded tracks, hence the model performed best when there was no activity. This was in line with the spatial distribution of errors, as smallest errors were found in regions with few tracks. For the click model, weekly periods of over- and underpredictions alternated over the season with highest absolute errors occurring in the middle of the season where highest click counts also occurred.

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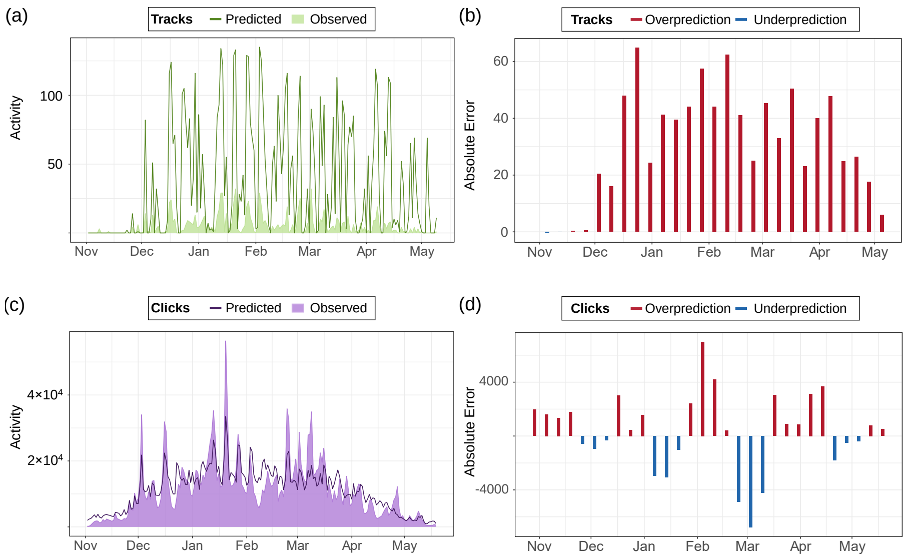

Figure 8. Temporal distribution of predictions and prediction errors for the example season 2023/24. Observed daily activity vs. predicted daily activity obtained from **(a)** the track model and **(c)** the click model. Counts were aggregated over the whole study area. Absolute prediction delta from **(b)** the track model and **(d)** the click model. The prediction delta was calculated as **(b)** the weekly mean absolute difference between number of regions where activity was predicted and number of regions where activity was observed and **(d)** the weekly mean absolute difference between predicted and observed clicks.

4.4 Influence of Variables on Prediction

Figure 9 shows the importance for each variable for the performance of the model, represented as points representing the importance values from each cross-validation seasons. For the classification model, variable importance was be calculated for each class separately. For the comparison with the click model, importance for the presence class was chosen, as the click data primarily included data points with click counts above zero, indicating ‘activity’ rather than ‘no activity’. Comparing the ranks of the variables in Fig. 9 showed that variable importance was very similarly ranked ($\rho = 0.81$, $p < 0.001$). Overall, the the range between the least and most important variables was smaller in the track model than in the click model, indicating a more balanced distribution of variable importance. Despite this, both models exhibited a similar pattern in variable importance, suggesting that the same underlying factors drove each data source, again confirming their relationship. *Ski route density* was the first, respectively second most important variable for the click, respectively the track model. For both models, two out of three temporal variables (*weekend* and *day of the season*) were among the four most important variables. Further, *holidays* and *new snow* were among the least important variables for both models.

While the relative importance of variables was similar across both models, partial dependency plots revealed that some variables had a somewhat different impact on activity (Fig. 10). Noteworthy differences were found for the variables *temperature*,

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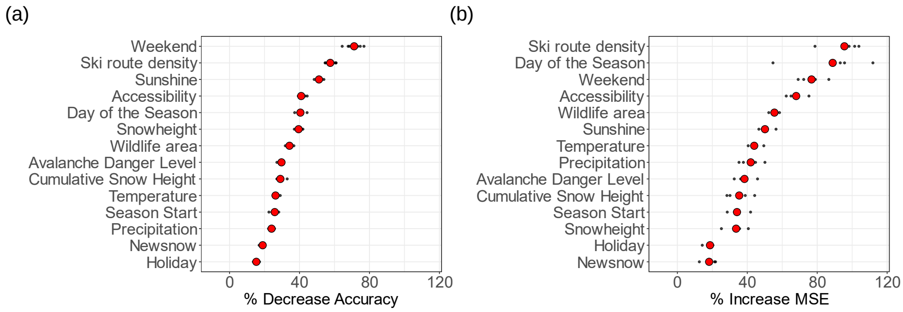

