UiT The Arctic University of Norway

Faculty of Health Sciences

Who skis where, when?

Quantifying the exposure and enumerating backcountry usage in avalanche terrain

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I. Preface

I never planned on doing a Ph.D.; my academic achievements were modest at best during my high school years, and I had no clear vision of what I wanted to do other than have a job like my dad; I liked the idea of flexible working hours, spending time outdoors, and using my brain to solve something.

For some time, I believed the best way to achieve a job like this would be to become an engineer. However, towards the end of high school, I needed more motivation to do schoolwork, and it became apparent to me that I would not be able to get into the best engineering schools.

Instead, I decided to go to an outdoor school in Nordfjord. At this time, I had never tried backcountry skiing, and avalanches had never really been a concern. For one year, my only agenda was to be outdoors, ski, bike, hike, kayak, surf, etc. During the first months, I learned that we were set to have an avalanche course in January. This sparked an interest that led me to read "Staying Alive in Avalanche Terrain" before any snow fell on the ground. I found avalanches to be an exciting topic. Over the next few months, I spent a lot of time skiing while trying to learn more about snow and avalanches. The idea that working with snow and avalanches could be one way of getting the type of job I wanted slowly developed as the months went by.

Next, I had to serve 18 months in the Norwegian Army, followed by the more compelling International Snow and Avalanche course in Alta, Norway. Over six months, I spent nearly 150 days in backcountry terrain, learning more about snow and avalanches and how decision-making in avalanche terrain differs from Norway to the Alps and Canada.

I figured Earth Sciences would be a relevant education for working with avalanches, so I earned my bachelor's degree in Bergen. I spent one of the semesters abroad at Montana State University (MSU), getting to know Jordy Hendrikx (one of my co-supervisors). During these months, I started working on mapping avalanche terrain with geospatial software. My project at MSU led to a part-time job at the Norwegian Water Resources and Energy Directorate (NVE), responsible for all regional avalanche forecasting in Norway. In parallel, I started my master's degree in geohazards at the University of Oslo. Within the first year of my master's degree, I applied for a job at NVE and was lucky enough to get a permanent position within the avalanche forecasting service.

When I finished my master's degree in 2021, the idea of doing a Ph.D. had emerged. Markus Landrø, one of my colleagues at NVE (and co-supervisor), had just finished his Ph.D. I planned to work for a few years to get some time to think about my goals. However, when Andrea Mannberg (co-supervisor) had remaining budget from another project, it created the perfect opportunity to start a fully funded Ph.D. with the support of NVE and without any specific constraints. I could research whatever I wanted, which was both exciting and frightening at the same time.

I remembered a presentation at the International Snow Science Workshop in Innsbruck in 2016, where someone used telecom data to count the number of backcountry skiers in Andorra. The main questions in my head were whether we could determine how many skiers are out there and whether the avalanche forecasts affect their behaviour. This topic also tied nicely into my previous experience with avalanche terrain. Simply put – to say whether avalanche forecasts affect skiers' terrain choices, we need to know **who skis where, when**, and what type of avalanche terrain the skiers expose themselves to.

II. Acknowledgements

I am now finalizing my Ph.D. after three years of hard work. I did not get as far as I intended, but I am pleased with my accomplishments. I have been given the freedom and support to start many projects (probably more than I should for my own good). Still, I have always gotten valuable advice along the road. Sometimes, it even helps to explain GIS programming to a psychologist (Audun Hetland) who has no idea what I am talking about. However, I have experienced that describing things in a simple manner is effective sometimes. This approach forces me to simplify my thoughts and focus on the key elements, which in turn helps me grasp the topics more clearly.

Along the road I have received valuable input from my four supervisors: Audun Hetland, Andrea Mannberg, Markus Landrø and Jordy Hendrikx. I think our student-supervisor relationship has slightly differed from what is expected from the typical course of a Ph.D., and I have thought more of you as friends and colleagues. Furthermore, I would like to thank my boss, Rune Engeset, for supporting and facilitating a Ph.D. through NVE in collaboration with the Center for Avalanche Research and Education (CARE) at UiT, the Arctic University of Norway.

I would also like to thank Kristoffer Karlsen, Tarjei Tveito Skille, Aron Widforss, and Finn Kristoffer Hovem for their assistance with fieldwork and validation of the beacon checkers in Tromsø, and SpareBank 1 Nord-Norge for providing funding for funding all checkpoints.

Finally, I want to thank my family, especially my wife, Andrea, and our newborn son, Theodor.

III. Abstract

Backcountry skiing has emerged as a so-called adventure sport in recent decades and has had a considerable social and economic impact in Northern Norway. Tourism, Norway's fifth-largest export industry, is experiencing significant growth and is especially important for small communities. However, recreation in avalanche terrain comes at a cost due to the risk of avalanches. Consequently, any change in avalanche risk could directly or indirectly impact a large proportion of the population in these areas. Moreover, many avalanche deaths with frequent search and rescue operations are unsustainable for these small communities.

There are currently no precise methods to calculate the risk of backcountry skiing or measure whether the avalanche forecast leads to a behavioral change among skiers, selecting less exposed terrain or avoiding avalanche terrain altogether when the forecasted avalanche hazard is high. Measuring avalanche risk or whether avalanche forecasts influence skiers' terrain choices requires comprehensive data on daily backcountry usage, detailed insights into skiers' locations, and slope-scale avalanche conditions. As a steppingstone, this thesis has developed an automated model (AutoATES) to classify avalanche terrain exposure, comparable in performance to human mappers. Such a model enables large areas to be mapped using a consistent and efficient method. Scalability is essential when we want to compare terrain exposure with backcountry usage in the future.

Furthermore, this thesis has attempted to enumerate backcountry usage using two methods. The first approach used signaling data. Unfortunately, there were considerable discrepancies between the estimated positions from the signaling data and our validation data using an independent GPS track. The second approach, using beacon checkers to count backcountry skiers, was far more successful. During two seasons, from December to May from 2021 to 2023, we recorded 56,760 individual trips from 26-29 trailheads within the ~2,600 km2 study area, offering valuable insights into backcountry usage as a function of time of day, week, and month.

In the future, it may be possible to estimate the proportion by analyzing the extensive database of GPS tracks submitted to Center for Avalanche Research and Education to measure what percentage of these activities originate at a beacon checkpoint. Once we know the proportion, it could be possible to compare our data with accident and fatality data to estimate the region's fatality rate of backcountry skiing.

IV. List of papers[1]

Paper I. **Larsen[2], H. T.**, Hendrikx, J., Slåtten, M. S. & Engeset, R. V. (2020). Developing nationwide avalanche terrain maps for Norway. *Natural Hazards*, 103(3), 2829-2847. doi: 10.1007/s11069-020-04104-7

Paper II. **Toft, H. B.**, Sykes, J., Schauer, A., Hendrikx, J., & Hetland, A. (2024): AutoATES v2.0: Automated Avalanche Terrain Exposure Scale mapping, *Natural Hazards and Earth System Science*, 24, 1779-1793. doi: 10.5194/nhess-24-1779-2024

Paper III. **Toft, H.**, Sirotkin, A., Landrø, M., Engeset, R.V. & Hendrikx, J. (2023). Challenges of using signaling data from telecom network in non-urban areas. *Journal of Trial and Error*, 3(1), 72-84. doi: 10.36850/e14

Paper IV. **Toft, H.B.**, Karlsen, K., Landrø, M., Mannberg, A., J. Hendrikx & Hetland, A. (2024). Who skis where, when? – A method to enumerate backcountry usage. *Cold Regions Science and Technology*. doi: 10.2139/ssrn.4689981 [under revision]

Paper V. Schumacher, J., **Toft, H.**, McLean, J. P., Hauglin, M., Astrup, R., & Breidenbach, J. (2022). The utility of forest attribute maps for automated Avalanche Terrain Exposure Scale (ATES) modelling. *Scandinavian Journal of Forest Research*, 37(4), 264-275. doi: 10.1080/02827581.2022.2096921

Paper VI. Griesser, S., Pielmeier, C., **Toft, H. B.**, & Reiweger, I. (2023). Stress measurements in the weak layer during snow stability tests. *Annals of Glaciology*, 1-7. doi: 10.1017/aog.2023.49

Paper VII. **Toft, H. B.**, Müller, K., Hendrikx, J., Jaedicke, C., & Bühler, Y. (2023). Can big data and random forests improve avalanche runout estimation compared to simple linear

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[1] Papers I-IV are part of the thesis and constitute the core research work conducted. Papers V-X demonstrate that I have conducted and published further research during the thesis period.

[2] I changed my name from Håvard Toft Larsen to Håvard Boutera Toft in August 2022, following my marriage.

regression? *Cold Regions Science and Technology*, 211, 103844. doi: 10.1016/j.coldregions.2023.103844

Paper VIII. Sykes, J., **Toft, H.**, Haegeli, P., & Statham, G. (2023). Automated Avalanche Terrain Exposure Scale (ATES) mapping – local validation and optimization in western Canada. *Natural Hazards and Earth System Sciences*, 24(3), 947–971. doi.org/10.5194/nhess-24-947-2024

Paper IX. **Toft, H. B.**, Verplanck, S. V., & Landrø, M. (2024). How hard do avalanche practitioners tap during snow stability tests? *Natural Hazards and Earth System Sciences*, 24(8), 2757-2772. doi: 10.5194/nhess-24-2757-2024

Paper X. Dahl, T., Dassler, T., Fjellaksel, R., Hetland, A., Mannberg, A., Pfuhl, G., Street, K., **Toft, H.B.** & Schulz, C. (2024). Boosting and Nudging Autonomous Winter Recreationists for Better Decisions in the Mountains. *Journal of Outdoor Recreation and Tourism.* [under revision]

V. List of presentations & conference proceedings

I. **Toft, H.** & Landrø, M. (2021). Hvem lager skispor hvor, når? – Forsøk på analyse av posisjonsdata fra mobilrecord. *Nordisk konferanse om snøskred og friluftsliv.* [oral]

II. **Toft, H.**, Verplanck, S. & Landrø, M. (2023). Klask-O-Meter – hvor hardt klasker vi – og har det noe å si? *Nordisk konferanse om snøskred og friluftsliv.* [oral]

III. **Toft, H.** (2023). Nye bratthet, løsne- og utløpsområde kart (i VARSOM) – hva er nytt? *Nordisk konferanse om snøskred og friluftsliv.* [oral]

IV. **Toft, H.**, Kosberg, S., Kvalberg, J., Landrø, M. & Müller, K. (2023). Development and validation of dynamic avalanche risk maps. *International Snow Science Workshop Proceedings 2023, Bend, Oregon.* [poster]

V. Huber, A., Hesselbach, C., Oesterle, F., Neuhauser, M., Adams, M., Plörer, M., Stephan, L., **Toft, H.**, Sykes, J., Mitterer, C. & Fischer, J.T. (2023). AutoATES Austria - testing and application of an automated model-chain for avalanche terrain classification in the Austrian alps. *International Snow Science Workshop Proceedings 2023, Bend, Oregon.* [poster]

VI. **Toft, H.**, Verplanck, S. & Landrø, M. (2024). The tap-o-meter: how hard do we tap and so what? *International Snow Science Workshop 2024, Tromsø, Norway.* [poster]

VII. **Toft, H.**, Mannberg, A., Stefan, M., Aase, M. & Hetland, A. (2024). Choosing to hold 'em or fold 'em – effects of avalanche forecast information on terrain exposure. *International Snow Science Workshop 2024, Tromsø, Norway.* [poster]

VIII. **Toft, H.**, Widforss, A., Landrø, M. & Hetland, A. (2024). Who skis where, when? – quantifying the backcountry skier population in Tromsø, Norway. *International Snow Science Workshop 2024, Tromsø, Norway.* [oral]

IX. Widforss, A., Barfod, E., Eckerstorfer, M., Haslestad, A., Kosberg, S., Landrø, M., Müller, K., **Toft, H.**, Aasen, J. & Engeset, R. (2024). Introducing a digital handbook for snow observations in Norway. *International Snow Science Workshop 2024, Tromsø, Norway.* [poster]

X. Dahl, T., Dassler, T., Schulz, C., Fjellaksel, R., Pfuhl, G., Street, K., **Toft, H.B.**, Mannberg, A. & Hetland, A. (2024). Boosting and nudging people to make smart back-country decisions: the case of winter Norway. *International Snow Science Workshop 2024, Tromsø, Norway.* [poster]

VI. List of abbreviations

Avalanche Terrain Exposure Scale	ATES
Automated Avalanche Terrain Exposure Scale	AutoATES
Global Positioning System	GPS
Checkpoint	CP
Beacon Checker	BC
Geographic Information System	GIS
The Norwegian Water Resources and Energy Directorate	NVE
UiT The Arctic University of Tromsø	UiT
Center for Avalanche Research and Education at UiT	CARE
Digital Elevation Model	DEM
Potential Release Areas	PRA
Avalanche Warning Service	AWS
Norwegian Avalanche Warning Service	NAWS
Decision Making Framework	DMF
Reduction Method	RM
Best Server Estimate	BSE
Base Transceiver Station	BTS
General Data Protection Regulation	GDPR

1 Introduction

In recent decades, a new category of sports has emerged, known as extreme, adventure, action, and lifestyle sports. These so-called adventure sports have transformed the landscape, surpassing many traditional sports in participation and influence (Brymer et al., 2020). Backcountry skiing is one of these sports and has a considerable social and economic impact in Northern Norway. Tourism, Norway's fifth-largest export industry, is experiencing significant growth, particularly in individualistic and often risk-prone activities (NOU, 2023). Avalanches pose a direct threat to people recreating in snow-covered mountains. Official records show that in the past 10 years (2014-2024), 750 people have been caught in avalanches in Norway. However, the actual number is likely higher. Out of these incidents, 58 were fatal, with 62% of the victims killed in Northern Norway alone (Varsom, 2024b).

Adventure sport tourism is often presented as a solution for sustainable development in Arctic communities with limited economic opportunities (Ryeng, 2019; Sisneros-Kidd et al., 2019). In Lyngen, Kåfjord, and Skjervøy municipalities, which have less than 9,000 inhabitants, backcountry skiers account for approximately 30,000 guest nights annually (Ryeng, 2019). This highlights the importance of ski tourism for economic development in the region. Ski tourism is also a multi-billion market worldwide attracting between 300 and 350 billion annual skier visits (Steiger et al., 2019). However, recreation in avalanche terrain comes at a cost. In approximately 90% of all fatal avalanche accidents, the avalanche is triggered by the victim or someone in the victim's group (Tschirky et al., 2000). This indicates that skiers' decisions often expose them to risk. This risk can be both intentional and unintentional. Some are aware of and accept the danger the activity entails. Others lack the necessary understanding of the avalanche formation and unconsciously expose themselves to avalanche risk (Techel et al., 2015). Most municipalities in Northern Norway are small and have limited resources, relying heavily on the economic opportunities adventure sports tourism provides. Consequently, any change in avalanche risk could directly or indirectly impact a significant proportion of the population. Moreover, many avalanche deaths with frequent search and rescue operations are not sustainable for these small communities.

Accurately calculating the statistical risk of death is challenging due to the scarcity of reliable data on backcountry skiers. The only reliable estimate to date is the four national surveys conducted in Switzerland between 1999 and 2020 (Bürgi et al., 2021; Lamprecht et al., 2008, 2014; Lamprecht & Stamm, 2000). Using their data, Winkler et al. (2016) found the statistical risk of death to be between 8.7 and 9.4 micromorts, where one micromorts represents one in a million chance of death per day (Howard, 1984).

To mitigate accidents, numerous countries have established avalanche warning services (AWS) aimed at enhancing public awareness and reducing avalanche-related deaths (e.g., R. V. Engeset et al., 2018). These services have been operational for more than two decades in many countries, but measuring their effectiveness remains challenging. The core issue is whether there is a behavioral change in response to the forecasts. If effective, we should observe backcountry skiers adjusting their behavior by seeking less exposed terrain or avoiding avalanche terrain altogether when the forecasted avalanche hazard is high. Without such behavioral changes, the impact of AWS on reducing fatalities could be limited.

Understanding whether avalanche forecasts influence behavior requires comprehensive data on daily backcountry usage, detailed insights into skiers' locations, and the slope scale avalanche conditions. This thesis, therefore, introduces two key developments as steppingstones: (1) methods to count backcountry skiers and (2) a model to classify avalanche terrain. These tools are crucial for assessing the impact of avalanche forecasts. If the forecasts are effective, skiers should alter their terrain choices in response to avalanche hazards. Therefore, to measure whether avalanche forecasts affect skiers' terrain choices, we need to know **who skis, where, when,** and the type of avalanche terrain backcountry skiers expose themselves to. The scope of the thesis does not extend into **why** skiers expose themselves to risk.

The structure of this thesis is designed to provide a comprehensive understanding of the research conducted and its significance. Following this **Introduction** section that sets the context for the study, the **Objectives** section outlines the research goals and key questions addressed. The **Background** is divided into two parts: general concepts related to avalanches and thesis-specific concepts, which focus on topics particularly relevant to this study. For readers already familiar with avalanches and this specific decision-making environment, it is suggested to skip to the thesis-specific section. The core of the thesis consists of the **Methods and Results** for Papers I-IV, detailing my research and findings. This is followed by a **Discussion** that explores the implications of the results and suggests avenues for future research. Finally, the **Conclusion** summarizes the key insights and contributions of the thesis.

2 Objectives

This thesis addresses the overarching research question: **who skis where, when?** This simple question can be divided into several detailed research inquiries. For instance, to explore the "**who**" aspect, we could investigate the demographics of backcountry skiers in avalanche-prone areas. The "**where**" aspect could involve determining the types of terrain that skiers, in general or specific groups recreate in. The "**when**" aspect could examine the timing of backcountry skiing activities, such as time of day, week, or month, or explore any correlations with the avalanche forecast. Furthermore, we could investigate the combination of terrain types being skied on specific days in relation to avalanche forecasts, thus addressing how many skies where at any given location when.

Given these possibilities, my initial focus on the broader question, **who skis where, when?** is defined by the following two research questions:

1. How can the terrain exposure of backcountry skiers be quantified using automated methods?
2. What methods could be developed to enumerate backcountry usage?

Quantifying the exposure of backcountry activities will enable us to compare where (or what type of terrain) backcountry skiers recreate in relation to time. Furthermore, by developing a method to enumerate backcountry usage, we can determine the baseline frequency of backcountry skiing as a function of time of day, week, or month. The baseline frequency could also be used to estimate a fatality rate, when compared to fatality statistics. This thesis therefore aims to establish a foundation for understanding the baseline frequency of backcountry recreation in Norway and to explore whether exposure can be automatically quantified as a proxy for terrain choices in the future.

Addressing the full width of the question, **who skis where, when?** is challenging and extends beyond the four papers included in this thesis. Therefore, in addition, I am currently conducting several further studies that are in the early stages and not yet ready for publication (IV. List of papers). However, to provide a comprehensive discussion of this challenge, I have chosen to include some of the broader context from these studies in the discussion section.

3 Background: general concepts

Understanding avalanche dynamics is crucial for backcountry safety and can be described using the avalanche triangle (Fredston & Fesler, 1994), which highlights three key elements: weather, snowpack, and terrain, with the human factor at the center (Figure 1). Weather impacts snow stability through factors such as temperature, wind, and precipitation. The snowpack consists of layers of snow that accumulate over time, each varying in hardness and strength due to snow metamorphism (Schweizer et al., 2003). Terrain determines where avalanches are likely to occur, influenced by factors such as slope angle, aspect, curvature, and forest density (Schweizer et al., 2003; Statham & Campbell, 2023). The human factor is central, as humans make decisions and interact with these three elements. The interplay between weather, snowpack, and terrain is complex and dynamic. Understanding these interactions is essential for making informed decisions in the backcountry (Hetland et al., 2024). In this following section I will describe some general concepts and terminology that are relevant to this thesis.

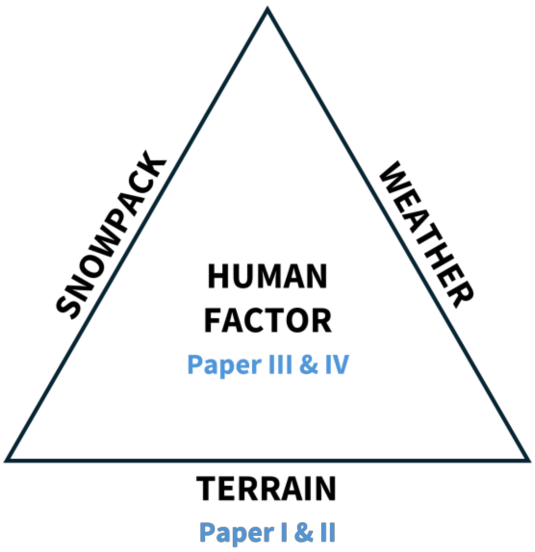

Figure 1: The avalanche triangle, consisting of snowpack, weather, terrain (Fredston & Fesler, 1994), and the human factor in the middle. Paper I & II is related to terrain, while paper III and IV is related to the human factor (where people go).

3.1 Avalanches

A snow avalanche is a mass of snow that slides, flows, or tumbles down a slope and can generally be categorized into two main types: loose snow avalanches and slab avalanches (McClung & Schaerer, 2006). Loose snow avalanches release at the surface of the snowpack, starting from a single point and widening as they descend. In contrast, slab avalanches, which cause most fatalities (Schweizer & Lütschg, 2001; Sheets et al., 2018), occur due to a failure within a weak layer of the snowpack. This failure leads to propagating fractures that cause large blocks of snow to break free and tumble down the slope. Both types of avalanches can be either dry or wet, determined by the moisture content of the snow involved, resulting in variations such as dry slab, wet slab, dry loose, and wet loose avalanches. Even though some infrequent avalanches release at lower angles, 30° is in most cases communicated as the critical angle for avalanches to release, with the majority releasing on slopes between 35 to 50°. The release mechanism for avalanches is caused by a change in the snowpack's stress balance, which could be due to additional weight from a fresh snowfall, the presence of a skier, or a reduction in the snowpack's inherent strength (McClung & Schaerer, 2006).

3.2 Avalanche terrain

Avalanche terrain is defined as all areas that could be affected by an avalanche under the right circumstances. An avalanche and its affected area are defined as an avalanche path, and could be divided into a start zone, transition zone and runout zone – also known as release area, the track and deposition areas respectively. The start zone is the area where snow begins to move, the transition zone is the area below the starting zone and above the runout zone where avalanche debris deposits (McClung & Schaerer, 2006).

As noted previously, most avalanches release on slopes steeper than 30° (Schweizer et al., 2003). The runout length of an avalanche could be defined using the travel angle (or alpha angle), which is the angle from the highest point of the starting zone to the lowest edge of the runout zone, measured along the natural flow path of the avalanche (Toft, Müller, et al., 2023). An analysis from a large database of events in Switzerland, and a smaller study from Norway found that the median travel angle for avalanches is around 33°, but there are numerous examples of avalanches reaching travel angles as low as 15-18° (Lied & Bakkehøi, 1980; Toft, Müller, et al., 2023).

Avalanche terrain often comprises multiple avalanche paths, each with distinct frequencies of occurrence, known as return periods. These return periods can vary substantially, making the precise mapping of avalanche terrain challenging. Variables such as the slope's steepness, forest density, the shape of the terrain, potential terrain traps, and the frequency and magnitude of avalanches must all be factored in for safe navigation (Statham & Campbell, 2023).

3.3 Decision environment

Decision-making in avalanche terrain is challenging, as no single cue or combination of cues can reliably predict avalanche risk (Landrø, Hetland, et al., 2020; Landrø, Pfuhl, et al., 2020). Backcountry skiers are forced to navigate this complexity with incomplete knowledge of the probabilities, making it an intricate task. The challenge lies in the fact that it is nearly impossible to eliminate all environmental uncertainties when assessing avalanche risk (R. V. Engeset et al., 2018; Furman et al., 2010; Landrø, Hetland, et al., 2020; Landrø, Pfuhl, et al., 2020; Statham et al., 2018).

The accuracy of a skier's decision is not merely a matter of logical and consistent reasoning rules (Fischhoff & Broomell, 2020; Hammond, 1966). Avalanche accidents often occur because the perceived risk does not align with the real danger, a clear indication of human error. Decision accuracy is how well a decision aligns with reality to achieve a goal, or in this case, not triggering an avalanche (Kozyreva & Hertwig, 2021). Backcountry skiers often rely on the outcome of their decisions to judge their accuracy. Unfortunately, in avalanche terrain, poor decisions often do not result in immediate negative feedback (Ebert, 2019; Johnson et al., 2020; Zweifel & Haegeli, 2014).

Triggering an avalanche indicates a poor decision, but not triggering one doesn't necessarily mean the decision was well reasoned. Many times, luck, rather than good decision-making, prevents an avalanche (Landrø, 2021). Thus, using the prior decision outcome as feedback is unreliable for evaluating decision accuracy in avalanche terrain. This lack of reliable feedback makes it difficult for skiers to improve their decision-making skills and correctly assess their abilities. Such a challenging learning environment can lead to overconfidence and the spread of poor decision-making practices (Hogarth et al., 2015). Even experienced skiers may misjudge the risk due to this combination of environmental uncertainty and cognitive biases. As such, developing a reliable decision-making strategy or trustable gut feeling to deal with this uncertainty takes a lot of experience, something most people do not achieve during their lifetime (Landrø, Hetland, et al., 2020).

3.4 Avalanche forecasting

To improve decision making and help backcountry skiers select appropriate terrain for the given avalanche conditions, many countries have established an avalanche warning service (AWS).

These services provide a forecast (also known as bulletin) with detailed information about the current snowpack and the expected avalanche hazard over the next 24-hour period for a defined geographic area. Most avalanche forecasts are presented using a danger level, avalanche problems and some general information about the snowpack. The avalanche danger level scale ranges from 1 (low) to 5 (very high/extreme) (EAWS, 2024; Statham et al., 2010).

3.5 Avalanche risk and exposure

The terms **avalanche risk** and **avalanche exposure** are two distinct concepts that are often used in avalanche safety and risk management (Statham, 2008; Statham et al., 2018).

Avalanche risk is the product of avalanche hazard, vulnerability, and exposure. These three factors represent the potential for harm or loss from avalanches. Avalanche hazard refers to the potential harm caused by avalanches and is determined by two main factors: the likelihood of triggering an avalanche and its potential size or destructiveness. In other words, it evaluates the chances of an avalanche to occur and how large it could be. Vulnerability refers to the susceptibility of people, infrastructure, or activities to be affected by an avalanche. Exposure indicates the extent to which people, infrastructure, or activities are present in avalanche-prone areas. By evaluating avalanche risk through these components, one can make informed decisions about navigating and mitigating dangers in regions susceptible to avalanches (Statham, 2008).

In summary, **avalanche risk** focuses on the likelihood and consequences of avalanches, while **avalanche exposure** deals with the extent to which elements at risk are situated within potential avalanche paths.

3.6 Base rate fallacy

In order to evaluate the level of or changes in exposure, or risk, we need to know the base rate. The base rate is the background information which describes how things usually are, in contrast to how things appear to be (Kahneman & Tversky, 1973). For example, males are notably over-represented in avalanche fatalities, accounting for as much as 86% of such deaths (Soulé et al., 2017). Assuming a balanced base rate of 50% males and 50% females in the population, males would be at considerably higher risk, with 50% of the population accounting for 86% of the fatalities. Conversely, if the base rate is 10% females and 90% males, females would be at greater risk, accounting for 14% of the fatalities while representing only 10% of the population.

Decision-makers often rely on how things appear to be. If they fail to consider the background information, or base rate, in relevant situations, it is known as base rate fallacy or neglect (Kahneman & Tversky, 1973). Surprisingly, this error isn't limited to amateurs; even experienced statisticians can get caught up in it when they lean more on gut feeling than deliberate calculation (Bar-Hillel, 1980). Ignoring the base-rate could have considerable consequences, affecting risk communication, forecasting, training, media, and the ability to determine which measures are truly effective.

I have identified four common types of base rate fallacies where the underlying base rate is often overlooked or neglected. Each type has a corresponding example to illustrate how neglecting the base rate can lead to misguided decisions and ineffective risk mitigation strategies.

<u>Fallacy 1.</u> Demographics (age, gender, nationality, training etc.)

> *Men are more likely to be in a fatal accident compared to a woman because they are overrepresented in the fatality statistics.*

<u>Fallacy 2.</u> Avalanche danger or problems.

> *To stay safe, it is best to avoid days with moderate and considerable danger levels because most fatal accidents happen during these periods.*

<u>Fallacy 3.</u> Terrain properties (aspect, elevation, release, runout, or ATES class)

> *To stay safe, it's best to avoid north facing slopes because most fatal accidents occur in this aspect.*

<u>Fallacy 4.</u> Time periods (year, month, week, or holidays)

> *To stay safe, it's best to avoid skiing in March and April because most fatal accidents occur during these two months.*

Although I will not develop methods to measure all these base rate characteristics in this thesis, I believe it is important to provide an overview of the issue of base rate fallacies in the avalanche field. Highlighting these common errors can raise awareness and encourage more comprehensive and accurate decision-making processes within the avalanche community. By understanding and considering the base rate information, we can improve risk communication, forecasting, training, and ultimately enhance the effectiveness of measures implemented to ensure backcountry safety.

3.7 Examples of base rate fallacy

The base rate information is crucial when deciding on the necessity and efficacy of an intervention such as avalanche forecasts, education or other risk managing strategies. One example of this is from Troms in Northern Norway where avalanche accidents are notably prevalent. A large percentage of these incidents involves international visitors instead of native Norwegians. As a result, local authorities and news outlets tend to highlight international visitors as the main problem. This perspective, however, might be misleading. By not considering the base rate of native Norwegians versus international visitors, they might ignore the fact that visitor traffic rates could match the visitor accident rates. This oversight can lead to two contrasting strategies: (1) investing resources mainly to reduce accidents among visitors, sidelining the native population, or (2) adopting a broader approach that benefits all, visitors, and locals alike.

Another instance where the base rate is important, is when developing decision making frameworks (DMFs). Even though Landrø, Hetland et al. (2020) found a mismatch between what factors experts use and what factors DMFs rely on, they are still being widely recommended to assess the avalanche risk when skiing in avalanche terrain. A significant limitation of DMFs, as noted by Winkler et al. (2021), is that all rule based DMFs were developed primarily using accident data, neglecting the base rate information. This oversight suggests an assumption that all terrains are visited equally, regardless of factors like steepness, topography, elevation, and prevailing conditions.