Figure 9. Variable Importance derived from the **(a)** track model and the **(b)** click model. The x-axis shows the percentage decrease in accuracy, respectively the increase of the mean squared error the model suffered when excluding given variable. Low values of '% Decrease Accuracy', respectively high values of '% Increase MSE' indicate high importance for the predictive power. For the track model, variable importance refers to the importance for predicting the presence class (hence activity of backcountry skiing), rather than for the absence class. Each black point represents one test season, the red point indicates the mean value.

avalanche danger, *new snow* and *day of the season*. The click model predicted higher activity for lower temperatures, higher avalanche danger, more new snow and early on in the season as compared to the track model. This highlights key differences between online and real-world behaviour – for instance, people tend to click on tours under riskier and more extreme conditions than those they actually pursue in practice. Additionally, the click model predicted more activity at the beginning of the season, which then gradually declined toward the end, whereas actual outdoor activity peaked in the middle of the season. For the other variables, as is exemplarily shown for *ski route density* and *sunshine*, the general pattern was the same for both models.

In the normalized PD plots, some variables may appear equally influential despite much smaller actual effects. By looking at unscaled plots (Fig. S10-S11 in the Supplement), the magnitude of activity change under certain conditions could be estimated. For example, the activity was predicted to be 30% (50%) higher on the weekend compared to the weekdays by the click model (track model). Further, the activity was 30% (60%) higher on a sunny day as compared to a day with no sunshine. For avalanche danger, we found differences in activity at different danger levels (Fig. 10), but the absolute changes were small (e.g., from level 2 to level 3, a 4% increase in the click model and a 7% decrease in the track model and from level 1 to 3, a 17% increase for the click model and a 6% decrease for the track model).

While some variables had a uniform impact over space, other variables had differing impacts in different regions. For instance, the amount of sunshine hours had a positive impact on activity in all regions, as can be clearly seen in Fig. 10c, where activity in all regions decreased as sunshine duration was lowered compared to the base state. Contrastingly, the impact of increased avalanche danger on activity varied across regions, with some areas experiencing a decline in activity while others saw an increase, when the danger level was elevated from 2 to 3 (Fig. 10). When danger level 4 was issued however, the decline in activity was consistent, though predictions for danger level 4 or higher should be interpreted with caution, since these conditions occur rarely and thus the underlying data basis is sparse.

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Table 1. Initial variables used to model backcountry skiing activity. For each variable, the data source, a short description and literature based on which the variable was chosen is presented. Variables that were used for the final model are marked in bold.

Dependent Variables	Group	Independent Variables	Data source	Description	Literature
Track Model (Classification): Absence/Presence	Weather	**Daily precipitation**	MeteoSwiss (2021c)	[mm/day]	Rutty and Andrey (2014)
		Morning precipitation	MeteoSwiss (2021a)	[mm/morning]	Verbos et al. (2018)
		Relative sunshine duration	MeteoSwiss (2021d)	[%] of potential maximum	Wegelin et al. (2022)
		Air temperature	MeteoSwiss (2021e)	Daily average [°C]	
	Snow	**Forecast avalanche danger**	WSL Institute for Snow and Avalanche Research SLF (2024)	Level 1-5, if no forecast: 0	King et al. (2014)
		Absolute snow height	Intercantonal Measurement and Information System IMIS (2023)	Measured snow height [cm]	Hendrikx et al. (2022)
		Cumulative snow height	WSL Institute for Snow and Avalanche Research SLF (2023)	Cum. snow height since season start [cm]	Furman et al. (2013)
		New snow height	Intercantonal Measurement and Information System IMIS (2023)	Fresh snow height of past 24 h [cm]	
Click Model (Regression): Click Count	Environmental	**Ski route density**	www.skitourenguru.com	Ski route length per area [m/m^2]	
		Ski route absolute number	www.skitourenguru.com		
		GPS track density	www.skitourenguru.com	GPS tracks per area [m/m^2]	Ingold (2005)
		Census count	Federal Statistical Office (BFS) (2022)		Koppen et al. (2014)
		Census density	Federal Statistical Office (BFS) (2022)	Persons per area	Olson et al. (2017)
		Road length	Federal Office of Topography (swisstopo) (2024)	[m]	Schirpke et al. (2018)
		Road density	Federal Office of Topography (swisstopo) (2024)	[m/m^2]	Willibald et al. (2019)
		Accessibility		Road density * census density	
		Designated wildlife area	Bundesamt für Umwelt BAFU (2025)	[%] of total area	
	Temporal	**Season start**		First issued avalanche forecast [day of the year]	
		Day of the season		Days since November 1	King et al. (2014)
		Day of the Week		Monday - Sunday	Madden et al. (2023)
		Weekend		Binary, 1 = Weekend	Techel et al. (2014)
		Holiday	https://date.nager.at/api	Binary, 1 = Holiday	