The Reduction Method (RM), conceptualized by Munter (1997), is one of the most used DMF in Europe, and the basis for many variants of the method. It is based on an equation that balances the danger potential against reduction factors. One reduction factor within the RM suggests the avoidance of North-facing, due to the more frequent accidents. This would be valid if there is an evenly distributed background traffic, or base rate. If the base rate is unknown, one might argue that there is a tendency for backcountry enthusiasts to favor North-facing slopes due to the superior snow conditions (e.g., Grímsdóttir & McClung, 2006). Luckily for the RM, Winkler et al. (2021) found North-facing slopes to be two times riskier compared to South-facing slopes when adjusting for base-rate. Alarmingly, fatality data from Norway contradicts the more frequent accidents in North-facing slopes, indicating a higher accident incidence on South-facing slopes. However, the base rate remains unknown (Aasen, 2023).

4 Background: thesis specific concepts

4.1 Avalanche terrain classification.

Avalanche terrain can be classified using various concepts on a map. One of the first examples consist of manually drawing avalanche paths onto topographic maps based on expert opinion using red and blue colors (SLF, 1960). Today, there are many different avalanche terrain classification systems designed for various purposes, but they can generally be divided into two categories: (1) hazard maps for roads, buildings, and other infrastructure (e.g., Rudolf ‐ Miklau et al., 2014), and (2) maps intended to assist backcountry recreation (e.g., Harvey et al., 2018). A key difference is that hazard maps for roads, buildings and other infrastructure typically are more conservative accounting for extreme events (e.g. destructive size 4-5) while recreational hazard maps are more interested in skier triggered avalanches (e.g., destructive size ≤ 3) (Harvey et al., 2018). Both categories can be created using manual methods, automated methods, or a combination of both (semi-automated).

Hazard maps are useful for managing avalanche risk in avalanche prone areas, as they identify high-risk areas where buildings and infrastructure should not be constructed (Rudolf ‐ Miklau et al., 2014). In many alpine countries, experts create these maps for specific avalanche paths or for a defined return period by combining historical records, field investigations, terrain analysis, forest data, and numerical modelling (e.g., NVE, 2020; SLF, 1984). These maps have proven to be effective in preventing damage and casualties from avalanches (Margreth & Romang, 2010). However, because they are labor-intensive (thus, expensive), hazard maps are typically only available in areas where infrastructure already exists (Bühler et al., 2022).

In Norway, avalanche hazard indication maps (AHIMs) take a more conservative approach by delineating potentially dangerous areas and are valuable for land-use planning. They help quickly determine whether a development site requires more detailed hazard assessments (Issler et al., 2023). These maps often cover large regions and are not restricted to settled areas. They typically provide broad, model-based estimates of hazard zones, particularly in extreme events, but need more detailed information about hazard intensity and runout. These maps are less precise than detailed hazard maps. While various methods have been tested in regions like

Switzerland, Italy, and Norway, many approaches struggle with accurately modelling avalanche runout (Bühler et al., 2022; Issler et al., 2023; Maggioni et al., 2018).

In recent years, the classification of avalanche terrain maps to support backcountry recreation has become increasingly common. These backcountry hazard maps generally fall into three categories: (1) maps that outline the terrain as categorical values like simple, challenging and complex terrain (e.g., Barbolini et al., 2011; Harvey et al., 2018; Statham et al., 2006), (2) continuous maps that use dynamic values (e.g. values ranging from 0 to 1), with higher values indicating higher risk (e.g., Harvey et al., 2018; Schmudlach & Köhler, 2016; Thumlert & Haegeli, 2018) and (3) maps that indicate potential starting zones, remote triggering and runout zones (e.g., Harvey et al., 2018; Varsom, 2024a).

All avalanche terrain classification schemes involve some level of conceptualization. Categorical classification schemes are the most abstract, as they create entirely new categories that don't exist outside of the model. A continuous classification, such as the severity score ranging from -3 to 4 developed by Thumlert & Haegeli (2018), is data-driven, but the severity score is still a conceptual idea. Even basic maps that categorize avalanche terrain into release areas and runout zones (e.g., Varsom, 2018; 2024) rely on conceptual definitions of these areas, despite being built on purely data-driven models.

4.1.1 The avalanche terrain exposure scale (ATES)

The avalanche terrain exposure scale (ATES) is a conceptual classification of avalanche terrain. The first version of ATES was created as a response to a fatal avalanche accident in Glacier national park. On February 1, 2003, an avalanche caught 17 students, resulting in seven fatalities. Following this event there was a demand for more accessible tools to understand and communicate avalanche risks. Although not directly recommended, it became apparent that a classification system for recreational use of avalanche terrain was essential, like existing systems for climbing and whitewater activities (Statham et al., 2006).

4.1.2 ATES v.1

As a response to the accident in Glacier National Park, Statham et al. (2006) introduced ATES v.1 to make it easier to evaluate, describe and communicate the complexities of popular backcountry routes. The initial concept was inspired by the ski area system's simple color codes for runs, aimed at matching individuals with terrain suitable for their skill levels.

Two distinct models were proposed: a communication model for the public (Table 1) and a technical model for professionals (Table 2). This dual-model approach ensured that both the public and professionals needs were met (Statham et al., 2006).

Table 1: ATES Public Communication Model (v.1) from Statham et al. (2006).

Description	Class	Terrain Criteria
Simple	1	Exposure to low angle or primarily forested terrain. Some forest openings may involve the runout zones of infrequent avalanches. Many options to reduce or eliminate exposure. No glacier travel.
Challenging	2	Exposure to well defined avalanche paths, starting zones or terrain traps; options exist to reduce or eliminate exposure with careful routefinding. Glacier travel is straightforward but crevasse hazards may exist.
Complex	3	Exposure to multiple overlapping avalanche paths or large expanses of steep, open terrain; multiple avalanche starting zones and terrain traps below; minimal options to reduce exposure. Complicated glacier travel with extensive crevasse bands or icefalls.

ATES v.1 uses eleven terrain properties (Table 2) to qualitatively describe the overall exposure to avalanche terrain independently of hazard conditions. Based on these terrain properties, backcountry routes are classified into three avalanche terrain classes: simple (1), challenging (2) and complex (3).

Table 2: ATES Technical Model (v.1) from Statham et al. (2006). Terrain that qualifies under an ***italicized*** *descriptor automatically defaults into that or a higher terrain class.*

	1 – Simple	2 - Challenging	3 - Complex
Slope angle	Angles generally < 30º	***Mostly low angle, isolated slopes >35º***	***Variable with large % >35º***
Slope shape	Uniform	Some convexities	Convoluted
Forest density	Primarily treed with some forest openings	Mixed trees and open terrain	Large expanses of open terrain. Isolated tree bands
Terrain traps	Minimal, some creek slopes or cutbanks	Some depressions, gullies and/or overhead avalanche terrain	***Many depressions, gullies, cliffs, hidden slopes above gullies, cornices***
Avalanche frequency (events:years)	1:30 ≥ size 2	1:1 for < size 2 ***1:3 for ≥ size 2***	1:1 < size 3 ***1:1 ≥ size 3***
Start zone density	Limited open terrain	Some open terrain. Isolated avalanche paths leading to valley bottom	Large expanses of open terrain. Multiple avalanche paths leading to valley bottom
Runout zone characteristics	Solitary, well defined areas, smooth transitions, spread deposits	Abrupt transitions or depressions with deep deposits	Multiple converging runout zones, confined deposition area, steep tracks overhead
Interaction with avalanche paths	Runout zones only	Single path or paths with separation	***Numerous and overlapping paths***
Route options	Numerous, terrain allows multiple choices	A selection of choices of varying exposure, options to avoid avalanche paths	***Limited chances to reduce exposure, avoidance not possible***
Exposure time	None, or limited exposure crossing runouts only	***Isolated exposure to start zones and tracks***	***Frequent exposure to start zones and tracks***
Glaciation	None	***Generally smooth with isolated bands of crevasses***	***Broken or steep sections of crevasses, icefalls or serac exposure***

4.1.3 Spatial ATES

The original purpose of the ATES v.1 terrain rating was to classify backcountry routes, but the framework has also been applied at a spatial scale, mapping areas (or zones) instead of routes. The original idea was that by integrating the linear ATES v.1 rating into a GIS algorithm would allow for consistent and efficient large-scale classification. However, the qualitative nature of ATES v.1 makes it challenging to map in GIS (Thumlert & Haegeli, 2018). The first example of spatial ATES was pioneered by Delparte (2008) who used GIS together with terrain properties like vegetation density and slope incline. Expanding upon this concept Campbell and Gould (Campbell & Gould, 2013) proposed a more deterministic model for spatial ATES

(Table 3). They also introduced the concept of non-avalanche terrain as an optional terrain class in the ATES framework.

Table 3: A proposed model for spatial ATES mapping (from Campbell & Gould, 2013).

		Class 0 (optional)	Class 1	Class 2	Class 3
Slope Incline[1] and Forest Density[2]	**Open**	**99% ≤ 20°**	**90% ≤ 20° 99% ≤ 25°**	**90% ≤ 30° 99% ≤ 40°**	< 20% ≤ 25° 45% > 35°
	Mixed	**99% ≤ 25°**	**90% ≤ 25° 99% ≤ 35°**	**90% ≤ 35° 99% ≤ 45°**	
	Forest	**99% ≤ 30°**	**99% ≤ 35°**	**99% ≤ 45°**	
Start Zone Density		**No start zones.**	**No start zones with ≥ Size 2 potential. Isolated start zones with < Size 2 potential.**	**No start zones with > Size 3 potential. Isolated start zones with ≤ Size 3 potential, or Several start zones with ≤ Size 2 potential.**	Numerous start zones of any size, containing several potential release zones.
Interaction with Avalanche Paths[3]		**No exposure to avalanche paths.**	**Beyond 10-year runout extent for paths with ≥ Size 2 potential.**	**Single path or paths with separation. Beyond annual runout extent for paths with > Size 3 potential.**	Numerous and overlapping paths of any size. Any position within path.
Terrain Traps[4]		**No potential for partial burial or any injury.**	**No potential for complete burial or fatal injury.**	**Potential for complete burial but not fatal injury.**	Potential for complete burial and fatal injury.
Slope Shape		Uniform or concave	Uniform	Convex	Convoluted

[1] Slope inclines are averaged over a fall-line distance of 20 - 30 m.
[2] Open: < 100 stems/ha or > 10.0 m tree spacing on average. Mixed: 100 – 1000 stems/ha or 3.2 – 10.0 m tree spacing on average. Forest: > 1000 stems/ha or < 3.2 m tree spacing on average.
[3] Position within paths based on the runout extent for avalanches with a specified return period.
[4] Terrain traps are features in tracks or runouts that increase the consequences of being caught in an avalanche. Thresholds are based on the potential increased consequences they would add to an otherwise harmless avalanche. For this purpose, terrain traps can be thought of as either trauma-type (e.g., cliffs, trees, boulders, etc.) or burial-type (e.g., depressions, abrupt transitions, open water, gullies, ravines, etc.). Degrees of burial used in this model are based on Canadian standard avalanche involvement definitions (Canadian Avalanche Association, 2009).

Even though an extensive area of 8,000 km^2 was mapped in Western Canada, the spatial resolution of these maps is too low for slope scale routefinding where a spatial resolution of 20-30 m is necessary, as noted by Thumlert and Haegeli (2018) with insights from Schweizer et al. (2003). To address this limitation, several other approaches has been attempted using a manual approach (Gavaldà et al., 2013; NVE, 2014; Sykes et al., 2020). Data driven methods such as the algorithm proposed by Schmudlach and Köhler (2016) and Thumlert and Haegeli (2018) holds more promise, but both studies conclude that for ATES to be widely implemented, a fully automated method needs to be developed. These prior attempts laid the necessary groundwork and impetus for GIS based ATES mapping.

4.1.4 ATES v.2

Since its introduction in 2004, ATES has been adopted widespread internationally and has been used in many more applications than what was originally intended as noted by Bogie and Davies (2010), Gavaldà et al. (2013), Larsen et al. (2020), Maartensson et al. (2013), and McManamy et al. (2008). It has become an important tool for both risk management and avalanche education, as highlighted by Floyer and Robine (2018) and Zacharias (2020) and has served as a research instrument for studying terrain use preferences, according to studies like Hendrikx et al. (2022), Johnson & Hendrikx (2021), and Sykes et al. (2020). In both Canada and Norway, the application of ATES has evolved from recreational use to being incorporated into legal and regulatory frameworks. ATES is now widely used in workplace avalanche safety protocols (CAA, 2016; Landrø et al., 2016; Statham & Campbell, 2023).

After years of development, Statham and Campbell (2023) published a revised ATES rating, now known as ATES v.2. The new version expands on the original ATES v.1 (Statham et al., 2006) by increasing from three to five classes. The new version includes non-avalanche terrain (0) as proposed by Campbell and Gould (2013), and a new class named extreme terrain (4). It also combines the original ATES framework with the spatial ATES model proposed by Campbell and Gould (2013), making it suitable for both linear and spatial ATES. Additionally, this version addresses various shortcomings recognized in earlier iterations over the last two decades (Statham et al., 2023). ATES v.2 continues to use two distinct models: a communication model for the public (Table 4) and a technical model for professionals (Table 5).

Table 4: ATES v.2 communication model for backcountry travel (from Statham & Campbell, 2023).

Terrain rating	Class	Description for Backcountry Travel
Non-Avalanche	**0**	No known exposure to avalanches. Very low-angle or densely forested slopes located well away from avalanche paths, or designated trails/routes with no exposure to avalanches.
Simple	**1**	Exposure to low-angle or primarily forested terrain. Some forest openings may involve the runout zones of infrequent avalanches and terrain traps may exist. Many options to reduce or eliminate exposure.
Challenging	**2**	Exposure to well-defined avalanche paths, starting zones, terrain traps or overhead hazard. With careful route finding, some options will exist to reduce or eliminate exposure.
Complex	**3**	Exposure to multiple overlapping avalanche paths or large expanses of steep, open terrain. Frequent exposure to overhead hazard. Many avalanche starting zones and terrain traps with minimal options to reduce exposure.
Extreme	**4**	Exposure to very steep faces with cliffs, spines, couloirs, crevasses or sustained overhead hazard. No options to reduce exposure; even small avalanches can be fatal.

4.1.5 Application

The new ATES v.2 framework opens for many more applications compared to the previous iteration which was made for rating backcountry routes. When implementing ATES, it is important to identify the objectives of the final product, as this will guide the assessment and mapping process. The objective and approach should match the intended application. For example, if the objective is to assist trip planning for the public, a single rating for a backcountry route might be sufficient. On the other hand, if the goal is to help backcountry skiers navigate in avalanche terrain, more detailed ATES zones are required (Statham & Campbell, 2023).

4.1.5.1 ATES features

Reviewing the use cases of ATES over the last two decades, four approaches to ATES classification have been identified (Table 6). Regardless of the method used, defining an area or route is essential for assigning an ATES rating. When evaluating an area, the focus is on the entire region without considering specific routes through it. In contrast, a route is determined by a travel path from start to end, including all terrain effecting the path of travel. The entire area or route could receive a single ATES rating, or it could be divided into zones, corridors, or route segments to enhance spatial detail (Statham & Campbell, 2023).

Table 5: ATES v.2 technical model (Statham & Campbell, 2023).

	Class 0 Non-Avalanche Terrain*	**Class 1 Simple Terrain**	**Class 2 Challenging Terrain**	**Class 3 Complex Terrain**	**Class 4 Extreme Terrain**
Exposure	No known exposure to avalanche paths	Minimal exposure crossing low-frequency runout zones or short slopes only	Intermittent exposure managing a single path or paths with separation	***Frequent exposure to starting zones, tracks or multiple overlapping paths***	Sustained exposure within or immediately below starting zones
Slope angle *and* **Forest density**	Very low-angle (< 10°) open terrain or steeper areas of dense forest	Low-angle (< 20°) terrain or steeper slopes in dense forest with openings for runout zones or short slopes	Moderate-angle (< 30°) open or gladed terrain with some open slopes or glades > 35°	Moderate to high-angle (< 35°) terrain with a large proportion of open slopes > 35° and some isolated glades or tree bands	High-angle, open terrain averaging > 35° with a large proportion of slopes > 45° and few or no trees
Slope shape	Straightforward, flat or undulating terrain	Straightforward undulating terrain	Mostly planar with isolated convex or unsupported slopes	Convoluted open slopes with intricate and varied terrain shapes	Intricate, often cliffy terrain with couloirs, spines and/or overhung by cornices
Terrain traps	No avalanche-related terrain traps	Occasional creek beds, tree wells or drop-offs	Single slopes above gullies or risk of impact into trees or rocks	Multiple slopes above gullies and/or risk of impact into trees, rocks or crevasses	Steep faces with cliffs, cornices, crevasses and/or risk of impact into trees or rocks
Frequency-magnitude (avalanches:years)	***Never***	***1:100 - 1:30 for ≥ Size 2***	1:1 for < Size 2 ***1:30 - 1:3 for ≥ Size 2***	1:1 for < Size 3 ***1:1 for ≥ Size 3***	10:1 for ≤ Size 2 > 1:1 for > Size 2
Starting zone size and density	No known starting zones	Runout zones only except for isolated, small starting zones with < Size 2 potential	Isolated starting zones with ≤ Size 3 potential or several start zones with ≤ Size 2 potential	Multiple starting zones capable of producing avalanches of all sizes	Many very large starting zones capable of producing avalanches of all sizes
Runout zone characteristics	No known runout zones	Clear boundaries, gentle transitions, smooth runouts, no connection to starting zones above	Abrupt transitions, confined runouts, long connection to starting zones above	Multiple converging paths, confined runouts, connected to starting zones above	Steep fans, confined gullies, cliffs, crevasses, starting zones directly overhead
Route options	Designated trails or low-angle areas with many options	Numerous, terrain allows multiple choices; route often obvious	***A selection of choices of varying exposure; options exist to avoid avalanche paths***	Limited options to reduce exposure; avoidance not possible	No options to reduce exposure

** The use of Class 0 is optional due to the reliability needed to make this assessment; otherwise, Class 1 can include Class 0 terrain.*

Table 6: ATES feature types and their spatial representation (Sharp et al., 2023; Statham & Campbell, 2023).

ATES feature	Example Application	Spatial Representation
Areas	Rating a commonly defined region that may have either a well-defined geographic boundary or an ambiguous boundary	Polygon or point
Zones	Rating a specific slope or terrain feature within an area where ATES parameters dictate the zone boundaries.	Polygon or raster
Corridors	Rating a physical or conceptual path of travel with navigational freedom between defined starting and end points.	Polygon or line
Routes	Rating a physical or conceptual path of travel between a defined starting and end point with limited navigational freedom.	Line

4.1.5.2 Spatial scale

The spatial scale is like the zoom level on a map. When we zoom in closely, we see finer details (high resolution), much like examining individual features in avalanche terrain. On the other hand, zooming out gives us a broader view (lower resolution), where we might only see larger areas such as entire ski runs. For ATES ratings, it's important to select the appropriate spatial scale. At times, a detailed view isn't necessary, and a wider perspective suffices, allowing ATES mappers to overlook smaller elements below a certain size, grouping them into larger, more general zones or routes (Statham & Campbell, 2023).

For example, if we are rating a specific backcountry route, the scale is predetermined by the route and the avalanche terrain interacting with it. However, there will be areas with less avalanche exposure which could be shown using different ATES ratings for different segments of the trip, or they could all be grouped together using the highest ATES rating along the route. The same concept applies to areal (spatial) mapping where a defined area could be rated to complex terrain, or there could be subareas with challenging or simple terrain within it (Statham & Campbell, 2023).

Making high resolution ATES ratings requires a lot of work and resources because the mapper would need to draw all relevant features at slope scale. For a map to be useful to be used for slope scale navigation, it needs to be very detailed, with terrain features as small as 20-30 meters included (Schweizer et al., 2003; Thumlert & Haegeli, 2018).

4.2 Methods to enumerate backcountry recreationists.

Counting the number of people participating in winter backcountry activities is important for understanding backcountry usage and characteristics, which is essential to make a customized AWS that works as intended. Langford et al. (2020) conducted a literature review to examine existing methods to enumerate the backcountry population. In their review, they assessed 22 established monitoring methods, ranging from manual observations to mobile tracking and surveys. The review concludes with five recommended approaches: National cross-sectional survey, extrapolation from direct counts, indirect counts, citizen science counts, and online engagement (Table 7). Both studies presented in this thesis (Papers III and IV) could be described as indirect methods of counting.

The first study using telecommunication network signaling data aligns with the **Indirect Counts** method (Table 7) because the process doesn't count the skiers directly. It uses a proxy (mobile phone signals) to infer the population, which makes it a modern adaptation of indirect counting, applying technological evidence instead of physical traces like tracks.

The second study uses avalanche beacon signals, which could also be defined by the **Indirect Counts** method. In contrast to the mobile phone signals, the avalanche transceiver doesn't transmit a unique signal which adds some complexity due to the possibility of repeated counting of the same individual. The possibility of counting the same person multiple times requires adjusting the data using a ratio based on a validation study that incorporates time-lapse photography. The time-lapse photography introduces elements from **Extrapolation from Direct Counts**, as it involves counting individual backcountry skiers in a specific area. So, the beacon signals are indirect counts, but they are validated using direct counts (Table 7).

Table 7: Description of the five different methods highlighted by Langford et al. (2020) in their review of available methods to estimate backcountry terrain usage. Paper III fits within indirect counts while Paper IV is a combination of indirect counts and extrapolation from direct counts.

Methods	Description
National cross-sectional survey	This method involves conducting a nationwide survey at a single point in time to collect data on the population, using a representative sample to infer the characteristics of the larger population.
Extrapolation from direct counts (Paper IV)	This method involves counting individuals in a specific area and then using this data to estimate the total population size by applying the observed numbers to a larger area or group.
Indirect counts (Paper III & IV)	This method involves estimating population sizes based on evidence of presence or traces left by individuals, rather than observing the individuals directly.
Citizen science counts	This method relies on the public to collect and report data on the population, often through organized projects where volunteers record sightings or other indicators of the population.
Online engagement	This method uses digital platforms and tools to gather data on a population, analyzing interactions, behaviors, and responses within digital environments to estimate population characteristics or sizes.

4.2.1 Demographics

Numerous studies have explored the demographic aspects of the backcountry skier population, though not all specifically measure base rates. Some examples include Sole (2008), which used a intersect survey and found a participant median age of 33, with individuals spending an average of 19 days yearly in avalanche terrain. The findings from Techel et al. (2015), Zweifel et al. (2016), and Hendrikx et al. (2022) converged on a median group size of approximately two individuals. However, Berlin et al. (2019) broadened the scope, investigating nationwide demographics without specifically focusing on skiers. Other research, such as that by Mannberg et al. (2018, 2020) and Winkler et al. (2016), provide additional insights into age, gender distribution, and skiing experience among participants. While these studies provide valuable information about the backcountry traveler population, each comes with its own limitations and should be interpreted with caution.

4.2.2 Instability properties (avalanche danger, problems, or other ratings)

Instability ratings, which include avalanche danger levels and other parameters, have also been scrutinized. Techel et al. (2015) and Winkler et al. (2021) examined the base rate of various avalanche danger levels, whereas Grímsdóttir and McClung (2006) assessed different stability ratings, comparing these with the likelihood of avalanche triggers.

4.2.3 Terrain properties and terrain classification

Terrain features, such as slope, elevation, aspect, have been explored by researchers like Hendrikx et al. (2016, 2022) and Winkler et al. (2021). While some studies found no notable trends, others, like Grímsdóttir and McClung (2006), pointed out specific inclinations regarding most-skied elevations and corresponding avalanche occurrences. Furthermore, many studies have connected movement data with terrain classifications (Degraeuwe et al., 2024; Hendrikx et al., 2022; Sykes et al., 2020; Thumlert & Haegeli, 2018; Winkler et al., 2021).

4.2.4 Temporal distributions

Analyzing temporal distributions—whether in terms of days of the week, months, or annual patterns – can shed light on behavioral trends and associated risks. Past conference proceedings have tried to quantify the yearly base rate of backcountry recreation, often resorting to what is being described in literature as rough estimates (Jamieson et al., 2009; Valla, 1984). Rough estimates are numbers that are presented without any background on where the numbers come from, or what methods are used to define them. They are still being cited due to the lack of better numbers.

Birkeland et al. (2017) suggest a possible decrease in the yearly fatality rate in North America, given the steady rise in bulletin usage (used as a proxy for yearly base rate of backcountry skiers), but there is no validation of whether bulletin data represents actual terrain usage. To the contrary, Winkler et al. (2016) do not find any evidence supporting that backcountry skiing is becoming safer using the results from the two decade-long Swiss national survey (Bürgi et al., 2021; Lamprecht et al., 2008, 2014; Lamprecht & Stamm, 2000) reveal a slight dip in the fatal accident rate from 9.4 to 8.7 micromorts between 1999 and 2013. The total number of hours per year for backcountry skiing was estimated to be 3.9, 4.8 and 4.9 in 2008, 2014 and

2020 respectively. The study highlights the importance of temporal base rate information in fatality research. Avalanche related fatalities in Switzerland increased from 6.5 to 8.6 between 1999 and 2013, which could be interpreted as backcountry skiing becoming more dangerous. However, when including the amount of backcountry skiing, there is no increase in fatality rate.

Walcher (2019) gathered historical incident and exposure data from helicopter- and snowcat-skiing operations to conduct a quantitative retrospective risk analysis. The dataset encompasses 47 winter seasons (1969/1970 to 2015/2016), including a total of 2,792,570 skier-days and 763 incidents resulting in injuries or fatalities among guests or guides. The fatality rate was found the be decreasing towards 2015-2016

4.3 Fuzzy logic and data analysis techniques

In the following subsections, I will present some data analysis techniques that are being used in AutoATES (Larsen et al., 2020; Toft, Sykes, et al., 2024), and are essential parts of the algorithm used to define avalanche release areas.

4.3.1 Fuzzy operator

Fuzzy operators are fundamental components in fuzzy logic systems, which handle reasoning that is approximate rather than precise. These operators, including the fuzzy AND, OR, and NOT, manipulate fuzzy sets and degrees of membership to produce a range of values between 0 and 1, rather than binary true or false outcomes. The fuzzy AND operator, specifically, combines the membership values of multiple fuzzy sets using a function, typically the minimum or the product, to determine the degree of membership in the resulting set. For instance, if the membership values of two sets A and B are 0.7 and 0.5, respectively, the fuzzy AND operation using the minimum function would yield a membership value of 0.5. These operators allow for more nuanced decision-making processes in systems where uncertainty and partial truths are inherent, enhancing the flexibility and robustness of the logic (Zadeh, 1965).

4.3.2 Cauchy membership values

Cauchy membership functions are used in fuzzy logic to describe the degree of membership of elements within a fuzzy set, characterized by the Cauchy distribution (Jang et al., 1997). The function is defined by a peak at a central value, with a shape that decays symmetrically according to Eq. 1.

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

where μ(x) is the Cauchy membership value; x is an input variable (e.g., slope angle, wind shelter, or forest density); and a, b, and c are parameters which control the weight of each input variable. This function is advantageous due to its heavy tails, meaning it assigns non-zero membership values to elements far from the center, providing a more gradual transition from full membership to non-membership compared to other membership functions like the Gaussian. This property makes Cauchy membership functions particularly useful in applications requiring robust modeling of uncertainty, where outliers or extreme values are present.

4.3.3 Sliding window

In raster processing, a sliding window refers to a moving subset of the raster grid used for localized analysis and computation. This window, typically a square or rectangular block of cells, traverses the entire raster grid, moving one cell at a time (or by a defined step size), to perform specific calculations or operations within its bounds (Figure 1). For instance, it can be used to compute terrain attributes like slope, aspect, or curvature by analyzing the elevation values within the window. As the window slides over each cell in the DEM, it allows for the extraction of local features and patterns, facilitating detailed spatial analysis and enhancing the understanding of the terrain's characteristics (Wang et al., 2024).

Figure 2: The red square represents the initial 3x3 window position, the blue rectangle shows the window after it has moved one cell to the right, and the green rectangle represents another cell to the right. The arrows indicate the direction of movement.

5 Methods and results

In this section, I present an overview of the methodologies and key results from the four research papers included in this thesis. The initial pair of papers focus on the evolution and improvements of automated ATES models over recent years. The latter two papers introduce innovative approaches for estimating backcountry populations through the analysis of signaling data from mobile networks and the implementation of beacon checkers at numerous trailheads surrounding Tromsø – but using a methodology that, with sufficient resources, could be applied elsewhere.

5.1 Study I: AutoATES v1.0

In our first study, the objective was to investigate whether an automated approach could be used to make high-resolution ATES v.1 maps for all of mainland Norway, as no such approach existed. An automated model of ATES could also improve existing practices for linear and spatial ATES mapping, being time consuming due to all the manual mapping needed. The ATES maps for Norway were then validated using existing areas and routes classified using the ATES v1.0 framework (Statham et al., 2006).

5.1.1 Methods

The input for the AutoATES v1.0 model is a 10 m raster digital elevation model (DEM). The first step is to calculate the slope angle which is used to determine a rough ATES classification inspired by the ATES zonal model (Table 3) proposed by Campbell and Gould (2013), followed by an analysis of release and runout areas.

The model expands on prior work by Veitinger et al. (2016) by utilizing the potential release area (PRA) model, which incorporates inputs such as slope angle, wind shelter, and roughness. The addition of the wind shelter index allows for the definition of release area scenarios based on prevailing wind direction or individual storm events. By introducing a multi-scale roughness parameter, the model captures fine-scale topography and its attenuation under snow influence, enabling a more accurate assessment of snow's impact on terrain morphology and, consequently, the size and location of potential release areas.

The three inputs slope angle, wind shelter and roughness are weighted from zero to one using a Cauchy membership function. The advantage with Cauchy membership functions is that they are easy to use, and let experts manually tweak the model output by using three input variables (see Section 4.3.2). The membership functions for slope angle, windshelter, and roughness are utilized in a Fuzzy logic operator (see Section 4.3.1) to determine a final score on a continuous scale ranging from zero to one. Here, a value of zero indicates areas where avalanches are not likely to release, whereas a score of one represents the areas with the highest likelihood of avalanche release. PRAs with values greater than 0.05 were classified as complex terrain, in line with the ATES v1 technical model, which defines release areas as complex terrain.

When PRAs are defined, the model estimates potential avalanche runout areas by utilizing the hydrological terrain analysis software TauDEM (Tarboton, 2005). By using the D-Infinity Avalanche tool, the model can calculate potential runout lengths using the travel angle. One of the benefits by using the travel angle to model avalanche runout areas is that it is an easy and powerful variable that could be used to define different runout scenarios.

The runout length estimations are based upon the foundational work of Lied and Bakkehøi (1980), who provided empirical data on avalanche runout lengths, to establish specific thresholds for categorizing runout lengths. Their analysis of the travel angle distribution from 423 Norwegian avalanches was later extended by Toft, Müller, et al. (2023) by analyzing 18,737 avalanches in Switzerland. This larger dataset confirmed that most avalanches stop at an angle of 18°, with 95% coming to a stop by 23°. Based on these findings, avalanche runouts that extend up to 18° from the release point are categorized as simple terrain. In contrast, runouts reaching 23° are considered challenging terrain, indicative of areas where avalanches occur more frequently.

In a final step, the classified slope angle layer is merged with PRAs (complex) and avalanche runouts defined as a travel angle of 23 (challenging) and 18° (simple). Compared to previous ATES maps which are often smooth and generalized, the output is very detailed. To make the maps more similar to previously existing maps, the output is smoothed out and areas smaller than 25,000 m^2 is assigned to the surrounding ATES class.

5.1.2 Results

A total of 365,246 km^2 of terrain was mapped according to the ATES framework, covering all of mainland Norway. The composition of the ATES maps was as follows: 71% of the area is classified as non-avalanche terrain, while the remaining portions are categorized into three levels of avalanche exposure – 13% as simple, 9% as challenging, and 7% as complex terrain.

To validate the spatial ATES maps, we compared them against areas and routes previously mapped by avalanche experts. The primary finding was that the AutoATES v1.0 demonstrated a high level of agreement with manually created maps in non-forested terrain. However, in forested regions, which was a small proportion our validation dataset, the results were more mixed. Additionally, we identified a shortfall in the AutoATES v1.0's use of the TauDEM hydrological flow process, which struggled to precisely simulate avalanche runouts in flat terrain. Despite these challenges, the AutoATES v1.0 model is still of significant value, particularly considering that a substantial portion of Norway's avalanche-prone terrain is located above the treeline. Consequently, the AutoATES v1.0 model could serve as a crucial tool for ensuring consistency in manual ATES mapping and enhancing the reproducibility of such maps.

5.2 Study II: AutoATES v2.0

After using the AutoATES v1.0 model for some time, we identified some limitations. Its simple approach did not take overhead exposure into account, and the hydrological flow model of the TauDEM runout simulation was flawed in flat terrain. Additionally, the v1.0 model did not account for forest density, which has been found to be one of the most important factors for ATES classification (Delparte, 2008; Schumacher et al., 2022). In our second study, we therefore address these limitations, as well as updating the model to reflect the changes made in ATES v2.0 (Statham & Campbell, 2023).

5.2.1 Methods

When developing the AutoATES v1.0 model, we relied extensively on proprietary software. However, at the beginning of the AutoATES v2.0 project, we committed to using only open and freely accessible software. To achieve this, we rewrote the entire model in the Python programming language, using exclusively open-source modules.

The minimum input data needed to run the AutoATES v2.0 model is two raster layers consisting of a DEM and forest density layer (stem density, canopy cover or basal area) with a spatial resolution ranging from 5 to 30 m. It is feasible to run the model with just a DEM raster, but the resulting output would only be applicable to open terrain.

The AutoATES v2.0 model chain consists of two main components: a pre-processing step and the AutoATES v2.0 classifier. During the pre-processing phase, we use the DEM raster to calculate slope angles, identify potential avalanche release areas, and determining runout zones, similar to the process in v1.0. However, a key improvement in v2.0 is the inclusion of forest density data, which now plays a crucial role in both the PRA and runout length calculations.

Even though we have made some changes to the new model, we still use Cauchy membership values for evaluating the significance of each input parameter. Our modifications included transitioning the codebase to Python from its original R and SAGA implementations. Furthermore, the original PRA model from Veitinger et al. (2016) did not include forest density data. Sharp (2018) incorporated this into a more comprehensive model that integrates this data alongside slope angle, windshelter, and roughness, which we have built upon.

When we reviewed the PRA threshold from Study 1, we found it to be overly conservative for our study areas in Western Canada. Consequently, we adjusted the threshold value from 0.05 to 0.15, aligning with the recommendations made by Sykes et al. (2024). Additionally, we refined the calculation of the windshelter index to better suit our requirements. Plattner et al. (2006) recommended a radius of 60 m around each cell for an optimal windshelter index. We therefore adapted the model to automatically select the optimal sliding window (see Section 4.3.3) size for spatial resolutions ranging from 5 to 30 m, ensuring the desired 60 m radius is maintained.

Another issue with the original PRA model by Veitinger et al. (2016) was that it was designed for a spatial resolution of 2 m, which have some implications for the roughness parameter at our spatial resolution ranging from 5 to 30 m. If we e.g. used a 20 m raster as input, the scale of the roughness would be 10 times as large as intended, being more towards a rough basin, more so than slope scale (Blöschl, 1999; Blöschl & Sivapalan, 1995). Additionally, the roughness calculation depended on snow depth values, which cannot be accurately determined without a thorough assessment of the snowpack properties at any given time. Due to these complexities, we decided to remove the roughness parameter from the PRA model used in AutoATES v2.0.

The Flow-Py model, introduced by D'Amboise et al. (2022), improved avalanche runout simulation by predicting potential avalanche tracks and deposition areas. Flow-Py introduces a flow process intensity parameter, allowing it to accurately simulate mass movements even in flat and uphill terrains, thus offering more reliable results than the hydrological tool TauDEM used in AutoATES v1.0.

Another advantage with Flow-Py is its ability to produce additional output layers, including overhead exposure and intensity. We use these two layers by scaling and averaging to generate an overhead exposure layer. Furthermore, it is possible to use a forest detrainment module, utilizing forest density data to improve the predictions on avalanche spread and runout distances. For a detailed explanation of Flow-Py's capabilities and applications, see D'Amboise et al. (2022).

Once the pre-processing for PRA and Flow-Py is finished, the AutoATES classifier employs a series of map algebra equations to identify and combine the ATES classifications based on slope angle, travel angle, and overhead hazard, maintaining a process similar to what was implemented in AutoATES v1.0. The subsequent step for the AutoATES classifier is to lower the ATES class in terrain with dense forest. The forest density is applied as a secondary step to increase the importance of the forest density criteria.

5.2.2 Results

To evaluate the performance of the AutoATES v2.0 model, we use the two benchmark maps made by Sykes et al. (2024) for Connaught Creek, British Colombia and Bow Summit, Alberta Canada. The maps are made by having three avalanche experts making individual maps for the same two areas. When all the maps where done, they collaborated to make a consensus map they all could agree on. The maps were developed using GIS, remote sensing imagery, local knowledge and field observations. More information about the development of these maps can be found in Sykes et al. (2024).

Even though these consensus maps are made in a collaborative way to reduce individual characteristics among each expert, we could never have a complete benchmark map that represents a sole version of the ground truth. The qualitative nature of the ATES framework allows for multiple interpretations, and human mappers will always struggle to make these maps at the same spatial scale. We consider the maps created by Sykes et al. (2024) to be the most accurate map currently available for validating spatial ATES maps.

The AutoATES v2.0 model has improved the performance of ATES maps substantially compared to v1.0. The development of the new model has been done in numerous iterations which means that the increased performance is due to multiple improvements. To measure each of these improvements, we used an ablation study which is a common method to validate complex machine learning algorithms (Meyes et al., 2019). An ablation study could be described using the following steps (from Toft, Sykes, et al., 2024):

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

To evaluate AutoATES v2.0, we conducted an ablation study focusing on six key internal components to determine their individual contributions to the model's effectiveness. The most significant improvements include integrating forest density data into the post-forest-classification process, incorporating forest density information into the PRA model, and adopting the new Flow-Py model. These improvements led to a notable increase in the model's overall performance, as measured by the F1-score. Specifically, the performance at Bow Summit improved from 64% to 77%, and at Connaught Creek, it increased substantially from 39% to 71%.

5.3 Study III: Using telecom data to enumerate skiers.

In our third study, we attempted to use signaling data to enumerate backcountry skiers in Northern Norway. The hypothesis was that if we would be able to get a representable sample of the traffic, we could calculate the fatality rate. Unfortunately, we found large discrepancies between the estimated positions from telecom signaling data and our validation data using an independent GPS track.

5.3.1 Methods

Telia, one of the largest mobile network providers in Norway utilizes telecom network data, one of the most extensive and constantly generated data sources, to provide insights into national movement patterns without compromising individual privacy. This methodology, compliant with General Data Protection Regulation (GDPR), ensures anonymity by aggregating data into groups and not storing or processing identifiable information. The process involves the use of signaling data, generated by smartphones during active or passive use, which includes a timestamp and the coverage area (Cell ID) connected to the phone.

The best server estimate (BSE), which is the estimated coverage area, is defined for each Cell ID and offers a more precise location compared to solely using the Base Transceiver Station (BTS) by linking multiple Cell IDs associated with different antennas. Although Telia does not employ triangulation due to privacy policies, analyzing signaling data over time allows for the creation of movement chains, which are particularly useful in urban areas but have in this study also been applied to assess movements in avalanche terrain.

Telia's methodology involves three types of reports: Activity reports that show where crowds spend time, Routing reports that track passing crowds, and Origin-Destination reports that detail trips between locations. For this study, we focus on the Activity report, which quantifies the time spent by subscribers in a specific area, adjustable in resolution to maintain privacy compliance.

This approach has been applied to a case study in Tromsø, Northern Norway, where avalanche terrain and populated areas were defined using GIS software. Populated areas were determined based on the number of inhabitants per square kilometer, while avalanche terrain was classified according to the ATES framework (Larsen et al., 2020). To avoid noise from other activities, any avalanche terrain within 300 meters of a house or road was excluded.

A mobility analysis was conducted by sharing the defined layers with Telia, who then distinguished between populated and avalanche-prone areas using their BSE. This enabled the counting of phones moving into avalanche terrain, with additional filters applied to consider only those in the terrain for a sufficient duration during daylight hours, accounting for typical backcountry trip durations and times.

The study also explores correlations between the number of people in avalanche terrain and various factors such as daylight, avalanche forecast page views, weekends and holidays, weather conditions, and avalanche danger levels. These correlations help understand the influence of different factors on backcountry usage and can inform safety measures and resource allocation for avalanche prevention and response.

The validation process involves an algorithm developed by Telia to assign the most likely position within a Cell ID. The algorithm is trained on data from populated areas and roads. We combine the output from this algorithm with GPS data from two known phones.

5.3.2 Results

The mobility analysis revealed that an estimated 13,666 individuals spent at least two hours in avalanche terrain during the 2019-2020 season, with daily figures ranging from none to 118 people, averaging 75 individuals per day. The analysis showed a weak but statistically significant correlation between the number of people in avalanche terrain and factors such as daylight, weekends, holidays, and avalanche forecast page views, with daylight having the most substantial correlation. Other weather-related factors like precipitation, wind, daily avalanche danger, and cloud cover did not show a significant correlation.

The positional validation, conducted using a specially configured phone that allowed comparison between telecom signaling data and precise GPS locations, highlighted notable discrepancies. The estimated positions from signaling data often placed individuals in less accurate locations, such as valley bottoms or along roads and fjords, rather than their actual GPS-tracked positions. The discrepancy between the signaling data and GPS locations varied widely, with a median difference of 6,523 meters and 95% of the points within 12,920 meters, indicating that while useful for broad movement patterns, signaling data cannot be used to pinpoint whether a skier is in avalanche terrain or not.

5.4 Study IV: Using beacon checkers to enumerate skiers.

A wide range of solutions have been experimented with to quantify the backcountry skier population, including tracking of cell phone location, surveys, light barriers, and voluntary registration boards. Unfortunately, all have different shortcomings. In Study IV, we have developed and validated a methodology to enumerate backcountry skiers in Tromsø, Norway.

5.4.1 Methods

To quantify backcountry skiers, a checkpoint (CP) sign equipped with a low-power consumption beacon checker (BC) system were deployed at trailheads throughout the study area. The BCs, operating on a 12V system, wakes up every 15 seconds to detect nearby avalanche transceivers (or beacons). To ensure continuous operation throughout the winter season, the system was supported by solar panels and robust LiFePo4 batteries, allowing the BCs to function effectively even during Tromsø's prolonged polar nights. Data was transmitted to a database every three hours using the mobile network.

The BCs were designed to count all avalanche beacon signals within a certain range, without distinguishing between individual skiers, potentially leading to overcounts if individuals passed multiple times. To select optimal locations for these CPs, the study utilized the Strava Heatmap and consulted with local avalanche experts, resulting in 29 strategically placed CPs for the initial season. The system's reliability was maintained through regular maintenance and the use of silica gel to prevent moisture accumulation inside the devices.

To validate the BC counts and address the issue of non-unique counts, a time-lapse camera was set up at a distance to observe three high-traffic trailheads covering six CPs. This method allowed for the comparison of actual skier numbers with BC data while adhering to privacy laws by ensuring individuals couldn't be identified in the images. This validation step was crucial for assessing the accuracy of the BC data and making necessary adjustments to account for the system's inherent limitations in distinguishing unique individuals.

5.4.2 Results

During the first season from 2021-2022, our aim was to deploy 29 CPs around Tromsø, to monitor backcountry skier traffic. Unfortunately, three of these CPs faced operational issues, leaving 26 CPs with an average downtime of 3.54%. In the subsequent season of 2022-2023, the plan was to set up 25 CPs. However, two failed to collect data, but the remaining 23 CPs showed a significant improvement in reliability, with a mere 0.19% downtime.

Validation of the BC counts was conducted using a time-lapse camera, which faced its own challenges, including erroneous setup and environmental conditions that rendered a third of the images unusable. Of the 101,470 usable images from 75 days, manual analysis identified 1,399 individuals passing the CPs, allowing a calibration of the count data to reflect the number of unique trips.

We identified that for trailheads where the path leading away from the parking lot is confined, it’s nearly impossible to avoid being counted in both directions. We have illustrated this problem in Figure 1, using two types of scenarios. In type 1, the CPs are positioned in such a way that skiers are likely to pass by them only once, typically at the beginning of their trip. Type 2 CPs on the other hand, are located where geographical or trail layout constraints cause skiers to pass by the CP both at the start and end of their trip, leading to potential double-counting of individuals (Figure 1).

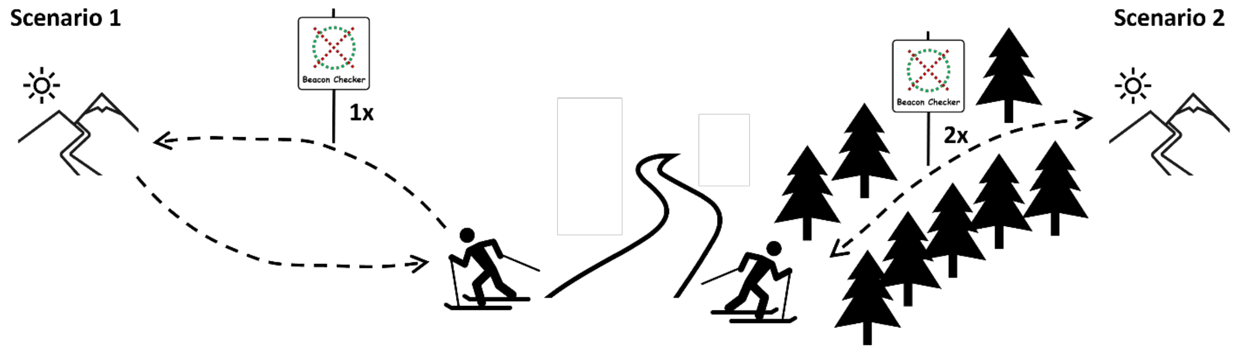

Figure 3: In most locations, the CP is placed so that it is logical to pass it on the ascent, while there is much room to avoid it on the descent (scenario 1). However, in some locations, it is most convenient to pass it on both the ascent and the descent (scenario 2) (from Toft, Sykes, et al., 2024).

After calibrating our count data to the number of unique, the data confirmed that for every person counted at a Type 1 CP, there was nearly a one-to-one correspondence (87%), whereas Type 2 CPs showed almost double the counts per person (192%), suggesting some overcounting due to the system's inability to distinguish unique individuals. The analysis of skier traffic revealed distinct patterns by time of day, week, and month. Skier activity increased from the early morning, peaking between 08:00 and 09:00, and gradually decreased until the evening, with some nighttime activity observed. Weekends saw the highest traffic, with a steady increase in activity from Monday to Friday. Monthly data showed a growing trend from December to April, with March and April being the most popular months, followed by a decrease in May. Seasonal comparison highlighted consistent skier traffic across both seasons, with a notable mid-season peak in February during the first season. The second season saw a more spread out increase in activity, culminating in a high at the season's end. These findings underline the effectiveness of CPs in monitoring skier traffic and the importance of operational reliability for accurate data collection.

6 Discussion

In this thesis, I have started to lay the groundwork to answer the important question: **who skis where, when?** To quantify where people ski and their exposure, an automatic terrain model that classifies avalanche terrain on a large scale is needed. Therefore, I have created an automated version of the well-known ATES classification scheme to measure skiers' exposure. First, I will discuss the implications of the new AutoATES v1.0 model and explain why a revised v2.0 version was necessary, before describing methods to enumerate backcountry usage and future research.

Automated ATES mapping presents some distinct advantages and disadvantages when compared to traditional manual mapping. One of the primary benefits of manual ATES mapping is its independence from digital elevation and forest density data. Human mappers can evaluate the terrain without relying on pre-existing digital models, allowing for flexibility in regions where high-quality models may not be available. Including local knowledge is a significant advantage of manual mapping, as it can be relevant when identifying micro-terrain or avalanche frequency data unavailable elsewhere. This can make decision-makers feel more confident in human-made maps, as they can be subject to direct quality control and validation. However, manual approaches are often subjective and may suffer from human bias, as different experts interpret avalanche terrain differently. Furthermore, manual mapping tends to have a lower resolution and is not scalable, making it time-consuming and impractical for covering large or remote areas.

On the other hand, automated ATES mapping offers both consistency and scalability. Both factors are essential when comparing terrain exposure with backcountry usage (e.g., Degraeuwe et al., 2024; Hendrikx et al., 2022; Sykes et al., 2020; Winkler et al., 2021). Automated methods eliminate human bias by using algorithms to analyze terrain data systematically, ensuring uniformity across large regions. The scalability of this approach is a significant advantage, as it can process large areas much faster and with higher resolution than manual methods, making it ideal for mapping expansive or hard-to-reach regions. However, these methods heavily depend on input data quality; poor or incomplete terrain models can lead to inaccurate assessments. Another disadvantage is that automated mapping does not incorporate local knowledge, which can be a critical component of hazard assessment. Moreover, while large areas can be mapped efficiently, there is no viable option to review all output, which makes it harder to ensure the same level of control.

Since its introduction, AutoATES v1.0 maps have been applied to a variety of different applications. However, like all new developments there is a need for improvements. Engeset et al. (2022) compared six color variations of the AutoATES v1.0 maps on individuals with and without color vision deficiency (CVD) varying in nationality, avalanche education and familiarity with ATES. Their results suggest that color's, legends, and maps used by the NAWS should be improved in combination with symbols to help users with CVD (Engeset et al., 2022). They also found that the European color scheme for ski runs is the best color combination for ATES maps for participants with and without CVD. Therefore, it is recommended as a worldwide standard for ATES. The accuracy of the ATES model also depends on factors like forest cover, not included in the ATES 1.0. Schumacher et al. (2022) made the first comparison of how forest density data would affect the AutoATES v1.0 model. The new maps were compared to manually classified ATES trips in Western Norway. The overall accuracy increased from 55% with the regular AutoATES v1.0 compared to 67% when utilizing a canopy cover. The ATES maps have also been used to track decision making process for backcountry skiers. Hendrikx et al. (2022) used AutoATES v1.0 to generate maps for selected avalanche regions in the USA and Canada. They then tracked the decision-making process of backcountry skiers by collecting skiers GPS tracks and providing them with surveys after the trip. In addition, the AutoATES v1.0 maps have also been used to define avalanche terrain for signaling data (Toft, Sirotkin, et al., 2023), satellite detected avalanches in Wyoming and Utah, USA (Keskinen et al. 2022) and Langtang, Nepal (Eckerstorfer et al. 2023).

Another application of the AutoATES v1.0 model is to generate avalanche runout maps for recreational use, as both release and runout areas are estimated as a part of the model workflow. Such maps have been available in Norway since 2020 (Varsom, 2020). These maps have also been incorporated into decision-making policies by guides on Svalbard, the Norwegian Armed Forces and Search and Rescue (SAR).

Even though AutoATES v1.0 has been widely applied, the model has several known limitations. Its simple approach to terrain characteristics does not take overhead exposure into account, and the hydrological flow model of the TauDEM runout simulation is flawed in flat terrain. Additionally, the model did not account for forest density, which has been found to be one of the most important factors for ATES classification (Delparte, 2008; Schumacher et al., 2022). A final challenge was that the model was heavily dependent on proprietary software (Larsen et al., 2020), thereby increasing the monetary and computing costs to operate the model and limiting open-source access (Toft, Sykes, et al., 2024).

To address these limitations, we have developed a new AutoATES v2.0 model which improve upon these known issues. This updated version was designed to be compatible with the new ATES v2.0, which consists of five classes instead of three (Toft, Sykes, et al., 2024). The performance of the new AutoATES v2.0 model is found to be comparable to that of human mappers (Sykes et al., 2024). More importantly, it serves as a comprehensive framework that facilitates the measurement of exposure for specific routes or areas.

Although AutoATES v2.0 is relatively new, it has already been applied in various contexts. Avis et al. (2023) used AutoATES v2.0 to generate maps and collaborated with avalanche professionals in Colorado, Montana, and Utah to gather local feedback on the model across over 1.7 million acres. They conducted five iterations of feedback. Even though this feedback did not include all the millions of acres mapped, focusing on key areas within each forecast region provided sufficient information to make improvements that enhanced AutoATES outputs across the entire region. Furthermore, Sykes et al. (2024) validated and optimized the AutoATES v2.0 parameters using a grid search method. The model was optimized by training it on two benchmark maps in Connaught Creek and Bow Summit in Western Canada, see Sykes et al. 2024 for more information. With all the improvements in AutoATES v2.0, another set of avalanche runout maps for recreational use was processed and published for all of Norway, Svalbard, and selected regions in Greenland (Varsom, 2024a).

Despite the fundamental differences between automated and manual methods for generating ATES ratings, manual maps created by experts is considered to be the most reliable dataset for validating AutoATES. Moreover, fine-tuning AutoATES input parameters based on these expert-generated maps for specific regions can enhance its accuracy beyond what can be achieved using only theoretically derived parameters (Sykes et al., 2024).

However, AutoATES has a significantly higher spatial resolution than manual ATES mapping, which creates challenges when manual mapping is regarded as the gold standard for validation. This presents a dilemma: if manual mapping is the benchmark, it becomes impossible for AutoATES to demonstrate improvements that surpass this standard. Should the gold standard remain the gold standard? AutoATES is capable of mapping terrain at a much finer spatial resolution than manual methods, potentially offering more detailed and accurate assessments of avalanche risk. Currently we are making the AutoATES output coarser to align with manual mapping, which may limit its potential. This raises an important question about whether the reliance on manual maps for validation is holding back the advancement of automated techniques. The challenge lies in the absence of a more advanced validation dataset. Without it, it is challenging to fully exploit the capabilities of AutoATES and to push beyond the limitations of traditional manual methods.

When evaluating the performance of automated ATES mapping it is also important to consider how the performance is measured. One common evaluation metric which we used in our paper is the F1-score (Toft, Sykes, et al., 2024). However, the F1-score does not account for the natural ordering of terrain difficulty within these categories. This limitation becomes especially relevant in avalanche terrain classification, where the severity of misclassifications varies. For example, in the context of AutoATES, which classifies terrain into non-avalanche, simple, challenging, complex, and extreme avalanche terrain, the F1-score treats all misclassifications equally. If the true terrain class is simple, and the model predicts challenging, or if it predicts complex or extreme, the F1-score does not distinguish between these types of errors in terms of severity. This suggests that the F1-score might not be the most suitable metric for evaluating multi-categorical models like AutoATES, where the classes follow a natural order and some misclassifications may be more consequential than others (e.g., Ebert & Milne, 2022). In the future, it would be beneficial to explore more appropriate skill score measures when validating AutoATES.

After having developed a terrain model to estimate backcountry skiers' exposure the next aim was to count how many people travel in avalanche terrain, and ideally, determine when and where they travel. First, we attempted to use signaling data from Telia, one of the largest mobile network providers in Norway. The main advantage of this method was that if successful, it could be scaled to cover all of Norway. The initial results were very promising. Unfortunately, when we validated our results, we found that there were substantial discrepancies between the estimated positions from Telia and the GPS reference positions. In essence, this meant that our results were not trustworthy, and we abandoned this method to get an estimate of the total amount of backcountry skiers within a region. The method also had its limitation as it is a relatively crude measure, meaning that we do not get any details on skier's terrain choices. This would limit the possibility to answer questions like whether the avalanche forecast affect skiers travel choices. By using the Telia data, we would have been able to compare how many skiers there were out on different danger levels or avalanche problems, but we would not be able to measure whether skiers e.g. opted towards less exposed terrain when the avalanche danger was higher. Hence, this study serves as an important lesson learned in understanding the limitations and potential of using telecom data for movement analysis in remote outdoor settings. The study identifies some important limitations regarding the use of telecom data for tracking movements in avalanche-prone areas. The large difference between estimated positions and GPS reference data shows the limitations of using signaling data for precise location tracking in non-urban areas. An important factor for this inaccuracy appears to be the lower density of base transceiver stations (BTS) in non-urban areas where most avalanche terrain is located. To make telecom data a viable option to enumerate skiers in avalanche terrain, the density of BTS should be much higher than what is currently available. In areas with a higher density BTS the results may be different (e.g. in the US or NZ where triangulation is permitted).

As signaling data is a crude measure of backcountry skiers, we also worked on a method using a large network of beacon checkers at common trailheads around Tromsø. Most mountains that are being used for backcountry skiing in Tromsø have an established starting point. Our hypothesis was that if we identified these sites and placed a large sign with a beacon checker between the parking lot and the most common route, most skiers would walk by to check whether their beacon is working properly. By including a data logger on these signs, we could monitor how many skiing trips that is being done at different trailheads each day or time of day. However, as beacon checkers is not an established method to count backcountry skiers, we first had to validate whether we could use these beacon checkers to get an accurate count of skier trips in the area. To validate our results, we used a time-lapse camera to compare the actual number of skier trips with the counts from each beacon checker. This enabled us to calculate a ratio which could be used to calculate the actual number of skier trips instead of number of beacon checker counts. We believe that our results represent a substantial methodological progress in terms of measuring backcountry usage at a regional scale. We have successfully measured a large part of the backcountry usage over an area of 2,589 km^2, providing detailed insights into base rates on hourly, daily, and monthly basis. We believe that using a widespread network of CPs, as we have done, is currently the most effective way to measure backcountry usage in hard-to-reach areas.

6.1 Current research

Based on my results and insights, I identified some promising new ideas that could better address my research questions. With additional time and resources available, I decided to explore new methods to answer these questions. This work extends beyond the four papers included in this thesis.

The beacon checker method has its limitations, being expensive and requiring substantial maintenance to provide consistent results over multiple seasons. To address this, we have developed a new battery-powered device that continuously searches for Bluetooth Low Energy (BLE) signals (BLE sniffer). This device has a theoretical battery life of 600 days, can detect all BLE signals within a 100-meter range, and transmits the results over LTE/IoT, like the CPs. The advantage of this method is that it requires no action from the skier, as most people carry at least one active BLE unit (e.g., phone, watch, or headset). This method will need to be validated using a time-lapse to determine the ratio of BLE signals to backcountry skiers. However, it is much more cost-effective, with each device priced at US$200 compared to US$1600 (excluding sales tax) for a CP with a beacon checker. Additionally, there is no need for maintenance during the season or a large vehicle with a trailer to transport the equipment. We have currently built 32 devices and placed them alongside each CP to enable a comparison at the end of the season. This will allow us to compare the results against CP data.

Unfortunately, the backcountry usage information from both the CPs and BLE sniffers only indicates when and from which trailhead a backcountry activity occurred. While this data is more detailed than the signaling data, which only tells us how many people were within avalanche terrain within a region, it still lacks specificity. There could be many different routes with varying levels of exposure from a single trailhead. In the future, we aim to explore the possibility of assigning the most typical ATES rating for each trailhead and comparing this information with daily trailhead usage and avalanche forecasts. However, due to the substantial variability in avalanche exposure from each trailhead, it is uncertain whether this method will prove valuable.

Backcountry skiing is not a coherent risk activity. It is possible to ski safely even under high avalanche danger if you choose your slopes carefully, while moderate avalanche danger can still pose significant risks depending on specific factors. The level of risk is highly dependent on the precise location and the specific conditions at that site. Thus, the regional avalanche danger rating does not always directly correlate with the actual risk faced by skiers in particular areas.

To resolve this lack of coherent risk, we need to know exactly where on the mountain people ski. To gather this type of data, we have initiated a study where skiers can voluntarily share their Strava activity data in the form of GPS tracks with the Center of Avalanche Research and Education (CARE) (Toft, Mannberg, et al., 2024). Currently, approximately 1,500 users share their activity data in real-time, which has resulted in 86,000 GPS tracks from 2014 to 2024 in Northern Norway.

In this future study, our aim is to track the precise locations of where people ski. Additionally, we need specific information of the snowpack at specific locations to calculate the avalanche risk from each GPS track. While regional avalanche forecasts provide some information, they have severe limitations as they do not reflect the avalanche conditions at slope scale. Ideally, we would need highly detailed information of the snowpack at each individual slope.

Currently, there is no method to obtain this level of detail, but one approach could involve asking skiers to evaluate and report the conditions immediately after their trip. To this end, we have implemented a GPS tracks study where participants provide reflections on the conditions, they encountered (Mannberg et al., 2024). Although this approach shows promise, we still do not have a clear method to calculate the individual avalanche risk that skiers expose themselves to while skiing.