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Table 2. Rank correlation between click and track data for each season separately with a significance level of $p < 0.001$.

Season	**Spearman's rank correlation ρ**
2015/16	0.46**
2016/17	0.60**
2017/18	0.62**
2018/19	0.63**
2019/20	0.66**
2020/21	0.67**
2023/24	0.73**

Table 3. Skill scores for different validation seasons for click and track model.

	Clicks (Regression)		**Tracks (Classification)**			
Season	**R2**	**RMSE**	**Sensitivity**	**Specificity**	**Bal. Accuracy**	**KSS**
2015/16	-	-	0.73	0.77	0.75	0.5
2016/17	-	-	0.67	0.78	0.73	0.45
2017/18	-	-	0.67	0.84	0.75	0.51
2018/19	-	-	0.75	0.78	0.76	0.53
2019/20	-	-	0.72	0.78	0.75	0.50
2020/21	0.63	97.13	0.80	0.69	0.74	0.49
2021/22	0.71	79.12	-	-	-	-
2022/23	0.61	68.48	-	-	-	-
2023/24	0.62	102.49	0.77	0.74	0.75	0.51
MEAN	**0.64**	**86.81**	**0.74**	**0.75**	**0.75**	**0.49**
STDV	**0.04**	**15.79**	**0.05**	**0.05**	**0.01**	**0.02**

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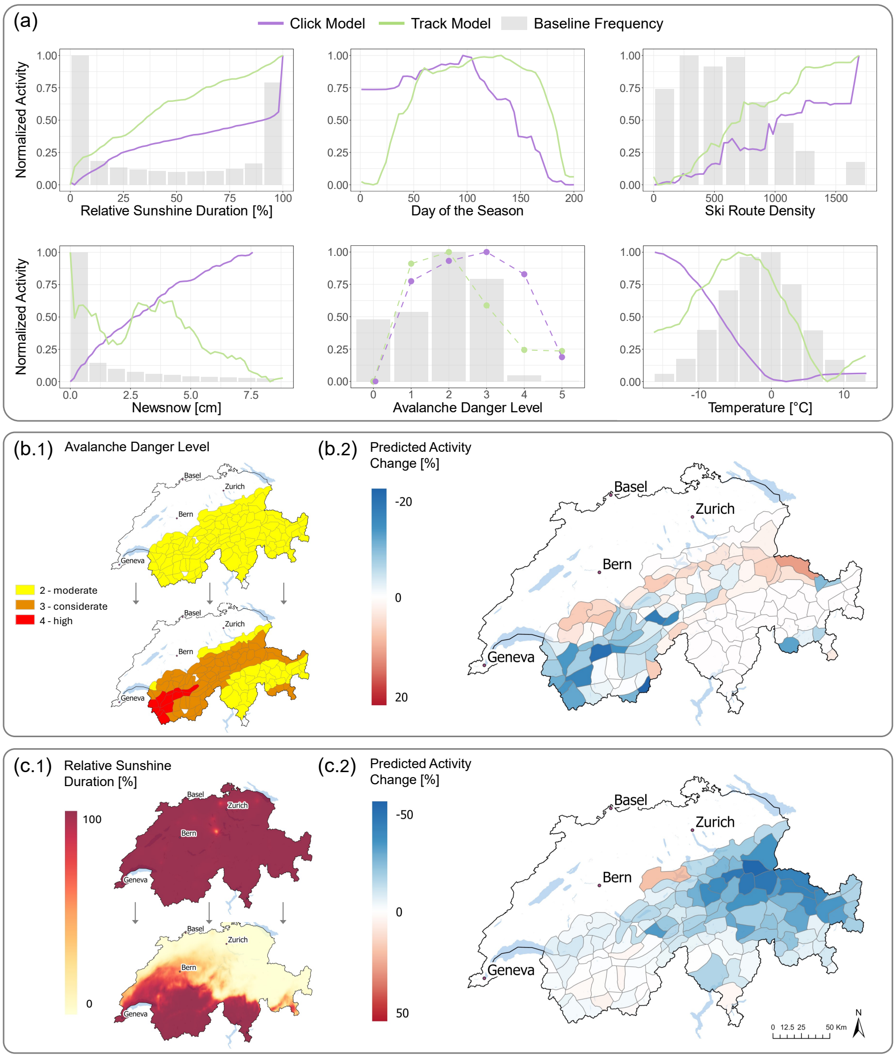