However, what we can do is to estimate people's terrain exposure. The obvious solution would be to assign an ATES rating to each GPS track, ranging from non-avalanche to extreme terrain (five classes). However, ATES is sensitive to the most exposed section of a trip, meaning that a GPS track with a brief exposure to steep terrain could receive the same rating as another trip with repeated exposure to similar terrain. To address this issue, we have started to develop an exposure score specifically for this application that provides detailed information on the theoretical exposure of the track, independent of avalanche conditions. Instead of evaluating exposure based on the most exposed section of a trip, the exposure score demonstrates the incrementally increase with the amount of exposure, giving a more accurate representation of the entire trip's exposure.

Although a thesis can only cover so much, this work has laid the groundwork for future research and provides a starting point to answer my main question: **who skis where, when?** By establishing these methodologies and concepts, I hope that they can be used in future research to improve our understanding of skier's terrain choices in avalanche terrain, and the associated risk.

6.2 Future research

When I made the initial proposal for this thesis, the idea was to: (1) research how dangerous it is to do backcountry skiing in Tromsø, and (2) whether the avalanche forecast affect skiers' terrain choices. Unfortunately, I have not progressed as much as I originally intended. To resolve these two overarching aims I would need precise data on the overall backcountry usage, accidents, and fatalities within the region, as well as how many skiers expose themselves to different degrees of avalanche terrain. Hence, the working title **who skis where, when?** We have a fair understanding of the number of accidents and fatalities within the region from the NAWS accident statistics, but we lack precise data on the overall backcountry usage and skiers' exposure.

To go from enumerating backcountry usage at the most frequented trailheads to estimating overall backcountry usage in the region, we need to determine what proportion of the total traffic our current studies are capturing with the CP and, in the future, with the BLE sniffers. One method to estimate this proportion is by analyzing the large database of GPS tracks to see what percentage of these activities originate at a CP. Once we know the proportion or ratio, we could compare our data with accident and fatality data to estimate the fatality rate of backcountry skiing in the region. Additionally, it could be possible to classify each GPS track according to the ATES framework to determine what proportion of the GPS tracks fall within each ATES class. This information could then be compared to the ATES classification of the terrain where accidents occur, providing insights into the fatality or accident rate across different severities of ATES terrain. Another addition could be to include the number of severe injuries reported by the hospital. A ten-year retrospective study on avalanche fatalities and severe injuries is currently being conducted at the hospital in Tromsø, which will provide a bigger picture than only fatalities (Dehli & Cronblad, 2024).

To measure a trend over time, we could monitor selected trailheads annually using CP or BLE sniffers. Focusing on a few representative trailheads makes the resources needed to maintain the project become more manageable. The methods described in this thesis allow us to identify which CP people start from and the general type of terrain they access. However, this approach has limitations since people can access various types of terrain.

We should review the extensive database of GPS tracks, calculate their exposure, link them to the regional avalanche forecasts, and compare the data. Recent studies have increasingly combined terrain classification with real-world travel data to better understand the relationship between terrain use and avalanche risk, providing insights into "where" and "when" individuals face heightened exposure. For example, Thumlert & Haegeli (2018) examined how heli-skiing guides utilized terrain exposure to manage risks, applying a severity score to different terrain types. Similarly, Sykes et al. (2020) used GPS trackers on side-country skiers over a few days to assess terrain use within the ATES framework, albeit with a small sample size of 136 tracks collected during 19 field days between 2017 and 2018. These studies capture how skiers engage with avalanche terrain in controlled or semi-controlled settings.

Larger-scale studies like Winkler et al. (2021) and Hendrikx et al. (2022) took a broader approach by crowd-sourcing GPS tracks from backcountry users. Winkler et al. (2021) analyzed 7,355 tracks submitted over several ski seasons (2005/06 to 2018/19), classifying avalanche terrain into a terrain indicator (TI) which consists of four classes similar to ATES. They found that the risk correlates strongly with the information of the avalanche forecast. Hendrikx et al. (2022) analyzed 482 GPS tracks and compared them with AutoATES v1 to examine how experience influences decision-making and terrain use. Their findings highlight that a skier's level of experience is correlated with avalanche terrain exposure.

Building on the work of Winkler et al. (2021), Degraeuwe et al. (2024) developed a fully probabilistic method for assessing avalanche risk, analyzing 8,558 backcountry tours. This study introduced a novel statistically derived terrain classification method that adjusts for population base rates using linear regression. By combining terrain indicators with national survey data and accident records, the approach of Degraeuwe et al. (2024) provides a probabilistic method for understanding personal risk based on terrain use in the backcountry.

The 86,000 GPS tracks in our database are growing at a rate of approximately 15,000 tracks per season. These data could be a valuable dataset for further analysis. Preliminary analysis indicates that roughly 50% of these activities are from a forecasting region in mainland Norway (excluding Svalbard). After manually removing activities that do not appear to be backcountry skiing, we estimate that we will have 31,000 valid activities remaining for analysis. Of these, 8.3% are within our study area in Tromsø, Northern Norway. A preliminary analysis using a subset of data from forecasting regions in Norway (approximately 12,800 GPS tracks from 321 users) is in progress (Toft, Mannberg, et al., 2024). This analysis will offer valuable insights into the relationship between skiers' terrain choices and avalanche forecasts.

7 Conclusion

While I have not directly addressed the overarching research question: **who skis where when?** I have developed a framework for quantifying exposure to avalanche terrain. This framework can create spatial ATES maps for larger areas, such as AutoATES v1.0/2.0. It can also be applied to develop recreational avalanche runout maps for AWS'. In the future, this framework could enable us to quantify the exposure of backcountry activities using collected GPS tracks.

Additionally, I have reviewed and tested various methods to enumerate backcountry usage. My first approach, using signaling data, would have considerable advantages if successful. Unfortunately, I found that the method was not as reliable as the preliminary findings suggested. My second approach, using beacon checkers, was far more successful, enabling me to find the base rates of backcountry usage in Tromsø, Northern Norway, for the time of day, week, and month.

These methods combined provide the foundation and a clear path forward to understand whether avalanche forecasts affect skiers' terrain choices, and what type of avalanche terrain the skiers expose themselves to, and ultimately, **who skis where, when?**

8 References

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9 Appendix

The original peer reviewed papers (I, II, III) and the revised manuscript (IV) are presented in the same order as in the manuscript.

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ORIGINAL PAPER

Developing nationwide avalanche terrain maps for Norway

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Abstract

Snow avalanches are a significant natural hazard in Norway. One method to manage the backcountry avalanche hazard is through detailed mapping of avalanche terrain. Avalanche terrain can be mapped using a variety of methods, including using the Avalanche Terrain Exposure Scale (ATES); however, manual classification of terrain using ATES is time consuming. This study has developed and compared a fully automated algorithm to provide ATES mapping for all of Norway. Our new algorithm is based on the technical model for ATES mapping. This model has specific terrain-based thresholds that can be applied for automated terrain-based modeling. Our algorithm expands on prior work by including the potential release area (PRA) model to identify and calculate the likelihood of an avalanche releasing from a start zone. We also use the raster-based TauDEM-model to determine the avalanche runout length. The final product is a 10-m resolution ATES map. We compared this nationwide ATES map with areas that have been manually mapped by avalanche experts, and find that the automated approach yields similar and reliable results. In addition to comparing mapped areas, we also examine manually mapped linear routes and compare these with the automated mapped ATES areas. Our results suggest that for open terrain, the vast majority of the manually classified tracks are predominantly in the same ATES class as our algorithm. For forested areas, we get mixed results, which can be attributed to a lack of suitable vegetation data at an appropriate scale. Despite this limitation, the current ATES algorithm and resulting spatial data are already valuable as a large portion (~70%) of the Norwegian backcountry terrain is above tree line. The automated algorithm is also useful to ensure consistent manual classification across different regions in Norway, or globally, and will permit greater reproducibility and easier updating of mapping for the future.

Keywords ATES · GIS · Algorithm · Mapping · Avalanche · Terrain

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1 Introduction

1.1 Background

A snow avalanche is a mass of snow that slides rapidly down an inclined slope, such as a mountainside. Snow avalanches are triggered by either natural processes (e.g., new precipitation, wind deposition, rapid temperature changes, etc.) or by human activity. Snow avalanches are a significant natural hazard in Norway. On average over the last 20 years, about six people die annually in Norway due to avalanches, with an order of magnitude more in reported close-call accidents. During the winter season 2018–2019, 13 people died due to avalanches (NGI 2019; Varsom 2019a). Furthermore, in every winter, key sections of the Norwegian road and rail networks are closed due to avalanches or avalanche danger. On average, 250 avalanches are registered on Norwegian roads every year (NPRA 2019). Numerous times, vulnerable settlements are completely isolated, forcing long detours due to avalanches blocking key transportation routes, or subject to evacuation by the police.

In Norway, as in several other countries (e.g., Birkeland et al. 2017; Techel et al. 2018), there is a tendency for most of the recent fatal accidents to occur in connection with outdoor activities. In response to this change in avalanche fatalities, there has been a greater emphasis on increased public education and avalanche forecasting, including in Norway (Engeset 2013; Engeset et al. 2018). To supplement the avalanche forecasting and education, efforts have been made to map avalanche terrain (e.g., Statham et al. 2006) and to develop decision aids to guide appropriate terrain use under varying conditions (Haegeli et al. 2006; Landrø et al. 2020).

In many regions around the world, avalanche hazard maps are being generated for different applications. Two distinct types of mapping are (1) hazard zoning maps developed for settlements, roads and industrial sites (e.g., Canadian Avalanche Association 2002; Arnalds et al. 2004; Sauermoser 2006); and (2) hazard maps developed for backcountry recreationalists to be used as a trip planning tool before entering avalanche terrain (e.g., Gruber and Bartelt 2007; Barbolini et al. 2011). The hazard maps developed in this paper are intended for backcountry guidance only and are not legally binding like a municipality risk map for avalanche zoning related to infrastructure. Their purpose is to inform and provide guidance for recreational users, rather than a regulatory framework for planning and enforcement.

In Norway, specifically aimed at outdoor recreationalists, there are two types of ski touring routes that have thus far been manually mapped; observer trips used by the Norwegian Avalanche Warning Service (NAWS) (Landrø et al. 2016), and trips described in some of the recent ski touring guidebooks. However, such routes are generally not available nationwide for backcountry terrain due to the level of manual work required to generate them.

To delineate avalanche hazard maps at national scales, automated models must be used (Bühler et al. 2018). Different types of backcountry hazard maps exist, they can be broadly divided into two types; (1) outlining degree of hazard, often low, moderate, high (e.g., Statham et al. 2006; Barbolini et al. 2011; Harvey et al. 2018), or (2) continuous which contains dynamic hazard values ranging from 0 to 1 where increasing value indicates increased hazard (e.g., Schmudlach and Köhler 2016; Harvey et al. 2018).

One approach that is of particular relevance and fits within this first category is the Avalanche Terrain Exposure Scale (ATES). ATES is a terrain classification system developed by Parks Canada to better communicate the complexities and risks of traveling in avalanche prone terrain (Statham et al. 2006). Campbell and Gould (2013) refined this approach and proposed a practical model for semi-automated classification of avalanche terrain.

In 2014, the Norwegian Water Resources and Energy Directorate (NVE) published a pilot study in collaboration with Grant Statham from Parks Canada to determine whether the Canadian ATES classification could be adapted for use in Norway. A Norwegian version was evaluated and a few locations across the country were manually classified by experts at the Norwegian Avalanche Warning Service (NVE 2014). Furthermore, during the winter season of 2018–2019, 123 popular routes used for ski-touring were manually classified by NVE using the modified ATES classification scheme (Varsom 2019b) in three test regions; Troms, Lofoten and Romsdalen in Norway. A total of 586 km of classified tracks are now available online to the public (Varsom 2019c).

1.2 Objectives

The objective of this paper is to expand on the manual ATES mapping and manual route classification in Norway, and develop an automatic algorithm for high spatial resolution ATES mapping for all of mainland Norway. The resulting map was then compared to areas and linear features (popular ski tours) mapped by avalanche experts using a manual approach.

Our specific aim is to present the automated mapping methods, compare them to expert generated maps and demonstrate how this new approach can provide quantitative assessment of manually assessed areas and routes, to increase consistent and reproducible ATES classification across different regions in Norway, or globally.

1.3 Study area

This study covers the mainland of Norway including islands in close proximity to the coastline. In total, 365,246 km^2 of terrain is mapped stretching from 58° N to 71° N and 5° E to 31° E (Fig. 1). The land surface is ranging from sea level to 2469 m a.s.l. and there is snow on the ground for a minimum of 3–8 months as a function of latitude and elevation. The landscape has a large variation of terrain and vegetation types due to its large range in latitude and longitude, as well as distance from the sea.

The NAWS produces daily avalanche forecasts for mainland Norway for 21 A-rated regions (Fig. 1) and 21 B-rated regions. Daily avalanche forecasts are published every day for all A-rated regions from 1st of December until 31st of May, and these forecasts are based on regular manual field observations of snow and avalanches using Regobs (Engeset et al. 2018). Avalanche forecasts are published for B-rated regions, if the weather forecast indicates the likelihood of an avalanche danger rating of high (4) or very high/extreme (5).

In northern Norway in Troms County, three popular ski touring mountains were manually mapped by avalanche experts using zonal ATES, collectively covering 25.3 km^2. These areas are Fagerfjellet, Gabrielfjellet and Skittentinden (Fig. 1). Furthermore, three popular ski-touring regions have been mapped in Troms (41 routes, 191 km), together with Lofoten (30 routes, 113 km) and Romsdalen (52 routes, 281 km). All in all 123 routes with a summarized route length of 586 km are analyzed. A portion of each region, with examples of the ATES regional mapping and mapped linear features, is shown in Fig. 1. The regions are characterized by a mountain fjord landscape with steep mountains and u-shaped valleys

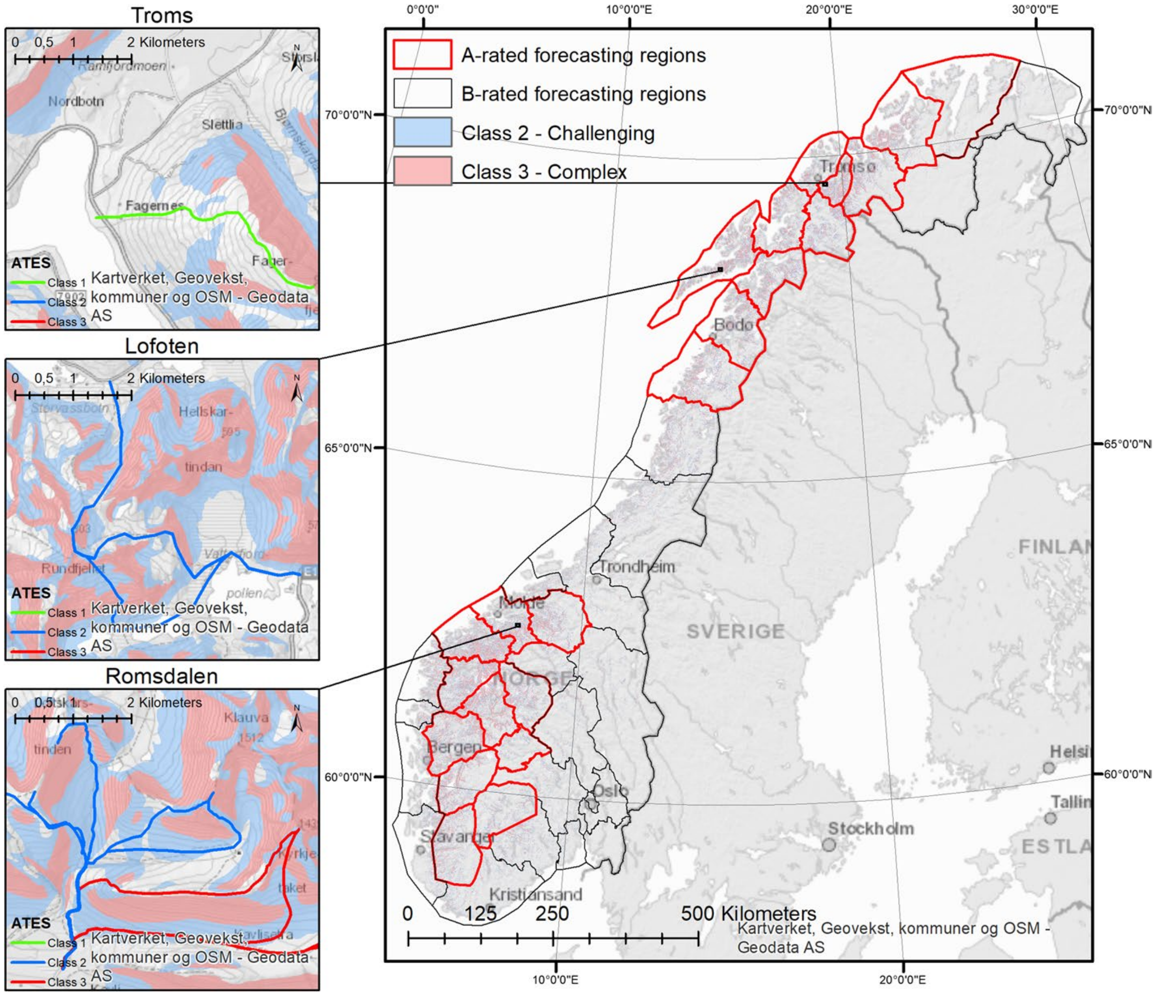

Fig. 1 ATES v.1.04 mapped for all of Norway where Challenging and Complex terrain is colored in blue and red, respectively. The Norwegian Avalanche Warning Service (NAWS) A- and B-rated forecasting regions are shown on the map (right). A portion of each case study region for Troms, Lofoten and Romsdalen are shown from the top, on the left

as a result of glacial erosion. The mountains rise from sea level to 1000–1500 m a.s.l. The elevation of the tree line decreases with latitude, from approximately 800 m a.s.l. in Romsdalen in the South to approximately 300 m a.s.l. in Troms in the North.

1.4 ATES

The ATES model was designed to easily communicate the avalanche terrain complexities and risks to novices. To do so, the model is divided into two separate components, a public communication model and a technical model. The technical model is used to guide experts using 11 parameters to categorize a route into a public communication model consisting of three classes; Class 1 “Simple”, Class 2 “Challenging”, or Class 3 “Complex” (Statham et al. 2006). The public model is only a text-based classification of a linear route. However, Statham et al. (2006) suggest that a future goal would be to apply this model spatially. Delparte (2008) made the first attempt to apply this model spatially, and identified slope angle and forest density as the most important factors. During the period 2009–2012, 4000 km^2 of avalanche terrain was mapped spatially using the qualitative method designed for linear routes. Campbell et al. (2012)

identified problems in this method and stated the need for a more quantifiable model, as well as the need for a non-avalanche terrain class. Having identified slope angle and forest density as the most important factors, 2000 km^2 of manually mapped terrain in British Colombia Canada was analyzed so that empirical thresholds could be quantified. As a result of this study, a set of terrain and vegetation thresholds (Table 1) were proposed as a model for mapping with the ATES model (Campbell and Gould 2013).

In Canada, as of 2013 over 8000 km^2 of terrain has been ATES mapped at the basin scale of 100 m to 1 km (Campbell and Gould 2013). This approach is useful for recreational trip planning or industrial planning operations, but not for detailed route finding in complex terrain, where a spatial scale of 20–30 m is needed. Larger scale (i.e., higher resolution) maps are therefore needed for more detailed route decision-making (Schweizer 2003; Thumlert and Haegeli 2017). To address this deficiency, several different approaches have been utilized so far. Using a 30-m DEM, Gavaldà et al. (2013) and NVE (2014) spatial mapped areas in Spain and Norway using a manual approach from the qualitative and linear ATES v1.04 model (Statham et al. 2006). In contrast, using observed terrain use of professional ski guides, Thumlert and Haegeli (2017) showed that it is possible to derive ATES empirically at a 20-m scale. Finally, Schmudlach and Köhler (2016) proposed a new method for an automated ATES classification at a 10-m scale; however, this model is not validated. They suggested that for the spatial ATES classification to become widely implemented, a fully automated algorithm would need to be developed.

2 Methods and data

2.1 Development of an automated ATES algorithm

2.1.1 Digital terrain model

A digital terrain model (DTM) for Norway was downloaded from the Norwegian Mapping Authority in the nationwide 10 × 10 m raster model (Kartverket 2013). The coordinate system EUREF89 Universal Transverse Mercator Zone 33, 2d + NN54, one of Norway's official coordinate systems, was used. The vertical standard deviation of the DTM used is ± 4 to 6 m and the scale is 1:10,000 (Kartverket 2013).

2.1.2 Slope

A slope raster was delineated according to the thresholds for open terrain proposed by Campbell and Gould (2013) in ESRI ArcMap 10.6. All slope angles above 40° were assigned class 3 (complex); values between 40° and 25° were assigned class 2 (challenging). Slope inclines below 25° were assigned class 1 (simple) and the optional class 0 (non-avalanche terrain) threshold was applied at 15°. Areas with slope angles below 15° could still be assigned a higher terrain class if the subsequent steps in the analysis showed this terrain to be in the runout of an avalanche path. The delineated classes were then exported as a shapefile for each class (Fig. 3).

Table 1 Proposed model for mapping with the Avalanche Terrain Exposure Scale

	Class 0 (optional)	Class 1 (simple)	Class 2 (challenging)	Class 3 (complex)
Slope incline[a] and forest density[b]				
Open	99% ≤ 20°	90% ≤ 20° 99% ≤ 25°	90% ≤ 30° 99% ≤ 45°	< 20% ≤ 25° 45% > 35°
Mixed	99% ≤ 25°	90% ≤ 25° 99% ≤ 35°	90% ≤ 35° 99% ≤ 45°	
Forest	99% ≤ 30°	99% ≤ 35°	99% ≤ 45°	
Starting zone density	No start zones	No start zones with ≥ Size 2 potential. Isolated start zones with < Size 2 potential	No start zones with > Size 3 potential Isolated start zones with ≤ Size 3 potential, or several start zones with ≤ Size 2 potential	Numerous start zones of any size, containing several potential release zones
Interaction with avalanche paths[c]	No exposure to avalanche paths	Beyond 10-year runout extent for paths with ≥ Size 2 potential	Single path or paths with separation Beyond annual runout extent for paths with > Size 3 potential	Numerous and overlapping paths of any size. Any position within path
Terrain traps[d]	No potential for partial burial or any injury	No potential for complete burial or fatal injury	Potential for complete burial but not fatal injury	Potential for complete burial and fatal injury
Slope shape	Uniform or concave	Uniform	Convex	Convoluted

Proposed model for mapping with the Avalanche Terrain Exposure Scale (Campbell and Gould 2013; CAA 2016)

[a]Slope inclines are averaged over a fall-line distance of 20–30 m

[b]Open: < 100 stems/ha or > 10.0 m tree spacing on average. Mixed: 100–1000 stems/ha or 3.2–10.0 m tree spacing on average. Forest: > 1000 stems/ha or < 3.2 m tree spacing on average

[c]Position within paths based on the runout extent for avalanches with a specified return period

[d]Terrain traps are features in tracks or runouts that increase the consequences of being caught in an avalanche. Thresholds are based on the potential increased consequences they would add to an otherwise harmless avalanche. For this purpose, terrain traps can be thought of as either trauma-type (e.g., cliffs, trees, boulders, etc.) or burial-type (e.g., depressions, abrupt transitions, open water, gullies, ravines, etc.). Degrees of burial used in this model are based on Canadian standard avalanche involvement definitions (CAA, 2014)

2.1.3 Potential release area

To calculate the avalanche path start zone density (Table 1), the potential release area (PRA) algorithm is used (Veitinger and Sovilla 2016a, b). The algorithm uses three criteria; slope, wind shelter index and roughness, as calculated from the input parameters; a DTM, average snow depth, and main wind direction (optional, but not used in this analysis) (Fig. 2). Using a 10-m DTM, the roughness criteria are neglected due to the coarse scale, as the script is optimized for a 2-m DTM (Veitinger and Sovilla 2016b). The PRA algorithm is written in the programming language R (R Core Team 2017). Important functions are accessed by the RSAGA package (Brenning 2008), connecting to the open-source SAGA GIS software (Conrad et al. 2015). The PRA output is an ASCII raster file assigning values between 0 and 1 for each cell, with higher values suggesting an increased likelihood of avalanches to release. In this paper, values below 0.05 are not considered to be a starting zone. The values between 0.05 and 1 were exported as a shapefile and assigned class 3 (Fig. 3).

Slope angles between 28 and 60° are considered to be possible release areas. Therein slope angles between 35° and 45° are assigned the largest membership value. On each side, the membership values decrease and slope angles below 30° and above 50° are assigned low membership values.

The wind shelter index, which is also a PRA calculation, is used instead of a curvature measure. Wind-exposed terrain have negative values and are assigned low membership values, wind-sheltered terrain have positive values and are assigned high membership values.

The roughness factor is derived from the neighboring tiles in the raster in a 3×3 window. Given that we are using a 10 m DTM, the scale of the roughness factor is therefore averaged over a line of 30 m. Planar and smooth terrain are assigned low roughness values and high membership values because these are more prone to avalanche. Rough surfaces are assigned high roughness values and are less likely to avalanche (Veitinger and Sovilla 2016a, b).

2.1.4 Avalanche runout

To estimate the potential avalanche runout, the hydrologic terrain analysis software TauDEM and TauDEM toolbox for ESRI ArcMap (Tarboton 2005) were used to derive interaction with avalanche paths identified from the DTM (Table 1). TauDEM is a suite of tools that can compute the avalanche runout length when a specified alpha angle is

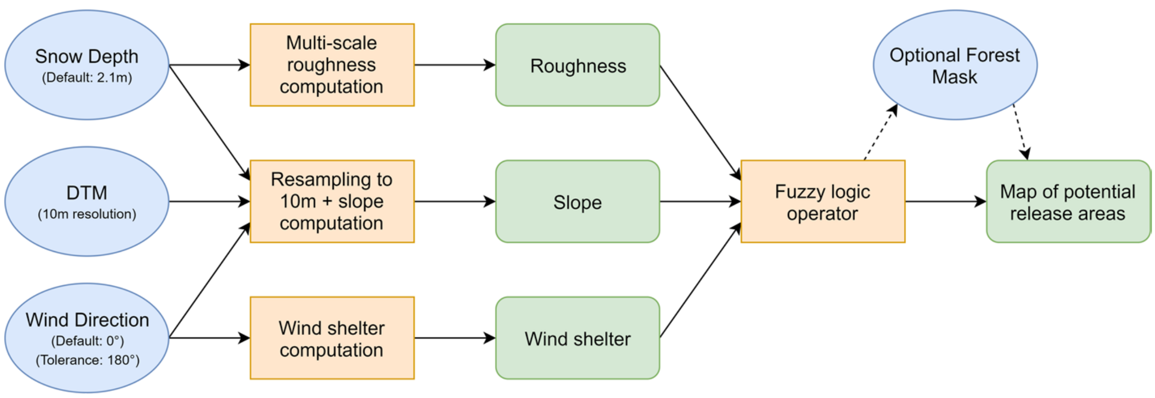

Fig. 2 Flowchart of the PRA algorithm (modified from Veitinger et al. 2016)

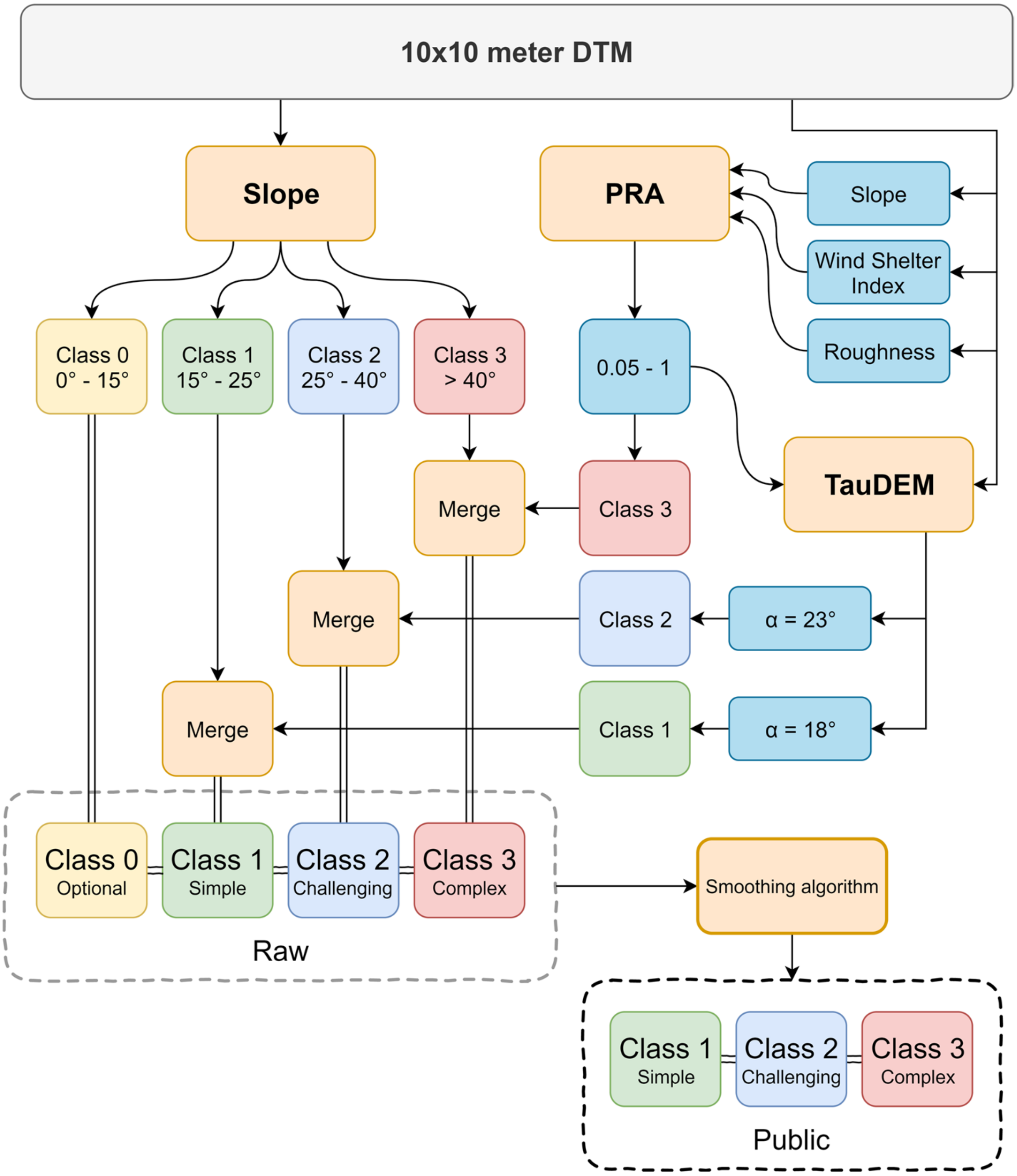

Fig. 3 Flowchart showing all processing steps of the automated ATES algorithm (v.1.0)

provided. The D-Infinity Avalanche is a function tool in TauDEM, which may be used to detect all locations downslope of a given starting cell(s) until a given alpha angle from the starting cell is reached (Tarboton 2013). In the algorithm, avalanche runouts were calculated for using the tools from TauDEM and chosen alpha angles. These runout alpha angles were based on studies of return periods of avalanche runouts in Norway (Lied and Bakkehøi 1980).

The advantage of using the alpha angle to estimate the runout length is that it is a powerful input variable to fine tune the algorithm runout estimations for different regions and climates. Lied and Bakkehøi (1980) undertook empirical studies on 423 well-known maximum extents of avalanche events in Norway. They found that 100% of avalanches stop within an alpha angle of 18° and 95% stop within 23°. Due to this, all runouts within an 18° alpha angle would be classified as simple terrain. Avalanches do not normally run that far downslope, so a 23° runout angle was set as the threshold for challenging terrain, having more frequent avalanches.

2.1.5 Large-scale ATES mapping

ATES mapping was first conducted for three small areas; Fagerfjellet, Gabrielfjellet and Skittentinden (approx. 25 km^2) in Troms county. These three areas were selected to permit direct comparison to the manual, expert-guided ATES mapping that had already been completed (NVE 2014). However, to go from the mesoscale (mountain) to macroscale (whole of Norway), the entire process had to be automated for efficient processing. All steps were automated in a script using Python 2.7 (Larsen 2019a, Fig. 3). To increase the efficiency of processing, the entire study area of Norway had to be divided into several smaller tiles. To eliminate the potential of having avalanche runouts stop along the borders of these tiles before they were modeled to their full runout potential, all tiles were created using watershed boundaries. With the available processing power, it was found that smaller tiles (<4000 km^2) were possible to process (using a desktop computer with 32 GB RAM, HDD and 3.6 GHz Intel Core i7 processor). The study area was divided into 395 watershed tiles with a given feature identification (FID) number, tiles were then processed one at a time following the list of FID numbers in a.bat file. The advantage of using this method is that if the processing of one tile was incomplete, the computer skipped to the next tile and the incomplete tile could be reprocessed at a later stage. The processing time for the entire mainland Norway was approximately 500 h.

2.1.6 Merging and generalization

The resulting "raw" output from the automated ATES algorithm is at very high spatial resolution compared to the previously mapped areas with ATES and includes some noise as a result of smaller terrain features. With the current DTM accuracy with a standard deviation error of up to 4–6 m, these resulting maps could be interpreted at a higher resolution than intended. To address this issue of the perception of increased accuracy due to this greater precision from the DTM, the resulting layers needed to be smoothed, such that smaller areas are combined into the adjacent ATES classes to produce a more generalized "public" version of the ATES mapping.

In the public available maps from Varsom (2019c), we use a smoothing factor of 500 m using the PAEK algorithm (Bodansky et al. 2002) as well as removing all polygons smaller than 25,000 m^2, assigning them the surrounding class value (Larsen 2019b). This final dataset which is exposed to the public is equivalent to the finer scale resolution that Avalanche Canada use in their manual ATES maps, which are presented at a 100–1000 m scale (Campbell and Gould 2013). However, the current version of the algorithm (v1.0, 2020), which is available to the public online has a scale lock set at 1:100,000, where further zooming in on this layer results in the layer disappearing from view.

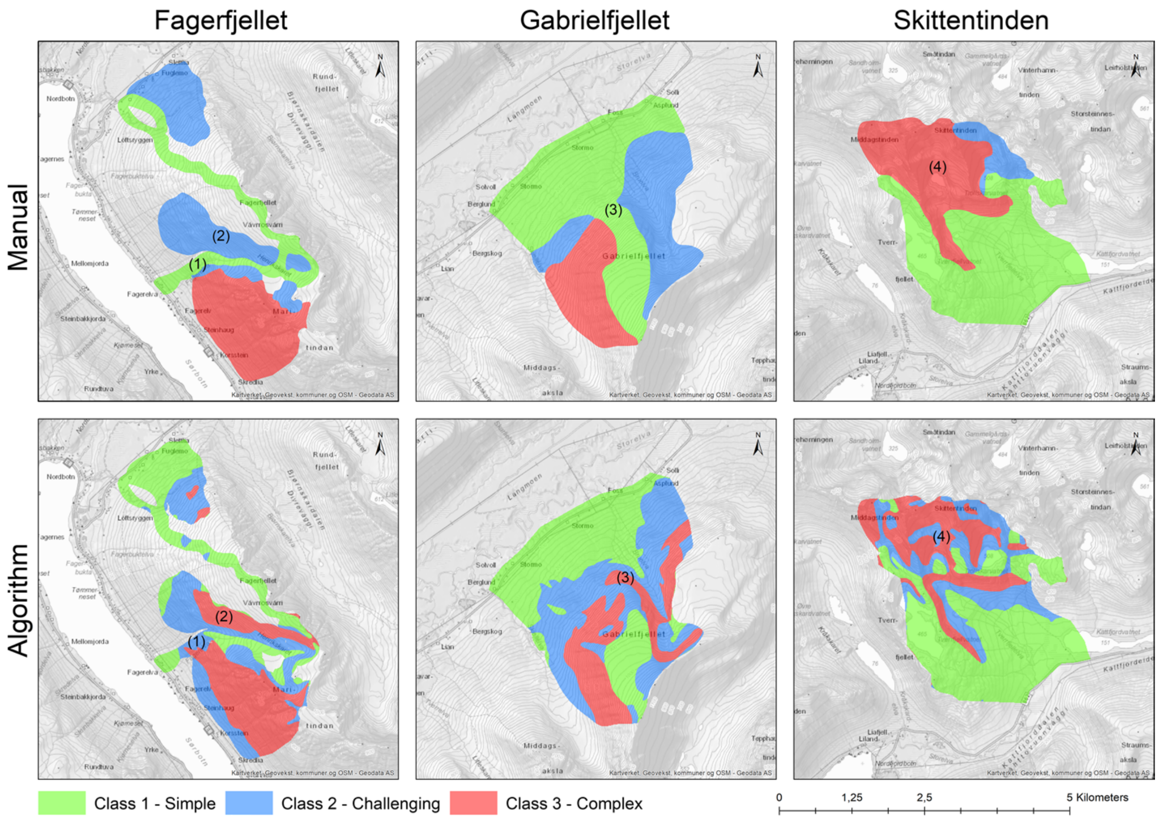

Fig. 4 The three case study areas Fagerfjellet, Skittentinden and Gabrielfjellet used to evaluate the ATES algorithm's performance (v.1.0). The upper three maps are from the NVE (2014) manual mapping, while the lower three maps are the output from the automated algorithm explained in this paper. The numbers in the figure are reference points mentioned in the discussion

2.2 Methods for model validation and comparison

2.2.1 Spatial validation

To assess how robust the automated ATES algorithm is, we compare it with manual ATES classification published by NVE in 2014 from the three mountains in Norway; Fagerfjellet, Skittentinden and Gabrielfjellet (Fig. 4). The spatial extent of the manual ATES classification maps is used to clip out a relevant area from the automatic ATES map, such that these rasters are equal in area and extent. Then, for each class in the manual ATES classification, the percentage agreement with each class in the automatic ATES map is plotted in a bar plot. This is then repeated for each class at each site, resulting in a total of 9 bar plots (Fig. 5).

2.2.2 Linear validation

Manual classification of ATES tracks is less complex and time consuming to map for an avalanche expert compared to spatial maps; therefore, a lot more data are available for comparison to the automatic ATES maps. Before the 2018/2019 season, NVE recruited one avalanche expert with local knowledge from each area of interest to map the mountains in their region using the ATES classification scheme. A GIS web tool in the browser

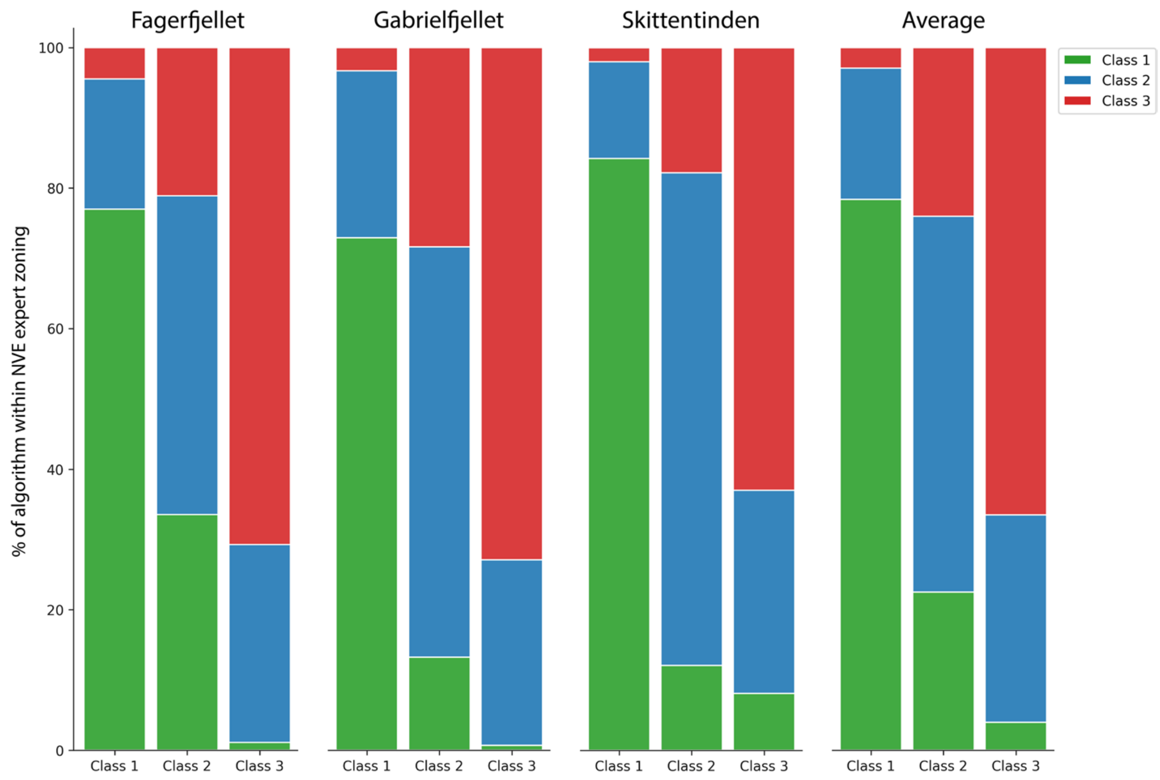

Fig. 5 Visual illustration of the percentage agreement score presented in Table 2

was created, making it easy for the experts to draw and classify each route. In the end of the project, they reviewed each other's work. In total, NVE classified 586 km of tracks from 123 different routes in the Troms, Lofoten and Romsdalen regions (regions are shown in Fig. 1). The Norwegian ATES classification differs slightly from the original version emphasizing cornices more and includes a class 0 (non-avalanche) terrain (Varsom 2019b). To compare these results against the spatial automated ATES maps, all manually classified tracks were sorted by their region and class value. Then, the tracks were split into points every 10 m. For each point, the corresponding value from the automated ATES map raster was extracted, and the resulting data were compared against each other. The results are presented in a table showing the percent agreement score for each class.

3 Results

In total, 365,246 km^2 of terrain was ATES mapped in Norway using our automated algorithm. This represents 100% of the total land area of mainland Norway including all of the 22 forecasting regions. Of this total area, 71% was non-avalanche terrain (class 0), 13% was simple terrain (class 1), 9% was challenging terrain (class 2), and 7% was complex (class 3). Since April 2019, the data are publicly available via a map-based online tool for trip planning on this webpage (Varsom 2019c).

3.1 Algorithm spatial performance

To assess the spatial properties of the new automated ATES algorithm, we compared the results to expert-guided maps classified by NVE (2014) for three areas in Troms county

Table 2 Percentage agreement score for each case study location comparing the manual NVE classification and the automated ATES algorithm

	Automated ATES (%)		
	Class 1	Class 2	Class 3
NVE expert spatial			
Fagerfjellet			
Class 1	**77.01**	18.54	4.45
Class 2	33.55	**45.33**	21.12
Class 3	1.11	28.17	**70.72**
Gabrielfjellet			
Class 1	**72.90**	23.78	3.32
Class 2	13.25	**58.39**	28.37
Class 3	0.82	32.35	**88.83**
Skittentinden			
Class 1	**84.22**	13.77	2.01
Class 2	12.10	**70.09**	17.82
Class 3	8.10	28.92	**62.98**
Average			
Class 1	**78.38**	18.72	2.92
Class 2	22.51	**53.45**	24.04
Class 3	4.00	29.51	**66.49**

Bold values represent the percentage agreement values where both the automated and manual systems provided the same ATES class

(Fagerfjellet, Skittentinden and Gabrielfjellet). A visual comparison of the manual maps vs. the automated algorithm is shown in Fig. 4 and the result of the comparison in Fig. 5.

The manual expert classification was undertaken by NVE in 2014 also considered forest density, terrain traps and interaction with avalanche paths, something which the current version of our automated ATES algorithm does not. Future work will address this deficiency once forest density layers at the appropriate scale are available. As such, areas below 300–350 m a.s.l. may be incorrectly classified in some locations as a result of the lack of forest cover consideration in the automated ATES version.

To measure the performance of the automated ATES algorithm compared to the expert-guided NVE maps, we use a simple agreement percentage to assess the algorithm performance. These values are presented in Table 2 and Fig. 5.

3.2 Algorithm linear route performance

To assess the performance of the new automated ATES algorithm, we compared the automated ATES data to 586 km of linear tracks from 123 expert-guided routes classified by NVE in 2019. These linear routes were manual classified and accounted for forest, which the current version of our automated ATES algorithm does not. For this reason, all areas with forest are removed from this analysis, and only "open" terrain is considered. For Romsdalen, this represented approx. 60% of all classified terrain, whereas for Lofoten and Troms, this represented approx. 80% of all classified terrain. We used a coarser forest layer (Gjertsen and Nilsen 2012), which only provided binary data of forest or open (and not density and vegetation type, which would be needed for full implementation into ATES),

Table 3 Percentage agreement score comparing 586 km of manually classified linear routes and the automated ATES algorithm (if more hazardous than the manual classification, marked in italics)

	Automated ATES (%)		
	Class 1	Class 2	Class 3
NVE expert linear			
Troms (191 km)			
Class 1	91.67	*6.29*	*2.04*
Class 2	61.43	35.66	*2.91*
Class 3	60.86	25.52	13.62
Lofoten (113 km)			
Class 1	90.77	*7.69*	*1.53*
Class 2	59.53	37.44	*3.03*
Class 3	44.04	42.82	13.14
Romsdalen (281 km)			
Class 1	88.30	*11.23*	*0.47*
Class 2	52.22	41.53	*6.24*
Class 3	34.29	55.92	9.79
Average			
Class 1	90.52	*8.00*	*1.48*
Class 2	57.10	38.53	*4.37*
Class 3	43.14	45.43	11.43

which permitted removal of these areas from this analysis. To measure the performance of the algorithm compared to the expert-guided NVE maps, the agreement percentage is again used to assess the algorithm performance. These values are presented in Table 3. Given the conservative nature of the manual ATES classification of these routes, we have highlighted (in italics) the % of terrain that the automatic ATES algorithm categorizes as more hazardous than the manual classification.

4 Discussion

4.1 Comparison to other avalanche mapping work

Various other automated models have been proposed to create ATES maps. Schmudlach and Köhler (2016) developed an algorithm that computes a 10-m continuous ATES map based on the statistical likelihood of human-triggered avalanches. A drawback with this method is that it is solely based on expert judgement without validation against other referenced ATES mapping (e.g., Statham et al. 2006) or ATES mapping (e.g., Campbell and Gould 2013). Thumlert and Haegeli (2017) developed a mapping algorithm from the movement of professional ski guides. They developed an ATES map with a spatial resolution of 20 m and showed that it was possible to make an ATES map based on observed terrain use from professional ski guides. However, they acknowledge that the method has several limitations including having to decide whether the skied terrain was a wise decision or not, and therefore to determine whether to include it in the dataset or not. The method is also computationally expensive and only derived from one snow climate over two seasons, making it vulnerable if applied for different climates and wildly different terrain types. In an alternative approach to mapping avalanche terrain, Harvey et al. (2018) developed avalanche terrain maps by combining avalanche terrain characteristics similar to our study, but then utilized multiple parameterizations of the RAMMS model to estimate runout distances. This method was used to make nationwide avalanche maps for Switzerland. They concluded that ATES was not appropriate for the European Alps because of too many trips being classified as “complex”, and they ending up creating a new classification. The output was both a continuous and discrete map providing information of the consequences of traveling in avalanche terrain. Barbolini et al. (2011) proposed a new methodology to perform avalanche hazard mapping over large areas. This method combine two modules; (1) used to define potential release areas based on slope, morphology and vegetation, and (2) a runout algorithm (AFRA) which provides an automatic definition of areas that could be affected by an avalanche. We believe that our approach, using an automated algorithm makes it possible to map large areas at a low cost using the well-known and pragmatic ATES classification scheme. The algorithm only needs a DTM as input and can be adjusted for different climates using different alpha angles, making it very versatile.

4.2 Algorithm spatial performance

To create an automated algorithm for ATES terrain classification, it is challenging to use the qualitative classification (v1.04) proposed by Statham et al. (2006). Therefore, the quantitative model proposed by Campbell and Gould (2013) is used. It is primarily derived from slope incline and land forest density, but the model additionally emphasizes start zone density, interaction with avalanche paths, terrain traps and curvature (Table 1).

When we apply our algorithm to open terrain, we can efficiently map terrain as per the thresholds proposed by Campbell and Gould (2013). In specific, when we compare our algorithm-based ATES map results with the more generalized manual ATES maps as produced by avalanche experts, we see that the algorithm-based maps are explicit in their classification (Fig. 4). Comparing the manual ATES maps with the thresholds from Campbell and Gould (2013), it was found that they were more generous in their classification and added more adjacent terrain to the classification, yielding a smoother, more generic ATES map than the algorithm approach. This first phase of manual ATES mapping was an early pilot project and as we see in Sect. 3.2, the later manual mapping is more consistent with our automated algorithm. Figure 4 shows that the algorithm produces a broadly similar spatial pattern as the NVE classification. Specifically for Fagerfjellet (Fig. 4, (1)), the long narrow corridor in the lower middle is identified in both maps. Some small areas of this corridor are determined as challenging by the algorithm, but these areas are located below the tree line and would possibly be classified down to simple terrain if a forest density mask was included. Above this corridor (Fig. 4, (2)), NVE has classified the area as simple and challenging terrain. The algorithm identified this as a potential start zone, and therefore been classified as complex. Likewise, for Gabrielfjellet (Fig. 4, (3)), the algorithm produces a broadly similar spatial pattern as the NVE classification, with the marked exception of an area of complex terrain in the algorithm-based map, where the manual map has classified this as simple terrain. This difference can likely be attributed to a section of cliffs that was overlooked in the pilot manual mapping project, while the algorithm identified this feature, leading to a higher class. Finally, for Skittentinden (Fig. 4, (4)), the algorithm produces a broadly similar spatial pattern as the NVE classification but with more nuanced spatial patterns differentiating challenging from complex terrain in the upper half of the mapped area. However, this increased spatial resolution expressed in this nuanced pattern is likely not helpful for the user because these pockets of challenging terrain are not useable without prior exposure to adjacent complex terrain. As evidenced by these three case study examples, and checked in multiple other areas throughout Norway, the algorithm works well for open terrain. However, with the limitation of not explicitly accounting for forest density, which the expert-guided maps do, there is an expected difference in the classification matrix for areas with mixed and forest terrain. Fortunately, for many areas in Norway most recreational ski touring occurs well above the treeline (e.g., in Troms and Romsdalen approximately 60–80% of the distance of the individual mapped tours are above the treeline). However, due to these limitations, the algorithm maps should not be compared directly with the manual ATES maps, but rather compared more broadly to assess if the resulting patterns are consistent with the manual expert mapping. Using this approach, it is clear that the algorithm is producing similar ATES results as the manual method, but with more nuanced details for terrain classifications. Furthermore, the ATES results are conservative results due to the exclusion of forest cover parameters.

4.3 Algorithm linear route performance

Directly comparing the algorithm-based ATES map and the manually categorized ATES linear routes is also complicated and with only moderate explanatory power. We do not expect an ATES linear route of "simple" to be 100% simple, but we do expect the vast majority of it to be in simple terrain. As we see in our results (Table 3), the values for agreement between the algorithm-based ATES map and the linear route for simple terrain range from 88 to 92%, suggesting that the vast majority of the route is within the simple class. However, one-tenth of a simple route is within challenging or complex terrain, suggesting either that our classification of simple terrain is either to conservative, or the experts from NVE are too generous in their classification.

Likewise, we assume that for "challenging" linear routes, that the majority of the route is in simple to challenging terrain, whereas very little should be in complex terrain. In our results, we get values of between 2 and 6% in complex terrain, suggesting that 94–98% of challenging routes are within terrain that the algorithm classifies as simple to challenging terrain. For "complex" terrain, we are unable to repeat this analysis because only a small fraction of a route can result in a manual classification of complex (e.g., 10% for Romsdalen region), even though most of the route is in simple or challenging terrain.

For validation of challenging terrain, we rely on the spatial comparison in Sect. 3.2, manual spot checks of areas clearly representing challenging terrain, and with knowledge that the algorithm performs within the thresholds proposed by Campbell and Gould (2013). In general, the linear tracks show broadly consistent results across all three regions and classes, suggesting that the experts from NVE do not display any regional bias in their classification of manual ATES routes. Furthermore, we see that the percentage agreements are very high for simple and challenging terrain, which is encouraging for the algorithm-based ATES maps. The challenge with this analysis is that we are unable to assess which of the methods, if any, is 100% accurate, so a direct comparison and direct interpretation of these results are problematic. Despite this, we see that the algorithm is producing ATES maps that compare very favorably, and in some cases produce more realistic maps than the manual ATES mapping approaches for both spatial- and route-based applications.

4.4 Limitations

While we are encouraged by the results of this algorithm, urge caution in their use due to a number of limitations. Slope angle is identified as the most important factor for ATES delineation. Using the thresholds proposed from Campbell and Gould (2013), it was possible to divide the terrain into rough classes early in the processing. It was found that when using the non-avalanche threshold of 20°, simple terrain was neglected, to avoid this, the threshold was lowered to 15° in the automated ATES algorithm. However, the consequences of mapping thousands of square kilometers as non-avalanche terrain with only minimal case study validation, and high public use, could lead to dangerous scenarios. Therefore, it was decided to remove the non-avalanche terrain entirely from the publicly available maps until a robust vegetation layer is available, and appropriate safety margins can be applied. A nationwide high-resolution DTM from aerial light detection and ranging (LIDAR) will be available in 2022 (Kartverket 2019), which will permit high-resolution assessment terrain, and greatly improve the current algorithm.

The second most important factor in the method is the forest density parametrization. Implementing this into the algorithm should be uncomplicated based on the published thresholds dividing the density into open, mixed and forest (Table 1). At this stage, however, it has not been implemented in the current algorithm due to the lack of reliable forest density data for Norway at the relevant spatial scale. Options such as the area resource map (AR5) have been considered, but the accuracy of the data is limited (Gjertsen and Nilsen 2012). Norwegian Institute of Bioeconomy Research (NIBIO) is working on a high-resolution forest resources' map (SR16) which is produced by automatic modeling of AR5, DTM, aerial LIDAR and photogrammetry data (NIBIO 2019). When this dataset becomes available nationwide, it could be implemented in the algorithm to account for the effect of forest on avalanches. Quantifying the effect of forest density for each region, we found that in Romsdalen, approximately 40% of the length of the mapped manual routes are within areas with mixed forest or forest, as compared to Lofoten and Troms where forest only covered approx. 20% of the total route length. Thus, it is more likely that the automated algorithm is correct at higher latitudes where the forest is less extensive, and the vegetation elevation is lower. Routes with a large percentage of forested terrain would however receive a conservative classification due to the exclusion of the forest parameter.

To account for start zones, the PRA script developed by Veitinger et al. (2016) is used. To calculate the release areas, the script uses the three parameters: slope, wind shelter index and roughness. This script was optimized for a 2-m DTM, but both a finer and coarser scale DTM could be applied (Veitinger et al. 2016). Currently, a 10-m DTM is the best available resolution for mainland Norway and is therefore used. In practice, the roughness parameter is currently being neglected due to the coarse scale of the DTM. The automated ATES algorithm has also been successfully applied at Nordenskiöld Land at a 5-m DTM resolution without doing any changes to the script. To account for downslope and cross-slope curvature, the wind shelter index is used. Numerous studies show that wind shelter index from a DTM can accurately reflect the accumulated snow patterns (e.g., Schirmer et al. 2011; Winstral et al. 2002). Despite these limitations, this automated algorithm and the workflow presented provide a tangible first step forward toward fully automated and consistent and reproducible ATES mapping. Future advancements will refine and improve this algorithm over time.

5 Conclusion

This paper presents a fully automated algorithm that is able to produce a high-resolution nationwide ATES map for Norway from a DTM. Validating the new ATES maps with regions that had expert-guided ATES maps and linear routes as produced by NVE showed high consistency in all regions, when only open terrain was considered. For forested areas, which comprise the minority of avalanche terrain assessed, we get mixed results. Thus, future work should focus on incorporating vegetation data at the appropriate spatial resolution when it becomes available to further improve the automated ATES algorithm. However, a large percentage of the Norwegian backcountry terrain is above the tree line (approx. 80% for Troms and ~ 60% for Romsdalen), thus the current algorithm is already a helpful tool for expert-guided mapping and as recreational trip planning tool. The automated algorithm is also useful to increase the consistency between different experts mapping ATES manually in different regions of Norway. Finally, another advantage of using an automated approach, in contrast to expert-based methods, is the reproducibility of the mapping and future updates and improvements can easily be performed.

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AutoATES v2.0: Automated Avalanche Terrain Exposure Scale mapping

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Abstract. Avalanche risk assessment is complex and challenging, with terrain assessment as one of the most fundamental factors. To aid people's terrain assessment, Parks Canada developed the Avalanche Terrain Exposure Scale (ATES), a system that classifies the severity of avalanche terrain into five classes from non-avalanche terrain to extreme terrain. Manual classification is laborious and dependent on expert's assessments. To ease the process Larsen et al. (2020) developed an automated ATES model (AutoATES v1.0). Although the model allowed large-scale mapping, it had some significant limitations. This paper presents an improved AutoATES v2.0 model improving the potential release area (PRA) model, utilizing the new Flow-Py runout simulation package. Furthermore, it incorporates forest density data in the PRA, in Flow-Py, and in a newly developed post-forest-classification step. AutoATES v2.0 has also been rewritten in open-source software, making it more widely available. The paper includes a validation of the model measured against two consensus maps made by three experts at two different locations in western Canada. For Bow Summit, the F_1 score (a measure of how well the model performs) improved from 64 % to 77 %. For Connaught Creek, the F_1 score improved from 40 % to 71 %. The main challenge limiting large-scale ATES classification is the determination of optimal input parameters for different regions and climates. In areas where AutoATES v2.0 is applied, it can be a valuable tool for avalanche risk assessment and decision-making. Ultimately, our goal is for AutoATES v2.0 to enable efficient, regional-scale, and potentially global ATES mapping in a standardized manner rather than based solely on expert judgment.

1 Introduction

Snow avalanches lead to a yearly average of 140 fatal accidents in Europe and North America (Techel et al., 2016, 2018; Birkeland et al., 2017). More than 90 % of fatal avalanche accidents are related to recreational activity and triggered by the victim or someone in their party (Schweizer and Lütschg, 2001; Techel and Zweifel, 2013; Engeset et al., 2018). This means that avalanche accidents are not random but rather a result of less-than-optimal decisions. Strengthening people's ability to make better decisions by raising awareness and providing information and education is important and may ultimately save lives. To do so, many countries have established avalanche forecasting services (Engeset et al., 2018). However, despite access to updated avalanche forecast, the complexity and variability of the of the snowpack still leaves avalanche risk management a complex task. The inherent lack of feedback from the environment also turns avalanche terrain into a wicked learning environment (Fisher et al., 2022). Reliable information and decision-making support are therefore crucial. The most efficient method to mitigate the avalanche hazard is to choose appro-

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priate terrain for the given avalanche conditions (Thumlert and Haegeli, 2018).

Assessing avalanche terrain may be intuitive for avalanche professionals (Landrø et al., 2020); however, this may not be the case for recreational users of avalanche terrain. To aid non-professional terrain assessment Parks Canada developed the Avalanche Terrain Exposure Scale (ATES v1.0). This is a terrain classification system to communicate the potential exposure to avalanches and thus how difficult avalanche management would be in different types of terrain (Statham et al., 2006). The complexity of avalanche terrain is the result of interactions of multiple release areas, tracks, and deposition areas. Within these three areas, other factors like, for example, terrain traps or forest density, could make terrain management more complex due to a more severe outcome.

Originally, ATES v1.0 categorized popular backcountry routes into three levels: simple (1), challenging (2), and complex (3). With the growing adoption of ATES, its application expanded beyond individual routes to spatial zones, such as the initiative by Avalanche Canada, which mapped several thousand square kilometers of avalanche terrain (Campbell and Gould, 2013). An update to the system led to ATES v2.0, which introduced two new classes: non-avalanche terrain (0) and extreme (4). This revised version also expanded the scope of ATES to include spatial representations like zones, areas, and corridors. The updated scale is referred to as ATES v2.0, and a more thorough description can be found in Statham and Campbell (2023). ATES classification has been used to provide guidelines for terrain use linked to people's specific avalanches management skills (CAA, 2016) or for recreational purposes (Campbell and Gould, 2013; Thumlert and Haegeli, 2018; Larsen et al., 2020; Schumacher et al., 2022). ATES mapping has also been used to describe backcountry users' terrain preferences recorded by GPS (i.e., Hendrikx et al., 2022; Johnson and Hendrikx, 2021; Sykes et al., 2020).