Figure 10. (a) Normalized partial dependency (PD) plots for six variables. Dashed lines indicate categorical data. The normalized baseline frequency of each variable is shown in light grey and is virtually identical for both the click and track data. Note that PDs in regions with limited underlying data (e.g., avalanche danger levels 4 and 5) are subject to higher uncertainty and should be interpreted with caution. For a complete list of variables see Fig. S9 in the Supplement. **(b.1)** Idealized scenario for a day in January 2024, where all variables were held constant except for the avalanche danger level. Only regions that contain ski routes (and thus click data) are shown, excluding two central Alpine regions and four peripheral ones. **(b.2)** Change in predicted activity resulting from **(b.1)** as predicted by the click model, as it offers more nuanced spatial detail. **(c.1)** and **(c.2)** illustrate the same type of scenario and resulting change, but with relative sunshine duration as the manipulated variable.

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5 Discussion

We modelled daily backcountry skiing base rates across avalanche warning regions in Switzerland using two different user-generated data sources – GPS tracks and online engagement – as proxies for activity – and linked them to snow, weather, temporal and environmental variables to identify the most important drivers for backcountry skiing activity. While previous literature proposed methods to enumerate backcountry skiers at a small scale (e.g., Toft et al., 2025; Zweifel et al., 2006), we explored methods that are scalable to larger regions and timescales, predicting backcountry skier behaviour across Switzerland on a daily basis.

We first summarize the main findings of this study, followed by a discussion of the data, methodology, variables and implications. The main findings can be summarized according to the research aims we proposed in the introduction:

(a) There is a significant correlation between GPS tracks and clicks using a 1-day time lag ($\rho = 0.61$, $p < 0.001$), especially when aggregated to a larger area, suggesting that online behaviour precedes real-world behaviour.

(b) Click data reflects a broader audience with a smaller participation bias, and captures spatially nuanced planning behaviour that often – but not always – translates into actual activity, while GPS tracks provide direct evidence of actual activity and insights on how different variables impact activity, though they are sparse and provide limited spatial detail.

(c) Drivers for backcountry skiing activity are similar for GPS track and click activity and include temporality (i.e., weekend, day of the season), accessibility of regions and skiing possibilities, and sunshine duration. However, the influence of certain variables differs between the models, highlighting differences in behaviour when planning versus actual skiing behaviour.

5.1 Data

The track and the click data are fundamentally different and come with different biases and uncertainties. Track data capture actual behaviour, while click data reflect potential behaviour during the planning process and both are examples of revealed, rather than stated, preferences. Although GPS tracks are direct evidence of physical presence in a region, they only cover a fraction of real activity. For instance, Degraeuwe et al. (2024) estimated that GPS data accounts for only 1 of 2'000 of backcountry activities, which is – considering the size of our datasets – in line with our analysis. Given previous literature on user-generated data, the participation bias in GPS data and the consequent false negative error in the classification of our training data was to be expected, since most users in online communities only observe but never contribute – a behaviour known as 'lurking'. (e.g., Nonnecke and Preece, 1999; Goodchild, 2007; Chen et al., 2019). This contrasts with click data, where lurking is impossible, since all users of the website automatically contribute to the data by clicking on a route. Consequently, click data likely captures a wider audience, as the effort of clicking on a route online is much smaller compared to the effort of tracking and uploading a GPS track, and participation bias is minimized. However, while capturing a wider audience, clicks do not necessarily translate into completed tours, leading to a likely overestimation of activity if we rely solely on clicks (false positive error).