The development of ATES maps for Avalanche Canada from 2009 through 2012 was done using a combination of manual mapping and a GIS-assisted workflow (Campbell and Gould, 2013). ATES zoning was labor intensive, relied heavily on expert judgment, and as a result ATES maps were typically only available in high-use areas. Campbell and Gould (2013) identified the limitations of this method and presented a more quantifiable zonal model that could leverage GIS tools for more systematic terrain classification. An automated model to classify avalanche terrain would need the following components: (1) a model of potential release areas (PRAs) for avalanches and (2) a runout simulation, which is an estimation of where and how far an avalanche would slide.

The first attempt at a fully automated ATES model was made by Larsen et al. (2020) using a combination of the zonal and technical model of ATES (Campbell and Gould, 2013; Statham et al., 2006). Larsen et al. (2020) developed an automated ATES (AutoATES v1.0) model that was able to make ATES zones for all of Norway, using only a digital elevation model (DEM) as input. This simple approach to terrain characteristics does not take overhead exposure into account, and the performance of the simple avalanche runout simulation is also insufficient in flatter terrain. In addition, the model did not account for forest density, which has been found to be one of the most important factors for ATES classification (Delparte, 2008; Schumacher et al., 2022). A final challenge was that the model was heavily dependent on proprietary software (Larsen et al., 2020), thereby increasing the monetary and computing costs to operate the model and limiting open-source access.

1.1 Improving potential release areas (PRA) model

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

1.2 Improvements for runout simulations

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

Two of the most common process-based simulation tools for avalanche hazard assessment are the RAMMS (Christen et al., 2010) and Samos-AT (Sampl and Zwinger, 2004) models. Both models are made to simulate an accurate prediction of avalanche runout distances, flow velocities, and impact pressures in a 3-dimensional space. These models are typically calibrated towards known avalanches with long return periods and define potential avalanche terrain. These models are suitable for avalanche terrain zoning, where the aim is to divide the potential avalanche terrain into different zones. Across large spatial areas such as regional forecast areas or entire countries, these models are less suitable. Even though the computational power required to apply the process-based models over large areas is a factor, it could be done at regional scales (e.g., Bühler et al., 2022).

In contrast to the process-based models, data-based models are computationally inexpensive and can more easily be applied to large geographic areas. A common data-based method to delineate avalanche runout is applying the classical runout angle concepts and path routing in 3-dimensional terrain (D'Amboise et al., 2022). Comparison of the model results to more computationally expensive simulation type models shows that they respond adequately for the delineation of broad-scale terrain classification.

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

Recently, D'Amboise et al. (2022) presented a new customizable simulation package (Flow-Py) to estimate the runout distance and intensity of dense core avalanches (not considering powder clouds). The model utilizes persistence-based routing instead of terrain-based routing, enabling the simulation to respond appropriately to flat or uphill terrain. Where the D-infinity model only considers flow direction, the Flow-Py model also considers flow process intensity. Both models use the same stopping criteria to estimate the runout distance by defining the alpha angle from the initial starting cell.

2 Model development

The main objective of the AutoATES v2.0 model is to improve large-scale spatial ATES mapping, update the mapping to reflect recent changes in ATES v2.0, and improve the model workflow. For AutoATES v2.0 to be a viable option for large-scale ATES classification, the model performance should be at least as accurate as manual mapping.

2.1 Implementation

To secure a broad adaptation of the new AutoATES model, it is important that the model is open-source and easy to use. The v1.0 model was written using proprietary software. We have resolved this by rewriting the entire v2.0 model into the programming language Python using widely available and open-source modules. The AutoATES v2.0 model is available on GitHub (Toft et al., 2024).

2.2 Input data

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

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

2.2.1 Percent canopy cover

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

2.2.2 Stem density

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

2.2.3 Basal area

The basal area is a unit used to describe the sum of the cross-sectional areas of all trees within a given space, specifically those in the dominant, co-dominant, and high intermediate positions within the forest canopy. It is a measure of the density of trees and is quantified in square meters per hectare (Sandvoss et al., 2005). The advantage with basal area over canopy cover and stem density is that it incorporates the size of trees in addition to the number of trees and is a more direct measurement of the density of the forest vegetation.

The basal area value can have any value starting from zero upwards. While theoretically, there is no upper limit to this value, practically it is generally capped at around $60\,\mathrm{m}^2\,\mathrm{ha}^{-1}$ to reflect realistic forest conditions.

2.3 Model components

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

2.3.1 PRA

The PRA model uses a Cauchy membership function to determine the importance of each parameter. A Cauchy membership value reflects how strongly an input variable belongs within a certain set (Jang and Sun, 1997). A Cauchy membership value must be defined for each input variable (Eq. 1).

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

where $\mu(x)$ is the Cauchy membership value; x is an input variable (e.g., slope angle, wind shelter, or forest); and a, b, and c are parameters which control the weight of each input variable. We use the membership values suggested by Veitinger et al. (2016) for slope angle and wind shelter while using the value suggested by Sharp (2018) for stem density (Fig. 2). In our modified version of the PRA model (v2.0), we have chosen to remove the roughness parameter due to the scale issues with 5–30 m cell sizes (the original PRA model was made to work with a 2 m cell size). The removal of roughness makes it less ideal for higher-resolution DEMs (< 5 m cell sizes); see Sect. 4.1.4 for a discussion around this. We have also defined new membership functions for canopy cover and basal area based on input from Parks Canada avalanche experts and through testing of the AutoATES model on our two study areas. These values could be fine-tuned for specific datasets and applications to improve the performance of the PRA model.

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

$$\begin{aligned}\mu_{\mathrm{PRA}}(x) &= \gamma \cdot \min\left(\mu_{\mathrm{s}}(x), \mu_{\mathrm{w}}(x)\mu_{\mathrm{f}}(x)\right) \\ &\quad + \frac{(1-\gamma)+\left(\mu_{\mathrm{s}}(x), \mu_{\mathrm{w}}(x)\mu_{\mathrm{f}}(x)\right)}{3} \\ &\quad x \in X, \gamma \in [0,1],\end{aligned} \tag{2}$$

with three fuzzy sets slope angle $\mu_{\mathrm{s}}t(x)$, wind shelter $\mu_w(x)$, forest density $\mu_{\mathrm{f}}(xt)$, and with γ defined in Eq. (3) as

$$\gamma = 1 - \min\left(\mu_{\mathrm{s}}(x)\mu_{\mathrm{w}}(x)\mu_{\mathrm{f}}(x)\right). \tag{3}$$

The PRA output is a continuous layer ranging between 0 (not likely) to 1 (very likely). Most data-based runout models need release areas in a binary format where 0 is no potential release areas, while the potential release areas are encoded as 1. To convert the PRA layer to a binary format, we select a cutoff threshold ($\mathrm{PRA}_{\mathrm{threshold}}$) where all pixels above this value are included in the potential release area for the runout modeling. We found the $\mathrm{PRA}_{\mathrm{threshold}}$ from Larsen et al. (2020) to be too conservative for our study areas and have therefore increased the value to 0.15. The $\mathrm{PRA}_{\mathrm{threshold}}$ could be adjusted depending on whether frequent or more extreme avalanche scenarios are of interest.

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

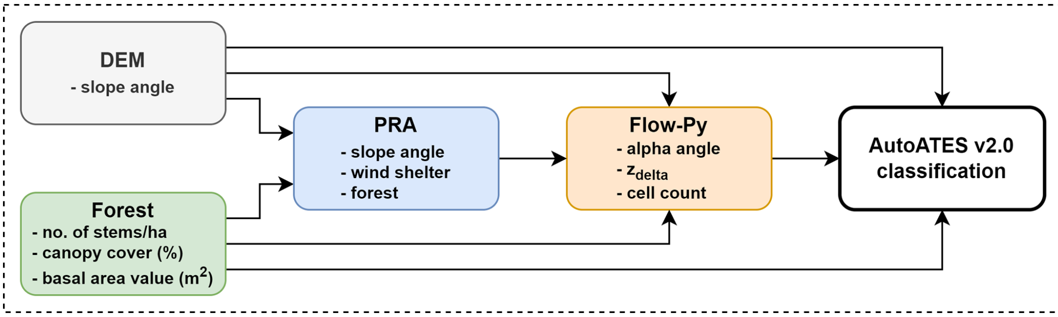

Figure 1. The main components of the AutoATES v2.0 model. First, a pre-processing step is completed to calculate all the necessary raster layers using PRA and Flow-Py. Finally, the AutoATES classifier is used to assign the final ATES classifications.

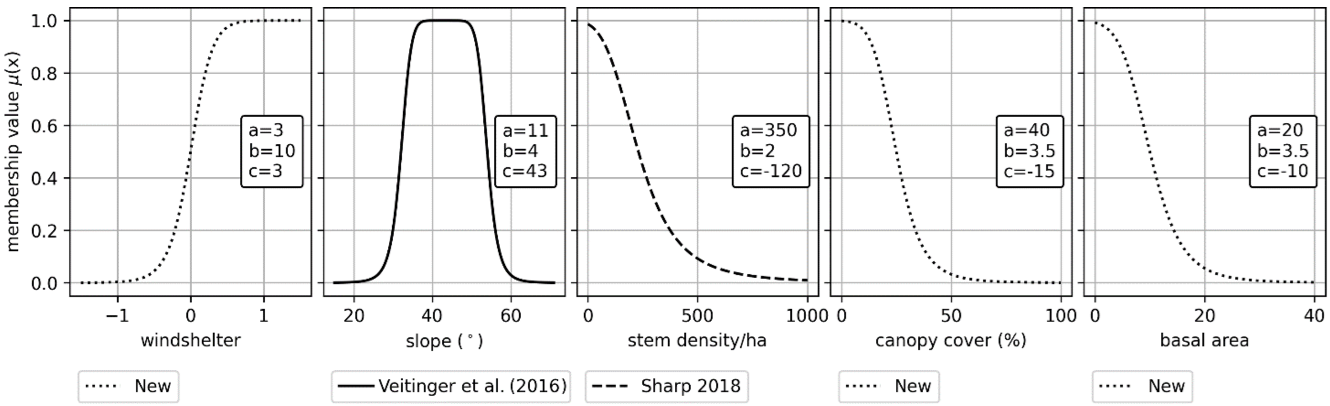

Figure 2. The different Cauchy functions used by Veitinger et al. (2016) and Sharp (2018) for slope angle and stem density. The values a, b, and c are inputs for the Cauchy membership value (Eq. 1). We have suggested new membership values for wind shelter, canopy cover (%), and basal area. We recommend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

2.3.2 Avalanche simulation

The Flow-Py model developed by D'Amboise et al. (2022) is used for the avalanche simulation of the potential track and deposition area. Flow-Py is a dense core model; thus AutoATES v2.0 is based on dense core runout extents and does not consider powder clouds. It is similar to the TauDEM model utilized in AutoATES v1.0, which uses the alpha angle to limit the flow (Larsen et al., 2020; Tarboton, 1997). Flow-Py also includes a flow process intensity parameter, which makes it able to handle mass movement in flat and uphill terrain, significantly improving the output compared to AutoATES v1.0. Another advantage of the Flow-Py model is the additional output layers, which represent the overhead exposure. We utilize the cell count and z_{delta} layer by scaling the two layers from 0–100 and taking their average value, which represents the overhead exposure layer. In the AutoATES v2.0 model it is possible to select cell count, z_{delta}, or both to represent the overhead exposure. The layer enables us to quantify the exposure from different release areas at every raster cell. We use the forest detrainment module of Flow-Py, which makes it possible to use forest density as an input layer to limit spreading and runout distance. An in-depth description of the Flow-Py simulation package can be found in D'Amboise et al. (2022).

2.3.3 AutoATES classifier

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

- slope angle (calculated from the DEM)
- forest density (provided by the user, as per Sect. 2.3.1–2.3.3)
- PRA (calculated from the DEM and forest data)
- runout distance as a function of alpha angle (calculated from PRA and Flow-Py)
- overhead exposure (cell count, z_{delta} or both) (calculated from PRA and Flow-Py).

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

Input parameter	Class	Range	Encoding
Slope angle threshold (SAT)	Simple (1)	< 18°	SAT12 = 18°
	Challenging (2)	18–28°	SAT23 = 28°
	Complex (3)	28–39°	SAT34 = 39°
	Extreme (4)	> 39°	
Alpha angle threshold (AAT)	Simple (1)	< 24°	AAT12 = 24°
	Challenging (2)	24–33°	AAT23 = 33°
	Complex (3)	> 33°	
Overhead exposure (OE)	Simple (1)	< 5	OE12 = 5
	Challenging (2)	5– 0	OE23 = 40
	Complex (3)	> 40	
Island filter size (ISL_{size})			30 000 m^2

Table 2. The recommended input parameters for AutoATES according to Sykes et al. (2023). The encoding is the same for all three forest types, but the forest input type can be defined by a string in the AutoATES script.

Input parameter	Class	Range	Encoding
Canopy cover (%)	Open	0–20	TREE1 = 20
	Sparse	20–55	TREE2 = 55
	Moderate	55–75	TREE3 = 75
	Dense	75–100	
Stem density (no. of stems per ha)	Open	0–100	TREE1 = 100
	Sparse	100–250	TREE2 = 250
	Moderate	250–500	TREE3 = 500
	Dense	> 500	
Basal area ($m^2\ ha^{-1}$)	Open	0–10	TREE1 = 10
	Sparse	10–20	TREE2 = 20
	Moderate	20–25	TREE3 = 25
	Dense	> 25	

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

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

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

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

2.4 AutoATES outputs

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

- continuous PRA
- Flow-Py raw outputs (D'Amboise et al., 2022)
- preliminary ATES classification of slope angle
- preliminary ATES classification of runout distance

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

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

– preliminary ATES classification of overhead exposure

– forest density criteria

– AutoATES v2.0

– AutoATES v2.0 with island size filter.

2.5 Model validation

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

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

We use the metrics accuracy, precision, recall, and F_1 score to evaluate the performance of the model. These metrics provide a more detailed assessment, accounting for class imbalance and varying prediction results. They have been widely used in various fields, including avalanche literature (e.g., Keskinen et al., 2022). For a more in-depth understanding of these metrics and their sources, see Liu et al. (2012), who provides a comprehensive review of evaluation metrics for classifiers.

3 Results and validation

3.1 Model accuracy

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

We use a confusion matrix for each study area to compare the ATES benchmark, which serves as the ground truth, against the results generated by the AutoATES v2.0 model (Table 4). The confusion matrices enable us to evaluate the performance of the AutoATES v2.0 model by calculating various metrics, such as accuracy, precision, recall, and F_1 score. For Bow Summit, the model performs well for simple terrain with 91.97 % accuracy, but the accuracy for challenging terrain is much lower at 65 %. Complex terrain and extreme terrain are closer to the average, both with an accuracy of 79 % (Table 4). The accuracy distribution between the four classes is slightly different for Connaught Creek. The v2.0 model performs the worst in simple terrain with an accuracy of 63 %. Challenging terrain has an accuracy of 71.0 %, complex has an accuracy of 78.0 %, and extreme terrain has an accuracy of 83 % (Table 4).

3.2 Ablation study

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

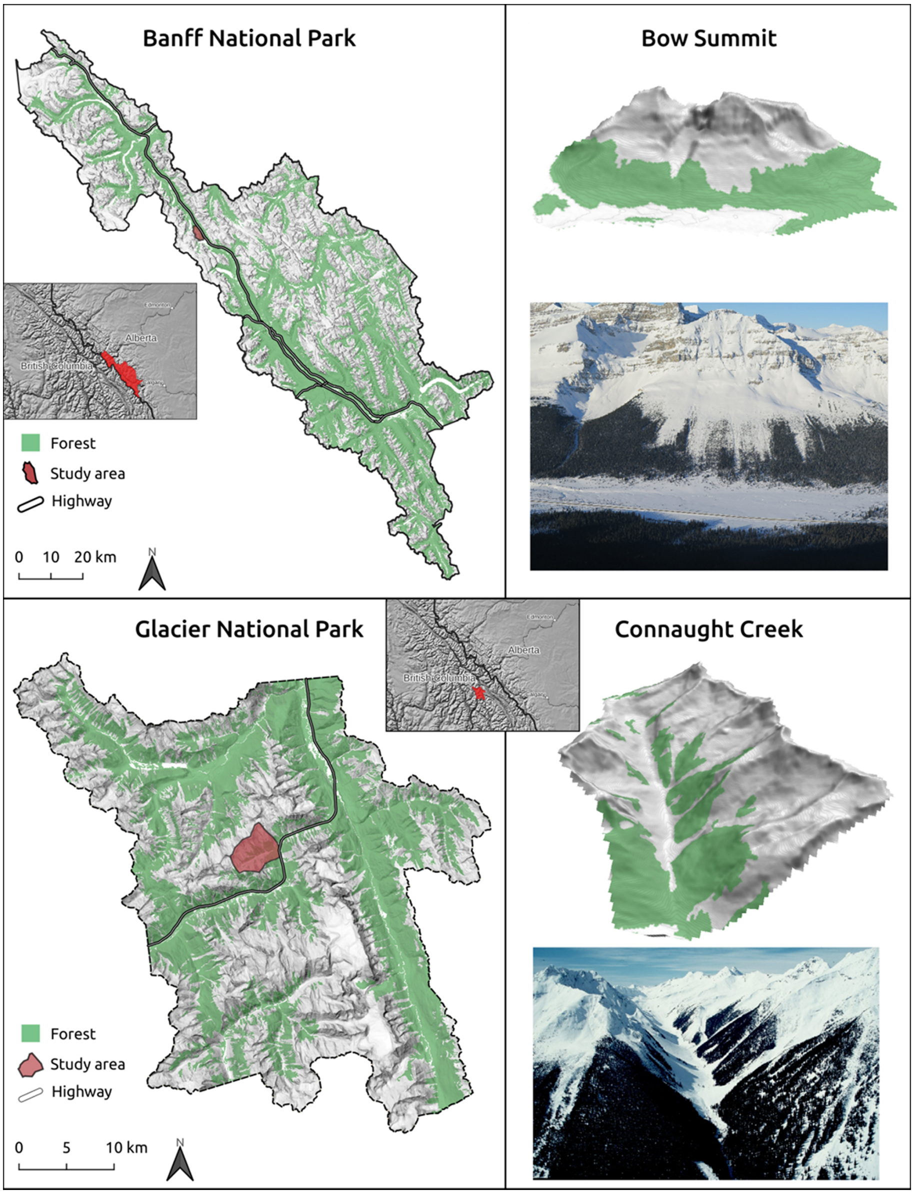

Figure 3. Two areas where benchmark maps for the updated ATES are available in Glacier National Park and Banff National Park. An overview of the greater area with the study areas in 3D view and overview photo (adapted from Sykes et al., 2023).

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

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

1. Train or develop the full model or system with all its components and parameters intact and measure its performance on a given task or dataset.

2. Systematically remove or disable one component or parameter at a time, keeping the rest of the model unchanged.

3. Measure the performance of the modified model without the removed component or parameter.

4. Compare the performance of the modified model to the performance of the original, complete model.

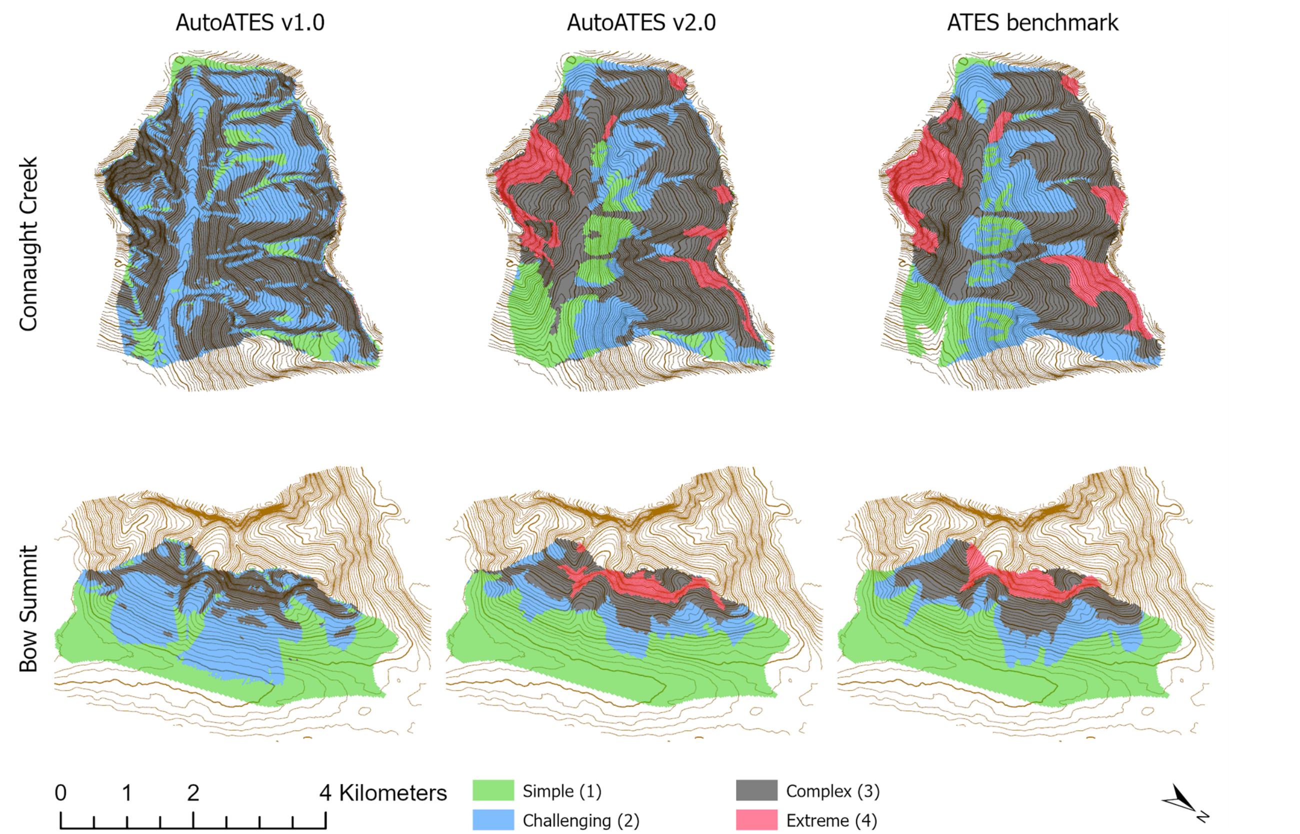

Figure 4. A visual comparison between AutoATES v1.0, v2.0, and the ATES benchmark maps for Connaught Creek and Bow Summit using the European ATES color scheme (Statham and Campbell, 2023). AutoATES v1.0 does not use the extreme (4) class.

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

		AutoATES v2.0			
		Simple (1)	Challenging (2)	Complex (3)	Extreme (4)
Bow Summit					
ATES benchmark	Simple (1)	4 527 848 m^2 (91.97 %)	140 608 m^2 (10.78 %)	16 900 m^2 (1.01 %)	0 m^2 (0.00 %)
	Challenging (2)	391 404 m^2 (7.95 %)	852 436 m^2 (65.34 %)	179 816 m^2 (10.75 %)	0 m^2 (0.00 %)
	Complex (3)	4056 m^2 (0.08 %)	310 960 m^2 (23.83 %)	1 316 172 m^2 (78.70 %)	110 188 m^2 (21.03 %)
	Extreme (4)	0 m^2 (0.00 %)	676 m^2 (0.05 %)	159 536 m^2 (9.54 %)	413 712 m^2 (78.97 %)
Connaught Creek					
ATES benchmark	Simple (1)	1 364 844 m^2 (63.31 %)	263 640 m^2 (10.64 %)	76 388 m^2 (1.03 %)	0 m^2 (0.00 %)
	Challenging (2)	683 436 m^2 (31.30 %)	1 757 600 m^2 (70.96 %)	884 208 m^2 (11.92 %)	676 m^2 (0.05 %)
	Complex (3)	102 752 m^2 (4.77 %)	449 540 m^2 (18.15 %)	5 787 236 m^2 (78.00 %)	237 276 m^2 (17.01 %)
	Extreme (4)	4732 m^2 (0.22 %)	6084 m^2 (0.25 %)	671 944 m^2 (9.06 %)	1 156 636 m^2 (82.94 %)

5. Repeat steps 2–4 for each component or parameter of interest.

For AutoATES v2.0, we have identified six components of the model that have been developed since v1.0. Using the concepts of an ablation study approach, we have calculated the precision, recall, and F_1 score by removing different components of the model (Table 5). The reference model is the final AutoATES v2.0. A lower F_1 score for a model compared to the reference indicates that an important component has been removed. In Bow Summit, the most impor-

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

	Version	Component removed	Pixel accuracy	Precision	Recall	F_1 score	F_1 score change
Bow Summit	v1.0*		67.40 %	68.75 %	66.07 %	64.06 %	−13.24 %
	dev1*	SAT34 threshold	87.63 %	78.74 %	76.05 %	81.81 %	4.51 %
	dev2	AAT23 threshold	84.20 %	82.82 %	80.97 %	77.16 %	−0.14 %
	dev3	Forest data from PRA v1.0	78.40 %	78.6 %	75.90 %	70.21 %	−7.09 %
	dev4	Forest data from PRA v2.0	76.80 %	71.29 %	70.61 %	68.03 %	−9.27 %
	dev5	Flow-Py (back to TauDEM)	79.10 %	69.82 %	68.99 %	72.66 %	−4.64 %
	dev6	Post-forest classification	80.30 %	73.38 %	72.12 %	75.49 %	−1.81 %
	v2.0	Reference	84.40 %	75.74 %	76.19 %	77.30 %	0.00 %
Connaught Creek	v1.0*		49.44 %	40.21 %	38.70 %	38.70 %	−32.68 %
	dev1*	SAT34 threshold	80.20 %	72.43 %	74.73 %	72.79 %	1.41 %
	dev2	AAT23 threshold	74.70 %	73.65 %	70.89 %	71.30 %	−0.08 %
	dev3	Forest data from PRA v1.0	71.80 %	71.23 %	64.12 %	66.71 %	−4.67 %
	dev4	Forest data from PRA v2.0	72.70 %	73.33 %	64.68 %	67.73 %	−3.65 %
	dev5	Flow-Py (back to TauDEM)	65.50 %	66.78 %	67.55 %	65.87 %	−5.51 %
	dev6	Post-forest classification	59.90 %	56.40 %	48.20 %	48.30 %	−23.08 %
	v2.0	Reference	74.90 %	73.80 %	70.94 %	71.38 %	0.00 %

* AutoATES v1.0 and dev1 use the old ATES v1.0 framework with three terrain classes, which could lead to higher F_1 scores. See Sect. 4.1.1 for an in-depth discussion.

tant component is the inclusion of forest data in the PRA model (dev4). In Connaught Creek, the most important factor is the post-forest classification (dev6). In general, all new components in AutoATES v2.0 improve the model by several percent, except the inclusion of the alpha angle threshold between challenging and simple terrain (dev2), which only improves by 0.08 %–0.14 % for the two study areas.

4 Discussion

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

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

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

4.1 Model performance

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

4.1.1 Extreme terrain (dev1)

The first modification to the AutoATES v2.0 model was to include the extreme terrain class from ATES v2.0. We incorporated the new class by including another slope angle threshold (SAT). We measured the importance of this change by using the results from the ablation study (Table 5, dev1). The result is that the ablated model performs better with regards to F_1 score (e.g., 4.51 % improvement for Bow Summit and 1.41 % for Connaught Creek) than the reference model. This means that excluding the SAT34 threshold (e.g., complex/extreme threshold) increases the accuracy of the model. However, without it, the model would be using the old ATES v1.0 classification excluding extreme terrain. This implies that excluding the SAT34 threshold enhances the model's numerical accuracy. Nonetheless, its absence would cause the model to employ the outdated ATES v1.0 classification, which does not account for extreme terrain and therefore diminishes its value for ATES v2.0.

When working with classification problems, decision boundaries are the borders or thresholds that separate different classes (Lee and Landgrebe, 1993). The complexity of the decision boundaries often depends on the number of classes. When there are fewer classes, the decision boundaries tend to be simpler, as there are fewer regions to separate in the feature space. With simpler decision boundaries, the model may have an easier time making accurate predictions, as there is less chance of overfitting or incorrectly assigning data points to the wrong class. This could lead to higher precision, recall, and ultimately higher F_1 scores. We believe the fewer classes in the ATES v1.0 is the reason why it performs better than the ATES v2.0 reference model.

4.1.2 Terrain traps (dev2)

To improve the model's ability to identify terrain traps such as depressions and gullies, another alpha angle threshold (AAT) was added to be included in complex terrain. The previous model only had AAT thresholds, which defaulted terrain into simple and challenging terrain. The extra component was added in the early stages of the development of AutoATES v2.0. The ablation analysis shows that this change has very little effect on the overall performance of the model (Table 5, dev2) with a 0.14 % decrease for Bow Summit and 0.08 % for Connaught Creek. This method would not help in modeling other common terrain traps such as cliffs, crevasses, and forests. We have not made any attempts to model other types of terrain traps because we believe it would have a very limited effect on the overall performance given our spatial resolution.

4.1.3 Forest data in PRA (dev3 and dev4)

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

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

4.1.4 Roughness in PRA

The PRA was initially developed and optimized for a 2 m DEM, while we utilize a 10 m DEM as the default. If roughness were calculated using a 10 m DEM, it would measure the roughness at basin scale, instead of the roughness at the slope scale (Blöschl, 1999; Blöschl and Sivapalan, 1995). The roughness is also dependent of a snow depth value, which is impossible to define without assessing the snowpack properties at a given time. Sykes et al. (2023) demonstrate minimal value in running AutoATES v2.0 using high-resolution DEMs (< 5 m). Sykes et al. (2023) further illustrate the impact of DEM scale on ATES mapping. We have therefore chosen to remove the roughness parameter from our version of the PRA model.

4.1.5 Flow-Py (dev5)

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

4.1.6 Post-forest classification (dev6)

Even though the inclusion of forest density in the PRA model improved the performance of AutoATES, we found the need to reclassify sections that were obviously densely forested and resulted in a higher ATES rating than needed. To improve this, we added a post-forest classification criterion. This was efficient for Connaught Creek but less efficient for Bow Summit (Table 5, dev6) (1.81 % decrease for Bow Summit and 23.08 % for Connaught Creek). The forest impact of dev6 is minimal at Bow Summit but important for Connaught Creek. The reason for this is unclear, but one hypothesis is that there is more steep forested terrain in Connaught Creek, and the model therefore relies more on the post-forest classification. Connaught Creek also has more large runouts and overhead hazard that rely on the post-forest classification.

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

4.1.7 Discrepancies

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

4.2 Application

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

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

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

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

Large-scale application

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

4.3 Limitations

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

In the context of large-scale ATES classification (e.g., Norway, 385 207 km^2), Flow-Py becomes computationally heavy, which may present challenges when processing large datasets or applying the model in real-time applications. We executed the Flow-Py algorithm across all of Norway on an Amazon Web Services Elastic Cloud Compute Instance (AWS EC2 c6g.metal), which took 30 d to complete at a cost of USD 1600. This could potentially limit the scalability and accessibility of the model for certain use cases and users with limited computational resources.

Determining the optimal input parameters for the AutoATES model is important to get the best performance possible. The suitability of these parameters across different snow climates and terrain types remains an open question. Further research and validation are needed to ensure that the chosen parameters provide accurate and reliable results in various contexts. Users should not adopt the input parameters stated in this paper.

The model does not account for changes in vegetation over time such as natural events like landslides or forest fires. Therefore, it is important to update the ATES mapping periodically to account for major changes in the landscape.

Due to the limited sample size of mapped class 0 terrain in the validation datasets that we used to develop AutoATESv2.0, we do not feel that there has been sufficient research on this topic to warrant publication at this time. AutoATES is a promising tool for estimating areas with no exposure to avalanche terrain; however there is significant liability associated with deeming an area safe from avalanche hazard. Further development of the autoATESv2.0 model and consultation with avalanche community stakeholders is necessary before delving into automated mapping of class 0 terrain.

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

5 Conclusion

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

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

Code and data availability. To reproduce the results from this study, please find the AutoATES v2.0 model and validation data from the ablation study in the OSF repository (https://doi.org/10.17605/OSF.IO/ZXJW5, Sykes et al., 2023. For future application of AutoATES v2.0, a GitHub repository (https://github.com/AutoATES, Toft et al., 2024) will be maintained with future iterations of the model available (Toft et al., 2024).

Author contributions. HBT was the developer of the first version of automated ATES. The model improvement has been led by HBT with substantial contributions from JS and AS. The ablation study has been carried out by HBT with inputs from JS. HBT prepared the final manuscript with input from AS and JS. JH and AH contributed with review and edits as their role as supervisors. All authors contributed to the final manuscript.

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Challenges of Using Signaling Data From Telecom Network in Non-Urban Areas

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Outdoor recreation continues to increase in popularity. In Norway, several avalanche fatalities are recorded every year, but the accurate calculation of a fatal accident rate is impossible without knowing how many people are exposed. We attempted to employ signaling data from telecom networks to enumerate backcountry travelers in avalanche terrain. Each signaling data event contains information about which coverage area the phone is connected to and a timestamp. There is no triangulation, making it impossible to know whether the associated phone is moving or stationary within the coverage area. Hence, it is easier to track the phone's movement through different coverage areas. We utilize this by enumerating the number of people with phones traveling to avalanche-prone terrain for the 2019-2020 winter season. We estimated that 13,666 phones were in avalanche terrain during the season, ranging from 0 to 118 phones per day with an average of 75 phones per day. We correlated the number of phones per day against amount of daylight (R^2=0.186, p < 0.01), weekends and holidays (R^2=0.073, p < 0.01), and number of bulletin views (R^2=0.045, p < 0.01). Unfortunately, the validation revealed discrepancies between the estimated positions in the mobile network and the true reference positions as collected with a GPS. We attribute this to the algorithm being designed to measure urban mobility and the long distance between the base transceiver stations in mountainous areas. This lack of coherence between the signaling data and GPS records for rural areas in Norway has implication for the utility of signaling data outside of urban regions.

Keywords *avalanche, risk, signaling data, telecom, non-urban areas*

The number of avalanche fatalities is generally well-documented (Thapa, **2010**; Willibald et al., **2019**), but obtaining a reliable measure of the total population (denominator) of people accessing avalanche terrain is difficult due to the open-access nature of these activities (Winkler et al., **2016**). However, there are multiple indirect proxies suggesting that backcountry travelers in avalanche terrain have increased in recent years (Birkeland et al., **2017**; Jekich et al., **2016**; Techel et al., **2016**; Winkler, **2015**). Backcountry travelers voluntarily expose themselves to avalanche risk during recreational activities such as skiing, snowboarding, snowshoeing, and snowmobiling (Johnson et al., **2020**).

If the entire population of backcountry travelers accessing avalanche terrain was known, it would be possible to calculate the likelihood of being killed by doing that activity in terms of micromorts. A micromort is a unit of risk, which denotes a one-in-a-million chance of death (Howard, **1984**). The calculation of micromorts is important as it would permit comparison to other recreational activities (e.g., skydiving, scuba diving and mountain biking) and a commensurate level of interventions, through targeted education and hazard awareness over time.

Several studies have tried to estimate the risk of death from recreational skiing, using such methods as rough estimates (Valla, **1984**), light barriers and counting at specific locations (Zweifel et al., **2006**), surveys (Sole & Emery, **2008**; Winkler et al., **2016**), and archived logs from mechanized skiing (Walcher et al., **2019**).

Take-home Message

We attempted to utilize signaling data to enumerate backcountry travelers in avalanche terrain. A representative sample would enable us to calculate the fatal accident rate. Unfortunately, the spatial validation revealed discrepancies between the estimated positions in the mobile network and the true reference positions collected with a GPS.

However, many of these methods only represent a crude measure of backcountry users for a small defined area, short time frame, or generalized survey data.

In Norway, an average of 6.5 avalanche fatalities have occurred per year over the last 10 years, but this has varied from 2 in the 2016-2017 winter season to 13 in the 2018-2019 season (Figure 1). While these fatalities provide some insight into avalanche risk, we are unable to estimate the fatality rate, as we do not have an estimate of the total number of people that expose themselves to this risk. Therefore, we are unable to assess if these changes in avalanche fatalities are due to changes in the number of people exposed, the snow cover, or the risk management. The latter is of great interest for avalanche forecasting services and educational institutions worldwide. Currently, no suitable methods exist to measure the effects of structured interventions, such as avalanche education or avalanche forecasting.

Furthermore, in the last 5 years, the trendline for avalanche fatalities has flattened out at approximately 6 fatalities (Figure 1, 10-year moving average). However, over this same period, we find it likely that there have been many more people in the mountains due to the increased popularity of backcountry travel. This increase is supported by various proxies, including the number of unique users accessing online avalanche forecasts (Engeset et al., **2018**). Therefore, does this increase in use and relatively steady count of fatalities suggest that the fatal accident rate has decreased over time? This is difficult to ascertain when we do not have a reliable base rate estimate of how many people are exposed to avalanche terrain every day or from year to year.

While our focus is on backcountry travelers in avalanche terrain, the same issue is shared by many other outdoor recreation activities, including but not limited to hiking, mountain biking, paragliding, trail running, and white-water kayaking. The fatalities and respective hazard-causing deaths are documented in all of these cases. The number of hours backcountry travelers expose themselves to avalanches, also known as the base rate, is absent (Johnson et al., **2020**; Kahneman & Tversky, **1973**). As such, a method to efficiently collect data on avalanche exposure is of value to the broader community of outdoor recreation.

Avalanches cause significant human and material losses (Schweizer, **2008**). Mitigation policies and prioritization require a qualitative basis from which to design strategies and allocate resources. WMO (**2021**) recommends a risk-based approach to warnings and mitigation (adopted by government agencies such as the Norwegian Water Resources and Energy Directorate) that requires base rate data. Due to the lack of exposure data, base rates are challenging to calculate in terms of people traveling in avalanche terrain. With base rate data, it is easier to understand which natural hazards need the most attention, the amounts of resources that are needed, and which measures are most efficient from a cost-benefit perspective.

The base rate information could also be used to validate whether an increase in objective danger correlates with avalanche danger levels. Winkler et al. (**2021**) calculated a relative risk between the danger levels, but without a base rate, they could not calculate the absolute risk (i.e., micromorts). Furthermore, without a valid base rate measure, Bayesian approaches, which utilize diagnostic tests (also known as stability tests) to assess avalanche decision-making, lack important input data (Ebert, **2019**; Techel et al., **2020**).

Given the ubiquitous use of mobile phones in Norway (Statista, **2021**), with 99.9% of the population having access to 4G coverage (MLGM, **2021**), there is a potential opportunity to obtain some insight into the total exposure to avalanche terrain. Telia, one of the largest mobile network operators (MNOs) in Norway, collects a vast amount of anonymized data through what is referred to as signaling data. Every time a phone communicates with a base transceiver station (BTS) (e.g., a phone

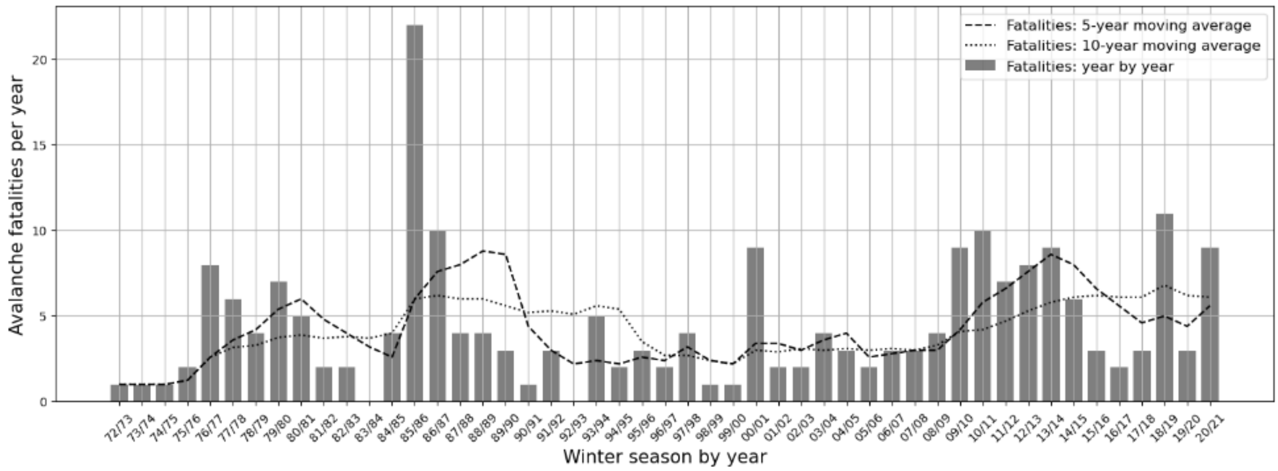

Figure 1 Recreational avalanche fatalities in Norway by winter season from 1972 to 2021 with a 5 and 10-year moving average (NGI, **2019**; Varsom, **2021**).

call, text message, or the phone itself checks for new emails), signaling data is generated. On average, a Telia subscriber generates around 300-400 active and passive signaling events a day, or roughly 15 events per hour. The vast amount of data collected makes it an appealing data source when studying human mobility (Zhao et al., **2016**).

During the last few decades, telecom data have been widely used in the research community. Many useful findings of human activity have been reported for urban areas (González et al., **2008**; Song et al., **2010**). To our knowledge, there is no research applying telecom data in non-urban areas other than Francisco et al. (**2018**). The reason for this could be the relatively lower density of BTSs in rural and mountainous terrain, with the majority located where people live, work, and travel (Zhao et al., **2016**).

Norway has a vast number of remote mountains, fjords, and islands. It is also among the least densely populated countries globally, with a population density of 15 people per square kilometer (UN, **2021**). Despite this, the MNOs in Norway have been ranked among the top 10 providers worldwide with respect to cell phone coverage for several years in a row (Speedtest, **2021**). As a result of the excellent coverage, most mountainous areas in Norway have full 4G coverage (Telenor, **2021**; Telia, **2021**), and therefore their signaling data are expected to have some utility in these areas.

In this study, we attempted to use anonymized and aggregated signaling data to count how many people expose themselves to avalanche terrain around Tromsø, Norway. We selected this area as historically, nearly 2/3 of all recreational avalanche fatalities in Norway occur in this county (Varsom, **2021**). However, because no one has been able to accurately estimate how many people enter avalanche terrain in this region, it is impossible to say whether this high number of fatalities is solely due to more users in the area, or if it is more dangerous to ski in the area around Tromsø compared to the rest of the country. Without the base rate information, we are unable to determine which of the two hypotheses is correct (Johnson et al., **2020**; Kahneman & Tversky, **1973**).

Secondly, we also want to use this method to help assess whether the fatal accident rate (FAR) from avalanches has increased or decreased during the last decade. Despite the number of avalanche fatalities over the last ten years having been relatively stable, there is a general agreement that there has been a significant increase in traffic amongst different groups of backcountry travelers in the same period. This view of increasing use is supported by a range of proxies, including the number of people seen in avalanche terrain, the number of vehicles at trailheads, and the sale of backcountry traveling equipment. This increase of use, combined with a relatively stable fatality count, suggests that the FAR has decreased during the last few decades (Techel et al., **2016**).

The challenges of determining the number of people exposing themselves to avalanche risk in the backcountry and calculating the risk of skiing in avalanche terrain, have been approached by several others using a range of imperfect methods. For example, Zweifel et al. (**2006**) used light barriers and voluntary registration boards at four sites near Davos, Switzerland. Using these methods, Zweifel et al. (**2006**) calculated the individual risk factor for this population and found it lower than the risk of driving a car. However, this was for very limited area of Switzerland, and represents an engaged and self-selecting audience that voluntarily provide registration information. There have also been several studies using GPS-tracking and surveys to assess terrain use (Buhler & Floyer, **2016**; Hendrikx & Johnson, **2014**; Hendrikx et al., **2016**; Sykes et al., **2020**; Thumlert & Haegeli, **2017**; Winkler et al., **2021**), but these studies are not representative for the whole population and are generally skewed towards more engaged and advanced users. Passive tracking of backcountry users with time-lapse camera technology has also been used (Saly et al., **2020**), but was also limited to a small geographic area. The use of telecom data for avalanche terrain is limited to a single study by Francisco et al. (**2018**), who undertook a case study to track backcountry users in the Sorteny valley, Andorra. They obtained access to raw call detail records (CDRs), including an estimated position for each record with an accuracy of 150 meters for a period of 20 days. From these CDRs, they created daily frequency plots and compared them with avalanche danger, temperature, wind, snow depth, solar radiation, and precipitation. Unfortunately, Francisco et al. (**2018**) did not provide any information regarding how the position (latitude, longitude) was established or validated.

Our study attempted to build on these prior studies and used truly anonymized signaling data from Telia Company to count the total number of backcountry users within one avalanche forecasting zone in northern Norway. We also explored how these counts changed in relation to known drivers of usage, including weekends and holidays, and variable environmental conditions.

Methods

Telia uses telecom network data, which is one of the most extensive and continuously generated datasets in society today. The network data exceeds billions of data points every day in each Nordic country. These are stored in the Telia database for billing, network optimization, and other purposes. However, in contrast to regular data services, Telia can safeguard that no individuals can be identified in the dataset, while still providing extrapolated national movement patterns that are statistically representative for the entire population and not just Telia subscribers.

Using signaling data, Telia can produce mobility insights through a GDPR-compliant method. They do this by never storing, processing, or exposing data that can identify an individual, and the smallest result generated is in groups of 5 individuals within the same movement chain (Ågren et al., **2021**).

Telia does not have the exact position of each phone in their signaling data, and new data is only generated when the phone is actively or passively used (i.e., calling, SMS, transfer of data), but most smartphones today are constantly checking for updates, and thus constantly generating signaling data.

Each signaling data record includes a timestamp and the coverage area (Cell ID) to which the phone is connected. The best server estimate (BSE), which is the estimated coverage area, is defined for each Cell ID. Most BTSs have several Cell IDs due to the different antennas pointing in diverging directions. Thus, the Cell ID provides more specific information about the position of the phone than only using the BTS. The BSE consists of uniquely shaped polygons representing the coverage area of each Cell ID. The MNOs collect a lot of data, but the utility of that data for research purposes is limited due to privacy concerns. Telia Company does not use any triangulation methodology to define a more exact location due to their strict privacy policy, but by analyzing the data over time, it is possible to generate movement chains from the signaling data. Telia's algorithms process the movement chains to form insights. They were originally intended for urban areas, but we have employed them to assess whether we can count skiers' phones in avalanche terrain using the insights from signaling data.

The algorithms that process the movement chains are designed to capture three different patterns. The overview below intends to provide a working understanding of how Telia distill relevant data for each report.

1. Activity report – where crowds are spending time without directional movement.
2. Routing report – where crowds are passing by without stopping.
3. Origin-destination report – the trips made by crowds between origins and destinations.

In this study, we utilize the activity report, which captures how many subscribers spend a defined amount of time in a defined geographical area. The activity report can be produced from a regional level and down to a statistical grid, with the lowest resolutions being 500 x 500 meters in a dense urban area. The resolution is flexible, so the grids are larger to secure GDPR compliance in rural settings. It is possible to filter the amount of time spent in a defined area, or use timestamps to reveal when visitors arrived or left an area during the day.

The spatial resolution of mobile network data is dependent on the size of the Cell ID that the cellphone has been communicating with. Each BTS has several Cell IDs with a geographic coverage area. When a device moves around it will connect to multiple different Cell IDs, leaving a movement chain. The initial processing involves turning this raw data trace into dwells (activities taking place in one location) and movements (Figure 2).

To utilize this methodology, we defined a geographical area for the avalanche terrain. We also defined where people live (i.e., populated areas) to identify areas that we could distinguish between avalanche terrain and populated areas. We defined populated areas and avalanche terrain on a map using GIS software (Figure 3). Definitions and methods for defining these areas are outlined in the sections below.

Populated areas

Statistics Norway (**2021**) has created a GIS layer with the number of inhabitants per 1x1 square kilometers. We used this layer and defined populated areas as grid cells with more than ten inhabitants.

Avalanche terrain

Avalanche terrain can be defined using the Avalanche Terrain Exposure Scale (ATES) framework (Statham et al., **2006**). Using the nationwide ATES layer developed by Larsen et al.(2020), we defined avalanche terrain as the sum of simple, challenging, and complex avalanche terrain. Numerous houses and roads lie within avalanche terrain (Kalsnes et al., **2021**). We removed all avalanche terrain within 300 meters of a house or a road from the GIS layer. The distance of 300 meters was chosen to avoid counting people that are driving a car or living in a house, but not moving between a populated area and avalanche terrain.

Mobility analysis

The two layers with populated areas and avalanche terrain were exported and shared with Telia. They applied the layers with their BSE of the coverage area and identified areas where it was possible to distinguish between populated regions (purple) and potential avalanche terrain (red) (Figure 4). Using the insights from the movement chains, Telia counted how many phones traveled into avalanche terrain using signaling data.

Given the nature of the terrain, the most common backcountry trips around Tromsø include a vertical elevation gain of between 800-1200 vertical meters. Assuming a regular uphill pace of 400-600 vertical meters per hour, this could cause uphill travel to take as few as 2 hours for the fittest recreationists. Most people also hike and ride during the daytime. Therefore, we added a filter that only kept phones that were in avalanche-prone terrain for at least 2 hours between 07.00-23.00, during the 2019-2020 avalanche forecasting season (1st of December until 31st of May). This period includes the spring season when the Covid-19 pandemic started. Large parts of Norway closed down on March 13th and there is likely a drop in tourists after this date.

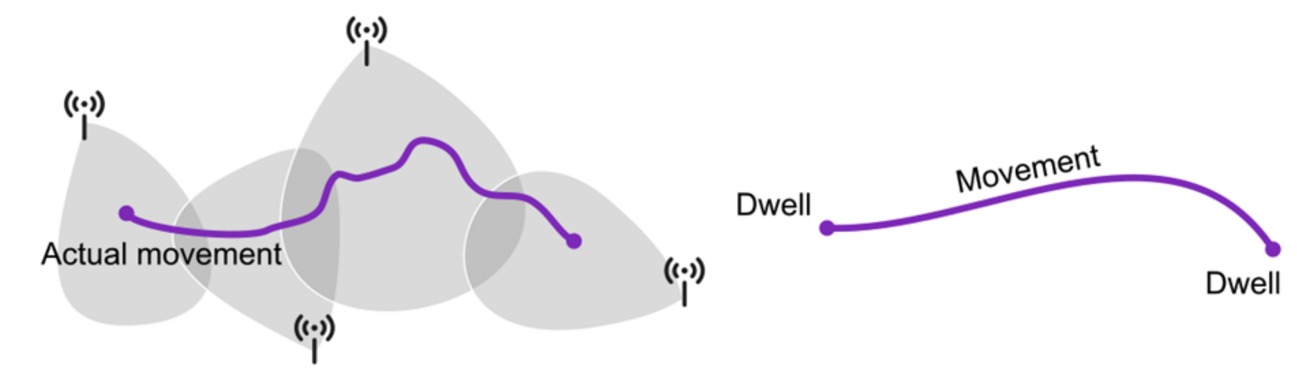

Figure 2 The movement of each cellphone could be tracked through different coverage areas.

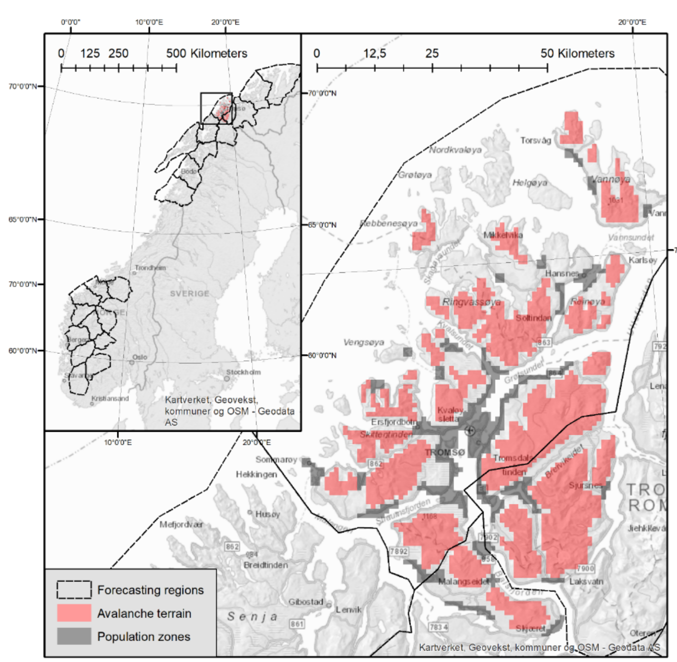

Figure 3 The case study area Tromsø, Northern Norway. Avalanche terrain is colored in red, while the populated areas are colored in dark gray. The avalanche forecast regions are delineated using a dashed line on the inset map.

Validation

To improve the insights from the movement chains, Telia has developed an algorithm that can assign the most likely position within the Cell ID. Telia has targeted the algorithm against normal behavior, which means that the positions will be biased towards populated areas and roads where most people travel. The in-depth details regarding the algorithm are considered a trade secret and are not disclosed due to Telia's commercial interests. Using the output from the algorithm enables us to compare the GPS position to signal data-derived position. The GPS on their watch has a position accuracy of 5-10 m (Wing et al., **2005**).

Correlation with other usage factors

We correlated the number of people per day against the amount of daylight, number of avalanche bulletin page views, weekends and holidays, the daily avalanche danger, percentage of cloud cover, wind strength, and precipitation. All weather parameters were aggregated between 07.00 in the morning and 23.00 in the evening to only account for the conditions during daytime. Amount of daylight was calculated for a latitude of 69° North (SatAgro, **2019**). The daily avalanche danger level was provided by Varsom (**2021**) and the number of page views for the avalanche forecast on Varsom.no was provided by Google Analytics.

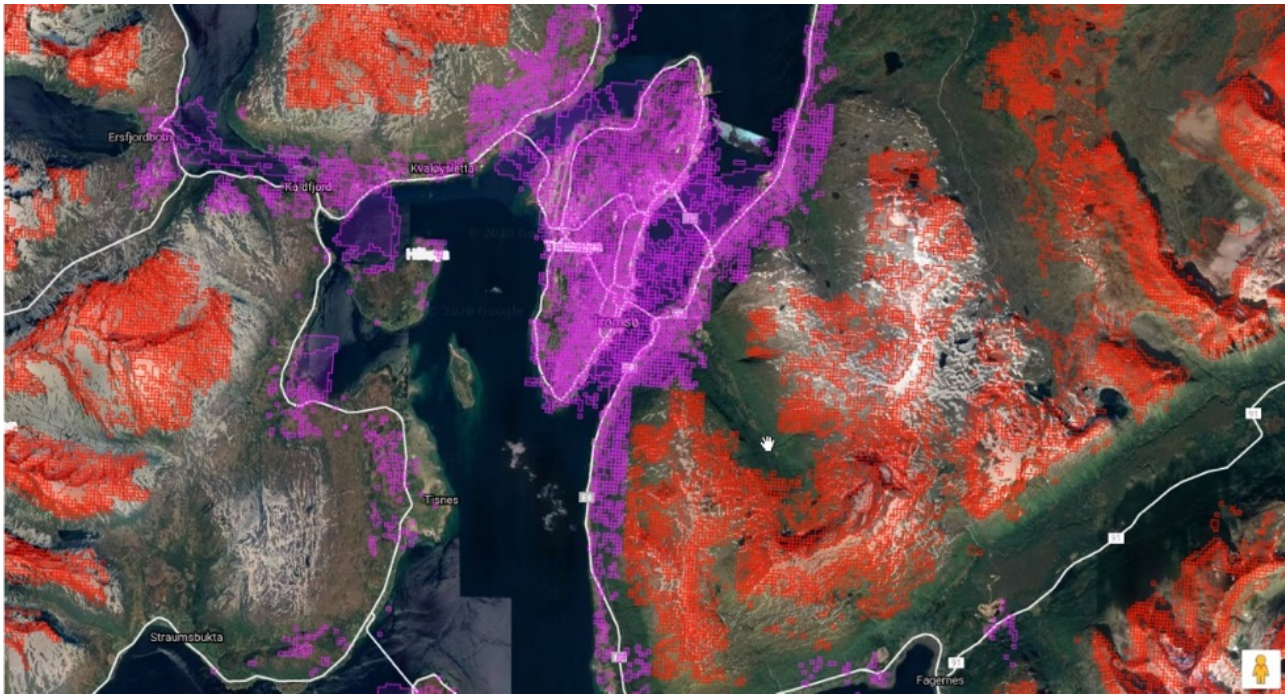

Figure 4 Example of identified areas around Tromsø where the Telia could distinguish between populated areas (purple) and potential avalanche terrain (red) given their BTS coverage in the region.

Table 1 Number of people in potential avalanche terrain versus different variables that could be controlling number of people in avalanche terrain. * Variable is not significant.

Number of people per day versus:	R^2	p-value
Amount of daylight	0.186	< 0.01
Weekend and holidays	0.073	< 0.01
Avalanche forecast page views	0.045	< 0.01
Avalanche bulletin	0.007	0.244*
Cloud cover	0.004	0.374*
Wind strength	0.002	0.521*
Precipitation	0.000	0.917*

Weekends and holidays were encoded as binary values of 0 or 1, with weekends and holidays coded as 1 and weekdays coded as 0. The weather variables were downloaded from the Norwegian Centre for Climate Services (**2021**) on an hourly basis.

Results

Mobility analysis

Using the mobility analysis methods, we estimated that 13,666 people were in avalanche terrain for at least two hours during the 2019-2020 season (December 1st, 2019, to May 31st, 2020, consisting of 182 days). The number of people in avalanche terrain per day varied from 0 to 118, with an average of 75 people per day.

Amount of daylight had the strongest, albeit very low, correlation ($R^2 = 0.186$, $p < 0.01$), followed by weekends and holidays ($R^2 = 0.073$, $p < 0.01$) and the number of forecast page views ($R^2 = 0.045$, $p < 0.01$). We also correlated against precipitation, wind, daily avalanche danger and cloud cover, but none of these parameters were statistically significant (Table 1).

Positional Validation

Using a phone with a special SIM card that was whitelisted (i.e., not anonymized in the

Table 2 Minimum, maximum, median, and 95% of all point distances between GPS track and signaling data spatial locations.

	Min	Max	Median	95% of points within	N (samples)
Trip 1	455 m	8,216 m	4,188 m	7,580 m	74
Trip 2	7,876 m	21,502 m	13,607 m	20,424 m	93
Trip 3	19 m	16,213 m	2,596 m	14,212 m	135
Trip 4	1,997 m	8,919 m	6,911 m	8,736 m	114
All trips	19 m	21,502 m	6,523 m	12,920 m	416

telecom network—users gave specific consent for this), our validation focused on the positional accuracy of the signaling data relative to the synchronous GPS records. When we compared these, we discovered that there was a discrepancy between the two data sets. In the examples (Figure 5), we can see that the estimated positions from the signaling data does not resemble the GPS track. Most of the signaling data positions are estimated to be in the valley bottom, following road corridors or out on the fjords. For all four trips, the positional difference ranged from 19 meters to 21,502 meters. The median positional difference was 6,523 meters and 95% of the points were within 12,920 meters (Table 2).

Discussion

A qualitative review of the four GPS tracks and the signaling data estimated locations shows discrepancies in the estimated positions from the two data sets as shown in Figure 4. This is further supported by our quantitative analysis, where all trips were off by several hundred meters to several kilometers (Table 2). Clearly these positional results are disappointing, and in strong contrast to the reported 150-meter accuracy of the geolocation in mountainous terrain in Andorra (Francisco et al., **2018**). It is difficult to directly compare our results regarding accuracy given that we do not know how Francisco et al. estimated their positional data, or how they validated the accuracy of the signaling data. The differences could be due to several factors, including the potential lower density of BTSs in Troms and/or the algorithm in Norway being designed by Telia for use in urban areas. By comparison, Jansen et al. (**2021**) found the position accuracy of telecom data to be roughly 500 meters in the cities and 3,000 meters in rural areas.

To validate our data, we wanted to check whether the Telia's algorithm estimated the correct locations in rural areas where the coverage areas for each Cell ID are much larger. The algorithm is tuned to work in populated areas where the coverage areas for each Cell ID are small, which makes it easier to estimate the position moving through different coverage areas. The difference in density of BTSs was one of the significant uncertainties in our study. After sending mountain runners out with whitelisted phones, we learned that the positioning of each phone did not work as well as we had initially hoped. When whitelisted phones were compared with actual GPS tracks, we found that the signaling data-derived locations would follow the road corridors leading to the mountains. When our mountain runners parked their cars at the foot of the mountain and started running up, the estimated position stayed in the valley bottom or out on the fjords. We quickly learned that what we initially believed to be a good dataset of ski traffic in the region from the signaling data was biased by the large coverage area of each Cell ID outside the cities. We think there are two primary reasons for this:

1. Telia's algorithm is targeted using data from people travelling on roads between houses, work, stores, etc.
2. The coverage area outside the populated areas is too large to define whether people are up in the mountains or not.