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Another uncertainty inherent in the click data lies in the algorithm and interface used by the website to present potential skiing routes. On Skitourenguru, search results are automatically sorted by their avalanche risk rating, and routes are colour-coded on the map according to the risk level. These design choices intend to nudge users toward safer routes, both through ordering and visual cues. As a result, user engagement may become skewed toward lower-risk options, potentially introducing a spatial bias if safer routes are more prevalent in certain regions. Understanding how such platform features shape user behaviour is therefore essential for interpreting online engagement data. Finally, it remains uncertain whether the users behind the data are representative of the broader skitouring population, or whether they systematically differ in terms of skill level, experience, or preferences for specific routes or regions. However, even if the datasets reflect different user groups, both the input data and the model predictions correlated across data sources (Sec. 4.1), and the variable importance rankings were similar (Fig. 9), suggesting that the underlying patterns in actual and potential behaviour are consistent despite these differences.

Given the differences in magnitude and uncertainty between the two datasets, it was notable to observe a fairly strong correlation between clicks and tracks when the click data was time-lagged by one day. This was visible particularly in popular regions or when aggregated at a broader spatial scale. This supports the hypothesis that online behaviour precedes real-world activity, a pattern previously observed for visits to tourist destinations (e.g., Clark et al., 2019; Owuor et al., 2023), and aligns with findings that most people now plan outdoor recreation activities online (Fedosov and Langheinrich, 2015; Schwietering et al., 2024; Arts et al., 2021; Schönenberger et al., 2018). However, mismatches in the relative click and track counts occur. For instance, in the southern regions of the Alps, such as Ticino, GPS tracks are relatively more abundant than clicks (Fig. 5). A notable example is the warning region 6132 (Mendrisiotto) in the far south (Fig. 2a), which is characterized by relatively low but steep mountains and a lack of mapped ski touring routes. In this case, the elevated GPS activity likely reflects an outlier, driven by a few enthusiastic local users, rather than broader trends in backcountry skiing. In contrast, relative click density exceeds track density in several regions in the centre of the Alps, which may simply reflect their popularity – these areas attract more attention online (Schönenberger et al., 2018), even if not every click results in a recorded tour. Despite these exceptions, the overall alignment between clicks and tracks across most regions suggests that both datasets are shaped by shared underlying drivers. Further, the overall spatial patterns mostly align with previous literature from Switzerland (Techel et al., 2015; Schönenberger et al., 2018).

5.2 Methodology

Calculating the predictors was not straightforward, as data availability varied – with some variables (e.g., snow measurements) only available at discrete point locations while others existed in gridded or interpolated formats (e.g., weather data) and all variables had to be generalized to the relatively coarse spatial scale of the warning regions. Linking variables related to weather and snowpack information to warning regions introduced some uncertainties, since, for example, varying elevation thresholds influenced the values of meteorological variables assigned to a region. Some calculations relied on very simple interpolation approaches – for example using the value of the nearest stations for snow depth – and are therefore potentially prone to larger errors, which could influence the importance rating for snow variables.

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A fundamental assumption when using GPS tracks or click data as proxies for backcountry skiing activity is that the absence of data implies the absence of activity. As a result, regions may be falsely labelled as inactive simply because no GPS tracks were recorded, leading to misclassification errors. Similarly, reduced click behaviour later in the season may reflect generally more homogenous spring conditions and simpler planning rather than a reduction in activity. This highlights that both the data and resulting models can, at best, reflect relative rather than absolute activity patterns. In general, the two datasets have differing trends: GPS data tends toward false negatives due to under-reporting, while click data tends toward false positives, as not every click corresponds to actual activity. Nonetheless, GPS and click data and their respective model predictions agree on broad patterns of daily activity (Table 2) and the variables driving this activity are similar for both models (Fig. 9). However, direct comparison of model performance is limited by their differing objectives – classification versus regression – and the use of distinct performance metrics.

5.3 Variables

While performance metrics are difficult to compare between both models, comparing the importance of different variables is more straightforward. We could show that both clicks and tracks are driven by similar variables, most importantly temporal variables which are constant in space (weekend, day of the season) and ski route density which does not vary in time (a measure of how many possibilities for skiing there are in a region). The most important weather related variable was sunshine, whereas snow and avalanche related variables were found to be less important than expected based on previous literature and the magnitude of change of predicted activity induced by different danger levels was small (e.g., Zweifel et al., 2006; Moss, 2009; Techel et al., 2015; Winkler et al., 2021). This may be explained by the fact that the different snow variables and the avalanche danger are correlated – though correlation was small enough for the variables to not be excluded – which might have decreased the importance of each one of the correlated variables. Nonetheless, our results suggest care in making assumptions about the importance of avalanche forecasts alone in influencing behaviour, with many other factors also playing an important role in revealed, rather than stated, preferences. Studies based around stated preferences should in the future better control for potential confounds with respect to behaviour. In summary, in Switzerland, people go backcountry skiing primarily at the weekend and in regions with many mapped touring routes when the weather is good.

When comparing the two models, partial dependency plots allow us to explore the overall changes in prediction as one variable is varied. For four out of fourteen variables we found striking differences in the relationships between the track and click model, namely for avalanche danger level, day of the season, new snow and temperature.

Although activity peaks at avalanche danger level 3 (considerable) for the click model and even stays relatively high for danger level 4 (high), the track model peaks at danger level 2 (moderate) and drops quickly for higher danger levels. Simply put, we observe that people are less likely to go backcountry skiing at danger levels above 2, but they click on more potential routes as danger levels become more critical. A similar trend was observed by Moss (2009) in Scotland, where online engagement (views of the avalanche forecast and a conditions blog) increased strongly with higher danger levels, while actual backcountry activity decreased. However, the models predicted smaller differences in activity for different avalanche danger levels than was found in previous studies. This is especially true for the most frequent danger levels 1, 2 and 3, where the predicted activity

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did not differ more than 17% for the click model and 7% for the track model, whereas Zweifel et al. (2006) reported 90% more tours in Davos, a region in eastern Switzerland, on days with danger level 2 compared to 3, and Techel et al. (2015) reported 110% more activity for the same scenario. A reason for this could be that we aggregated all clicks and tracks to the spatial level of the warning regions, and did not look at specific routes. It is likely that under more dangerous avalanche conditions people chose less challenging tours, however we did not consider difficulty (e.g., as expressed through exposure and slope) as a variable. Nevertheless, we observed a spatial trend where higher avalanche danger in the Alps was associated with increased activity in the northern Pre-Alps (Fig. 10b), consistent with the findings of Techel et al. (2015). Further, the amount of new snow and cold temperatures had a positive impact on the click activity, while decreasing track activity. Lastly, the click activity was higher in the beginning of each season with a decreasing trend towards the middle, while track activity peaked in the middle of the season. These differences reflect key differences in the different types of behaviour each model describes. While online behaviour was driven by more extreme conditions (more new snow, colder temperatures and higher avalanche danger), actual skiing behaviour is shifting towards less dangerous (lower avalanche danger) and more comfortable (higher temperatures) conditions. Also, it appears that people do more research in the beginning of the season when planning activities, while being more active outside in the middle and towards the end of the season.

More consistency, both between the two models and in relation to previous literature, was found for the weekend variable. Here, predicted activity was 30 - 50% times higher on the weekend as on weekdays, in line with Moss (2009) (50 - 90% higher) and Toft et al. (2025) (70%). Higher weekend/weekday ratios were reported by Techel et al. (2015) (130 - 220% higher) and Schönenberger et al. (2018) (300% higher) for observed and planned tours.

5.4 Implications

As social media platforms and web communities have grown, user-generated content has increasingly been used as a proxy for human presence for visitor monitoring, ecosystem services mapping and tourism research where its effectiveness for researching human activities in the outdoors and nature has been demonstrated (Fisher et al., 2019; Levin et al., 2017; Norman et al., 2019; Manley and Egoh, 2022; Nyelele et al., 2023; Schirpke et al., 2018; Sonter et al., 2016; Tenkanen et al., 2017; Wartmann et al., 2021; Wood et al., 2013). In this study, we compared two different UGC datasets – click data and GPS data – which differ significantly in terms of user effort and the types of behaviour they capture. Despite these differences, we demonstrated a correlation between the two, highlighting the potential of click data as a more abundant, less privacy-sensitive, and cheap alternative to GPS data capturing potential backcountry behaviour. Even though this line of research has shown potential to deepen our understanding of human behaviour, it has received little attention in the context of backcountry skiing and more generally outdoor recreation so far. We therefore suggest further exploring such online engagement data in outdoor recreation research.

UGC has been previously used in backcountry skiing research (Techel et al., 2015; Toft et al., 2025), but it has not yet been explored as a tool to predict activity rates for the upcoming days. Using random forests we used such data to predict daily backcountry skiing activity across the Swiss Alps. Although the click model overestimates activity – not every click directly translates to a completed tour – it provides valuable insights into backcountry skiing activity, because it captures a broader

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sample of recreationists compared to GPS tracks. Aggregating GPS tracks over larger temporal and spatial scales – such as an entire season – may reveal trends, such as the low activity during a snow-sparse winter like 2016/17 (MeteoSwiss, 2017). However, when examined at the daily scale, GPS tracks more often represent noise rather than general patterns. Click data on the other hand, is richer, portrays a broader set of users and can show general trends and patterns even though there was a partial mismatch in variables impacting behaviour compared to actual activity. Nonetheless, the model captured the fluctuating activity levels well using the given set of predictors. While it is difficult to translate click data to an actual number of skiers, it can shed light on relative popularity of regions on a given day. Future work could include comparing ground truth data (e.g., Toft et al., 2025) with the model to validate and scale its predictions to quantify skiing activity in absolute numbers.

5.5 Conclusion

In this study, we used user-generated GPS tracks and online engagement data to predict daily backcountry skiing activities on a regional scale. We showed that activity can be predicted using random forests and relatively small set of variables. By linking both data sources with snow, weather, environment, and temporal variables, we identify key drives of backcountry skiing activity, which can be used in the operational avalanche forecasting process to estimate skiing activity. Lastly, we found that that online engagement data corresponds to GPS activity on the next day, which highlights the potential of using online engagement data as an alternative to privacy sensitive GPS data or resource intensive in-situ counts to measure recreational activity in the backcountry.

Appendix A: Holidays

The following official national holidays* and bridge days are considered (in chronological order): Neujahr (Jan. 1)*, Berchtoldstag (Jan. 2)*, Karfreitag (variable date)*, Ostersamstag und -sonntag (variable date), Ostermontag (variable date)*, Tag der Arbeit (May 1)*, Auffahrt (variable date)*, Auffahrtsbrücke (variable date), Pfingstsamstag und -sonntag (variable date), Pfingstmontag (variable date)*, Weihnachtsabend (Dec. 24), Weihnachten (Dec. 25)*, Stephanstag (Dec. 26)*, Weihnachtswoche (Dec. 27 - Dec. 31).

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Appendix B: Equations

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{B1}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{B2}$$

$$\text{Balanced Accuracy} = \frac{\text{Sensitivity} + \text{Specificity}}{2} \tag{B3}$$

$$\text{KSS} = \frac{(TP \times TN) - (FP \times FN)}{(TP + FN) \times (FP + FN)} \tag{B4}$$

$$R^2 = \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{B5}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \tag{B6}$$

$$\text{Prediction Delta } d = \hat{y}_i - y_i \tag{B7}$$

$$y_i = \text{prediction},$$

$$\hat{y}_i = \text{observation},$$

$$\bar{y} = \text{mean observation}$$

$$\text{Spearman's } \rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{B8}$$

$$d_i = \text{difference between ranks of paired observations},$$

$$n = \text{number of observations}$$

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Appendix C: Training Data

Table A1. Description of training data for classification and regression model.

	Track Data	**Click Data**
Model	Binary Classification	Regression
Presence Data	6'894 (tracks)	86'205 (days with >0 clicks)
Absence Data	213'810	10'971
Total Data	220'704	97'176
Time Period	2013 - 2024	2020 - 2024
Winter Seasons	2015/16, 2016/17, 2017/18, 2018/19, 2019/20, 2020/21, 2023/24	2020/21, 2021/22, 2022/23, 2023/24
Warning Regions	126	122

Code and data availability. The R-Code is available at: https://gitlab.uzh.ch/geocomp/backcountry-skiing-acitivity.

Author contributions. LS: conceptualization, methodology, software, data curation & analysis, vizualisation, writing – original draft, funding acquisition. RS: conceptualization, methodology, writing – review & editing, supervision, funding acquisition. FT: conceptualization, methodology, writing – review & editing, supervision. GS: data curation, writing – review & editing, supervision.

Competing interests. The authors declare that they have no conflict of interest.

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