In the bigger picture, these problems are not that surprising. Mobile networks are built and optimized for urban areas where most people live, work and travel. Telecom companies specifically design and build their networks to cover large areas with the fewest possible number of antennas. We are trying to achieve the opposite, capturing signaling data from unpopulated areas where people usually do not travel due to lack of infrastructure. In a broader sense, this is the main limitation of our ability to accurately estimate the position of each phone in rural areas.

We also compared the data with parameters we expected would affect the number of people out in the mountains to initially verify our data. The parameters were amount of daylight (expected positive correlation), number of bulletin page views (expected positive correlation), the occurrence of weekends and holidays (expected positive correlation), rain (expected negative correlation), cloud cover (expected negative correlation), wind strength (expected negative correlation), and avalanche danger (expected negative correlation). For weather data, we only investigated data between 07.00-23.00 because this was the period, we counted people and would likely affect the decision to go skiing or not. The most important coefficient was amount of daylight,

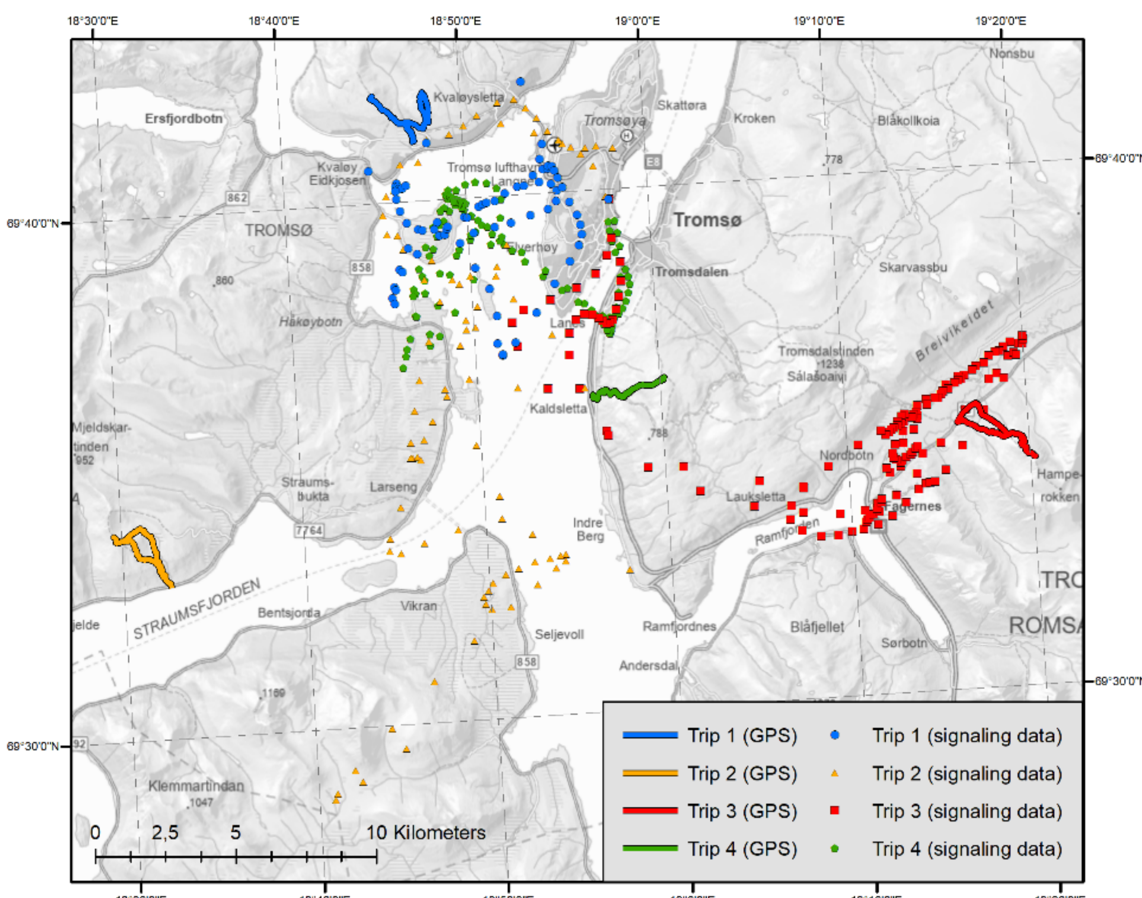

Figure 5 Comparison of 4 different color-coded trips using GPS data (line) and estimated positions from the signaling data (circle, triangle, square and pentagon).

followed by weekend/holidays and number of bulletin page views. The various weather parameters were not significant and had very low coefficient scores. The results are logical because most backcountry travelers are outside when there is daylight in the Arctic, but we had hoped for a better fit towards the weather parameters. This lack of fit in our simple correlations is most likely due to the inaccurate location positions from the signaling data, resulting in the additional counts of users that were not in avalanche terrain, but were included in our data set. This resulting data set is therefore much noisier and includes people in other areas outside of the immediate populated areas, but not necessarily in avalanche terrain.

Original Purpose

The objective of this manuscript is to document our attempts to use signaling data from telecom networks to count the number of backcountry travelers in avalanche terrain within the Tromsø avalanche forecasting region in Northern Norway. If this method had permitted an accurate count of people in avalanche terrain, we would have been able to obtain a very representative sample of overall terrain usage. Combined with the observed number of fatalities in the same avalanche forecasting region, we would also have been able to calculate how risky the activity is in terms of micromorts. Furthermore, we could have tracked terrain usage over several winter seasons to obtain data to assess whether there are any trends concerning the number of people accessing avalanche terrain over time and whether increased interventions, including the uptake of avalanche awareness courses and improved avalanche forecasting, is evident in a change in micromorts over time. To our knowledge, there have not been any studies utilizing telecom network data in non-urban areas. We believe that our results are significant for a broader audience to showcase potential pitfalls when using this type of data. We also highlight the importance of validating this type of data.

Limitations

As already noted in our discussion above, the positional accuracy of the signaling data when compared to the GPS data is the main limitation to the use of this methodology as currently presented. Access to the raw data, prior to analysis by the algorithm, which is targeted for urban use, might alleviate some of these issues, but this was considered outside the scope of the current study.

Furthermore, the reliability of any mobile phone tracking in avalanche terrain depends on users leaving their phone turned on for the duration of their trip. Many backcountry travelers elect to turn their cell phones off to purposefully save battery power for emergency calls. Travelers are also generally encouraged to turn their cell phones off or to flight mode to prevent potential interference with avalanche transceivers. This reality was reflected in a winter backcountry survey by Ortega et al. (**2018**) in Alaska, which showed that of the 63 users interviewed, approximately half of them typically leave their phone turned on whereas the rest turn theirs off or to flight mode.

The main limitation in making telecom data viable for counting people in avalanche-prone terrain is the lack of numerous BTSs in mountainous areas. A more specific algorithm could improve the data quality for this use case, but the BTS density is likely the key factor that would make the method more viable if a mountainous area with a higher density of BTSs is found.

Conclusion

In urban areas, each BTS with several Cell IDs is close together, which means that Telia can estimate more accurate positions given the small coverage area for each Cell ID. Even though Norway has exceptional cellphone coverage compared to many other countries, it is still insufficiently dense in our non-urban and mountainous study area case study. The long distances between the BTSs, and therefore large coverage areas, combined with the populated area-targeted algorithm, are the most likely reasons for the inability to accurately calculate the position of each phone in avalanche terrain. The poor correlation between the GPS track and the position of the whitelisted phones means that we cannot trust the positional accuracy of this initial dataset as provided by Telia. Future work should focus on making a model that is independent of where most people travel. This study provides a useful, yet unsuccessful, case study that demonstrates the limits of signaling data for use in non-urban mountainous areas. It has relevant implications for the application of signaling data tracking to other outdoor recreation activities. We highlight the importance of validating positional data from signaling data to be used in mobility studies in remote areas.

Data

The data that support the findings of this study are available at https://zenodo.org/record/7891581.

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Conflict of interest

The authors declare that they have no conflict of interest.

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Who skis where, when? – A method to enumerate backcountry usage

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Abstract:

Backcountry skiers, travelling in avalanche terrain, account for a large proportion of avalanche fatalities worldwide. Despite this, the exact count of the number of recreationists exposed to avalanches (also known as the background information), is poorly documented in most countries. Without detailed background information on temporal and spatial backcountry usage, making well-reasoned decisions from fatality statistics is impossible. This study developed a methodology to enumerate a large proportion of backcountry usage from a 2 589 km^2 study area in Tromsø, Northern Norway. We use an extensive network of specially adapted beacon checkers – small, waterproof devices that detect and count signals from avalanche transceivers. Over two seasons, from December to May from 2021 to 2023, we recorded 56 760 individual trips. Our findings indicate that most (60.0%) backcountry trips begin between 07:00 and 12:00, with noticeable activity in the afternoon as well. Saturdays and Sundays see the highest daily activity rates, comprising 40.1% of total weekly traffic, while weekdays, though less busy per day, account for the remaining 59.9%. The peak season for winter backcountry skiing is during March and April (when counts from the period December to May are considered), accounting for 56.3% of all traffic. This monthly usage aligns with avalanche incident data, where 55.8% of incidents occur during the same two months.

Our study demonstrates the use of our methodology and advances the understanding of temporal trends from winter backcountry skiing, quantifying the movement characteristics of backcountry skiers in Tromsø, Norway.

1 Introduction/background

Snow avalanches pose a significant hazard in mountainous regions, resulting in an average of 250 fatalities annually worldwide (Schweizer et al., 2021). Over the past decade in Norway, there have been an average of 6.5 yearly fatalities due to avalanches. The annual count has varied, ranging from 2 in the winter of 2016-2017 to 13 in the winter of 2018-2019 (Toft et al., 2023). In the Norwegian subset of fatality data, 90% of the incidents occur due to recreational activities in avalanche terrain (Varsom, 2023). Furthermore, there has been a noticeable increase in fatalities over the last two decades, especially in Northern Norway. This is believed to be related to the increase in popularity of winter backcountry recreation(e.g. Birkeland et al., 2017). Birkeland et al. (2017) argue that the avalanche **fatality rate** (the number of deaths per unit of usage) is likely decreasing in North America. This decline is attributed to the growing number of recreationalists, often referred to as backcountry skiers[1], who are often exposed to avalanches. Evidence for this increase in backcountry skiing can be seen in the rising use of avalanche bulletins between 1995 and 2017. However, no reliable method of directly or indirectly counting the number of backcountry skiers at different times and locations at regional to national scales is available today (Langford et al., 2020). Despite the noteworthy work by established avalanche warning services (AWS) and significant focus on avalanche education (Greene et al., 2022), the trend of the fatality rate remains unclear due to poorly documented numbers of backcountry usage in most countries.

The main objective of this paper is to introduce a method that can enumerate backcountry usage within a set area, throughout the entire winter season. This is important, because without an accurate

[1] We use this term to also includes snowboarders. Snowmobilers are not relevant in our study as they are illegal in most backcountry terrain in Norway.

understanding of the number of skiers in an area (i.e. the background information), it is impossible to estimate an accurate fatality rate. The absence of a background information when interpreting fatality count data provides an incomplete understanding of the population level risk, and any changes in the fatality rate over time. The nature of backcountry skiing, dispersed across mountainous terrain without predefined “trails”, makes it challenging to quantify the entire population within an area. In most cases, there is no single point where everybody skis through, and the starting location and skiing patterns in the terrain might change throughout the season depending on snow conditions, and skier traffic. The diverse nature of backcountry skiing makes it challenging to use more conventional counting methods at larger spatial scales, such as thermal counters or induction loops where skiers would have to be led towards a single point or follow the same trail.

In this paper, we present a method to quantify backcountry usage by making a large network of modified, counting, beacon checkers in Northern Norway. Although the technology has been previously documented by Waller et al. (2012) and further explored in Waller (2014), no results have been published to date.

2 Background

In many sports such as climbing, biking, skydiving, and alpine skiing, we understand the background information (Feletti et al., 2017). However, when it comes to travel in avalanche terrain, the understanding of the background information (e.g. how many are out there) is limited. This is particularly challenging when studying backcountry skiers because of the interaction between avalanches as a natural phenomenon, with limited feedback to those who interact with it, combined with human decision-making. Ideally, the background information, and corresponding fatality data which could aid decision-makers should include information related to demographic insights, details about the total backcountry usage, or statistics on backcountry usage broken down by days, weeks, months, or even hourly patterns.

Ultimately, this would allow for an improved understanding of the drivers of changes in avalanche fatality rates, and thereby allow for more targeted solutions.

Similar to backcountry skiing, road traffic statistics has many related patterns. Just like with avalanches fatalities, there are daily and seasonal fluctuations influenced by travel behaviors or natural factors such as snow, ice, and rain (Malin et al., 2019). Demographic data also plays a crucial role here; for instance, men are statistically more prone to traffic accidents than women, and this observation is supported by extensive research (Cullen et al., 2021). To gain a similar understanding and making informed decisions in the avalanche community, a more in-depth investigation of the background information is needed compared to what is available today.

Analyzing temporal distributions, whether in terms of days of the week, months, or annual patterns, can shed light on behavioral trends and associated risks. Past studies have tried to quantify the yearly terrain usage, although often resorting to educated estimations (Jamieson et al., 2009; Münter, 2003; Valla, 1984). Zweifel et al. (2006) was the first to enumerate backcountry skiers within a limited area by directly counting. Using an experimental setup of light barriers, observations from ski patrol and voluntarily registration boards they were able to estimate a total of 2 922 off-piste runs from the Rinerhorn ski resort in Switzerland.

In Canada, Sole (2008) estimated the number of recreational skiers, using a survey (n=447) to find the percentage of people with a recreational avalanche safety course through Canadian Avalanche Association (CAA) between 2005 and 2007. The courses were taught by independent avalanche course providers, but the CAA developed the curriculum. Using the total number of students (provided by CAA), he was (simply put) able to estimate a backcountry population of 34 485. A similar study was conducted by Procter et al. (2014) in Italy, where they surveyed 5 576 individuals over a 1-week period to learn more about the demographics of backcountry skiers. Furthermore, Techel et al. (2015) used social media platforms to extract 15 586 tours from Switzerland. Using the information available, they estimated the background information as a function of weather, snowpack, avalanche danger and day of week.

One of the most comprehensive studies on the backcountry population is the Swiss cross-sectional national survey, conducted in 2000, 2008, 2014 and 2020 (Bürgi et al., 2021; Lamprecht et al., 2014, 2008; Lamprecht and Stamm, 2000). The results indicate a rapid growth in the backcountry skiing population over the last decade, from approximately 1.4% of the population from 2000-2014 to 3.4% in 2020 (Table 1). Although, the median number of hours spent in avalanche terrain decreased from 56 hours in 2014 to 20 hours in 2020, meaning that the total number of hours spent by the entire population did not change substantially. These data suggests that the growth in the backcountry skiing population may be due to less experienced individuals taking up the sport, who typically spend fewer hours per year in avalanche terrain.

Table 1: Results from the Swiss cross-sectional survey between 2000-2020 (Bürgi et al., 2021; Lamprecht et al., 2014, 2008; Lamprecht and Stamm, 2000).

Year	Proportion of the population [%]	Touring days per year [median]	Average No. of hours per year [median]	Total No. of hours per year [in million hours]
2000	1.3	10	-	-
2008	1.5	10	-	3.9
2014	1.4	10	56	4.8
2020	3.4	6	20	4.9

When Winkler et al. (2016) compared the survey results with avalanche fatalities, the data revealed a minuscule decrease in the fatal accident rate from 9.4 to 8.7 micromorts (i.e. 9.4 to 8.7 x 10^{-6}) from 1999 to 2013, where one micromort is equivalent to a one-in-a-million chance of death in a given year (Howard, 1984). For comparison, a skydiving jump in the US has a probability of 5.1 micromorts (United States Parachute Association, 2022). The study by Winkler et al. (2016) is a compelling example of the importance of considering background information when assessing outcomes. If we only consider the fatality data alone, there appears to be a concerning 32% increase in deaths during that same period (1999 to 2013) in Switzerland.

Using another approach, in work in Montana, USA, at Saddle Peak near Bridger Bowl ski area, Saly et al. (2020) used remote time-lapse photography monitoring from a fixed distance to record terrain metrics of all skiers in avalanche terrain. Saly et al. (2020) counted 525 skiers over a period of 13 days and identified 7,499 skier point locations (the timelapse camera took photos every 10 seconds resulting in multiple locations for each skier). This method captures all skiers but is limited by visibility. In the same season, Sykes et al. (2020) counted and tracked 136 participants over 19 field days using intercept surveys and GPS tracking, but this method is limited by the high personnel costs, and location conducive to capturing participants on their route. Both methods are limited to counting skiers at slope scale and are difficult to apply at scale for a region or entire country.

In Northern Norway, Toft et al. (2023) attempted to quantify backcountry skiers using signaling data from mobile network operators. Unfortunately, when they compared the positional accuracy with actual GPS data, it became evident that the method was highly inaccurate in remote terrain typically used by backcountry skiers.

Langford et al. (2020) conducted a literature review to examine existing methods to estimate the overall backcountry usage. They considered 22 methods and narrowed them down to five categories. If we compare these methods with current research, most studies fit within these categories (Table 2).

(1) When conducted properly, cross-sectional surveys can accurately reflect the broader population, yet they typically offer limited spatial or temporal insights, as Winkler et al. (2016) noted.

(2) Extrapolation from direct counts provides valuable spatial and temporal information. However, its scalability is challenging over larger areas, a limitation highlighted in studies by Zweifel et al. (2006), Saly et al. (2020), and Sykes et al. (2020).

(3) Indirect counts (e.g. Toft et al. 2023),

(4) Citizen science counts feature extensive spatial coverage and gather detailed spatial-temporal data (Johnson and Hendrikx, 2021). However, studies have yet to secure a sample size sufficient for national or global statistical validity. The method also assumes that the user-reported trips are representative, which is unlikely, given self-selection bias to participate in crowd-sourced data collection.

(5) Online engagement has shown promise, particularly in Switzerland, where extensive user-reported datasets are leveraged (Techel et al., 2015; Winkler et al., 2021). This method can extract spatial and temporal data, assuming the representativeness of user-reported trips as for citizen science counts.

All these methods attempt to capture a representative sample of the population to allow for an accurate estimate of the background information, but each of these methodologies have limitations when applied to large regions or entire countries.

Table 2: Comparing available methods and example studies with their spatial scale, spatial and temporal resolution, length of season and type of sample.

Approach	Examples	Spatial scale	Spatial resolution	Temporal resolution	Length of season	Sample
Cross-sectional surveys	Lamprecht et al. 2000; 2008; 2014; Bürgi et al. 2021	Nationwide	Low	N/A	N/A	Representative[1] (n=10 652)
Extrapolation from direct counts	Zweifel et al. 2006	Ski resort	Moderate	High	All season	Subset (n=5 337)
	Saly et al. 2020	Slope	High	High	All season	Subset (n=525)

	Sykes et al. 2020	Slope	High	Low	Selection of 19 days	Subset (n=136)
Citizen science counts	Johnson & Hendrikx, 2021	Worldwide	High	High	All season	User-reported (n=482)
Online engagement	Techel et al. 2015	Nationwide	Moderate	High	All season	User-reported (n=15 586)
	Winkler et al. 2021	Nationwide	High	High	All season	User-reported (n=7 355)
Indirect counts	This study	Regional	Moderate	High	All season	Representative[2] (n=56 752)

[1] *Representative in terms of number of touring days per season.*

[2] *Representative in terms of time of day, week, and month. No number of overall touring days per season.*

3 Methods

3.1 Study area

The study was conducted in a 2 589 km² area surrounding Tromsø, Norway, located within the Arctic Circle. This region experiences polar nights for extended periods during the winter (Figure 1). The region was selected due to its large percentage of Norwegian avalanche fatalities, accounting for 56% of the country's total from 2018-2023 (Varsom, 2023). Tromsø's appeal as a tourist destination, particularly for foreign visitors who now represent over half of the regional avalanche deaths, adds to its relevance in avalanche research. The area's Arctic Transitional climate, which alternates between maritime conditions with frequent rain-induced crusts in warmer periods and extensive depth hoar formation in colder seasons (Velsand, 2017).

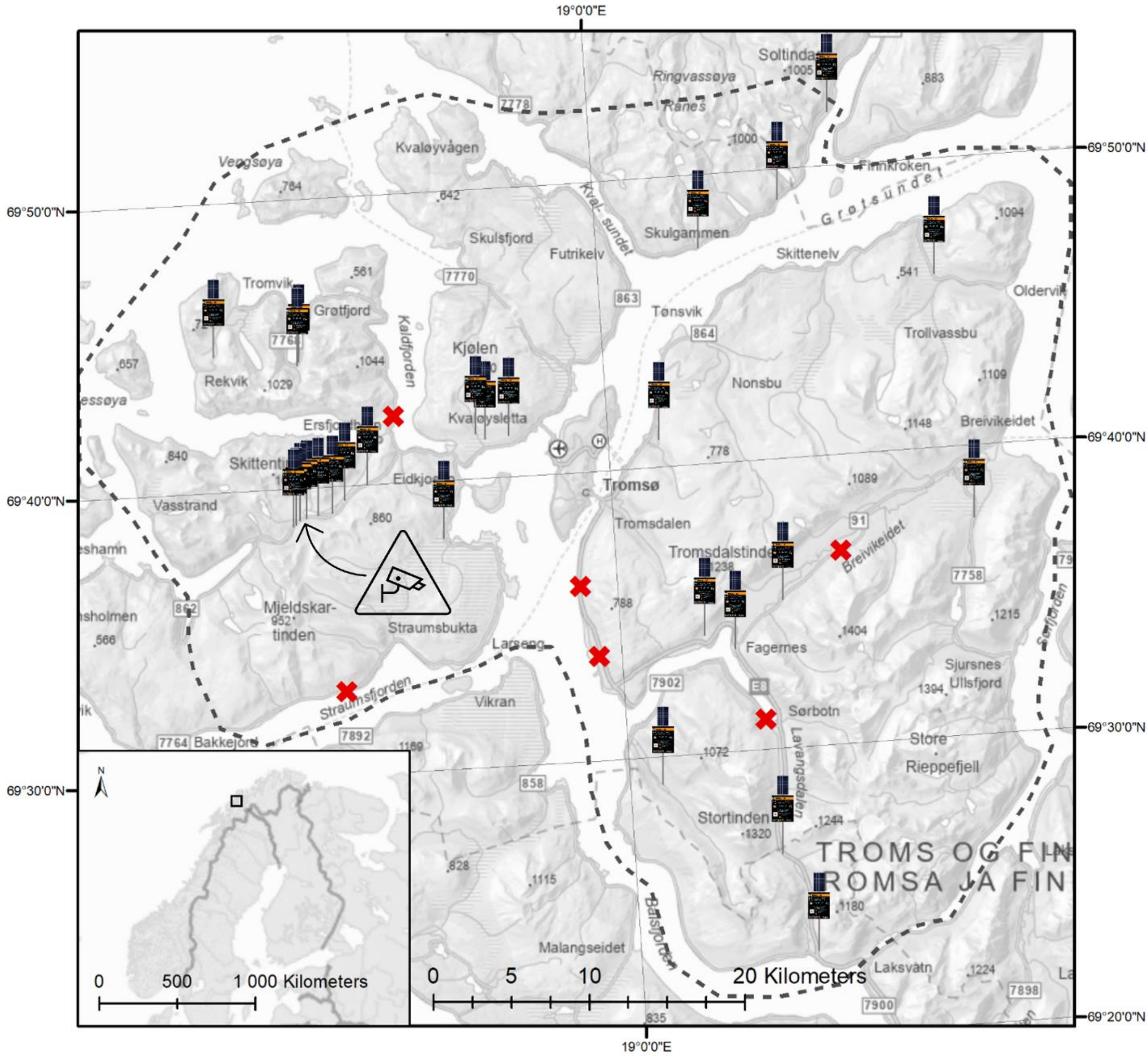

Figure 1: The study area (black dotted line) in the vicinity of Tromsø, Norway. The location of the 29 signs with beacon checkers deployed during the first season are shown (bottom of the pole marks the spot). The red x's illustrate the 6 locations that were considered, but not implemented. The location of the time-lapse camera is marked with a camera icon.

3.2 Setup and components

The beacon checker are a small waterproof device that constantly searches for avalanche transceiver signals. An avalanche transceiver (combined transmitter and receiver) or avalanche beacon is an emergency locator beacon used to find people buried under snow. They are widely carried by backcountry travelers, for use in the case an avalanche burial (Schweizer and Krüsi, 2003).

When a transceiver signal is within a threshold distance, the beacon checker can be programmed to flash with green LEDs, beep or both. The response is a confirmation to the backcountry skier that their avalanche beacon is on and transmits a searchable signal. beacon checkers are most commonly used at large ski resorts or popular backcountry trailheads in North America to remind people that they are accessing terrain where an avalanche beacon is recommended, and that it should be in transmitting mode at this point. It is also possible to use the beacon checker to activate a gate, requiring an avalanche beacon to access certain types of higher risk avalanche terrain. This feature utilizes an electrical current being transmitted by the beacon checker when a beacon is within the threshold range. Our methodology is built around this feature, where the electrical current is used for counting the number of people passing by the beacon checker. We present the first data of this type, collected for a large geographic area, an estimate of backcountry usage from avalanche terrain in Northern Norway.

The beacon checker runs on a 12 VDC system, with a power consumption of roughly 15-20 mAh in sleep and power save mode. In sleep mode, the device wakes up every 15 seconds to search for signals in the area. In power save mode, a red and green LED lights flash instead of being constantly illuminated. The red light shows that there is no beacon within the range, and it turns green when an avalanche beacon is within the threshold distance. Because a lot of the trailheads used in this study are along roads, we disabled the red light to avoid disturbance for road users. The power consumption of the beacon checker is estimated to be 0.42 Ah per day.

Figure 2 shows the setup of our system for counting backcountry users at trailheads with beacon checkers. To keep the system running from the beginning of December to the end of May, we also added a solar panel (12 VDC, 30 W). The solar panel charges the batteries from the beginning of March (halfway into the season) and through May. However, due to the polar latitude of the region (~69°N), it is affected by the polar night for a large part of the winter season, we had to use two 12 VDC LiFePo4 batteries. In total, each beacon checker had a battery capacity of 2x24 Ah, which is enough to be running for roughly four months under optimal conditions.

To gather data from the beacon checker every time it's being used, we added a data logger and pulse counter with IoT/LTE capabilities. To translate the 12 VDC current signal from the beacon checker, we added a SPST-NO type of reed relay. When the relay is exposed for a 12 VDC current, it closes the circuit between the two wires from the datalogger, triggering a count each time (Figure 2). The datalogger was set to record the number of counts per 5-minute interval. A total of 32 units were prebuilt by us and shipped to Tromsø, Norway for their deployment and the operational phase.

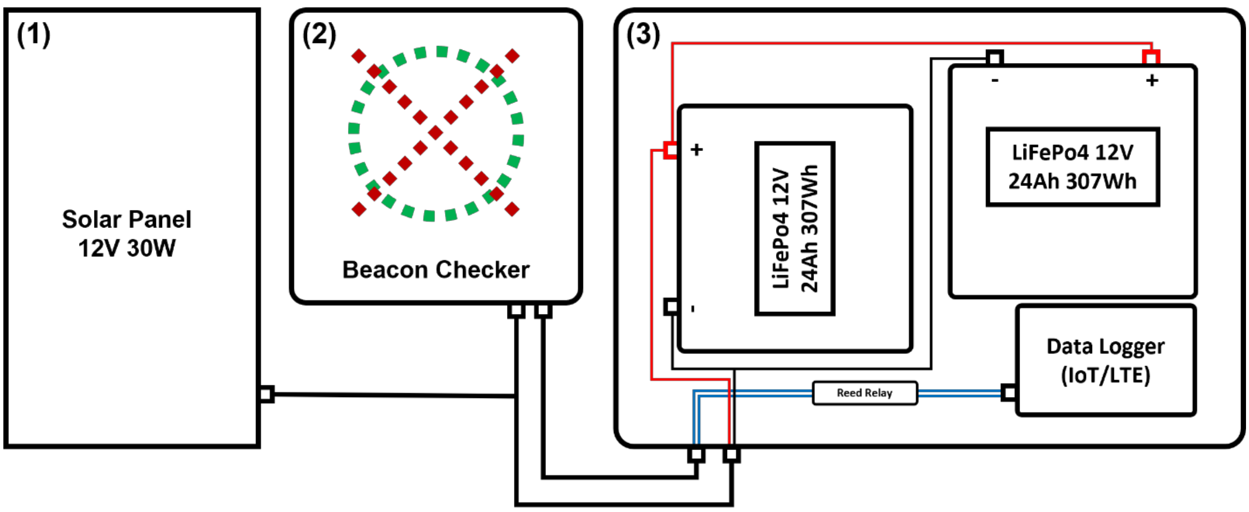

Figure 2: The technical system consists of three parts: (1) a solar panel, (2) a beacon checker and (3) a hard case with 2 batteries and a data logger.

During the operational phase, the technical system was mounted on a post with appropriate signage. Using the same layout as the information signs in the neighboring municipality, Lyngen, we developed a design for the beacon checkpoints (CPs) using a 90x75 cm template (Figure 3a). The signs were attached 110 cm above the ground using a single pole measuring 270 cm x 60 mm. The upper 70 cm was used to attach the solar panel using brackets, making the whole installation 270 cm in height and roughly 35 kg. The pole was attached to the ground using a metal foundation where a rock surface was available using 12 mm expansion bolts and glue (Figure 3a). If the ground consisted of mud or soil, an 89x900 mm ground screw was used. The material cost of a single CP, including the beacon checker, signage, and pole, was approx. US$1,600 (excl. Norwegian sales tax) when purchased in 2021.

To enable convenient transportation and storage of the 32 CPs, with a total weight of 1 120 kg, two custom trailers were built using mounting brackets and a canoe stand. This made it possible to bolt each CP to the trailer, with a maximum capacity of 16 CPs per trailer (Figure 3b). To make sure that the CP keep running with no malfunction, they were mounted at the end of November and retrieved again at the beginning of June. Retrieving the CPs at the end of each season enables service, including recharging the batteries and making sure that each beacon checker is dry and ready for a new season in a harsh winter climate. The main limitation of the system reliability is the beacon checkers which frequently gets filled with water in the spring season. We have now added silica gel inside each device at the beginning of the season to limit this issue.

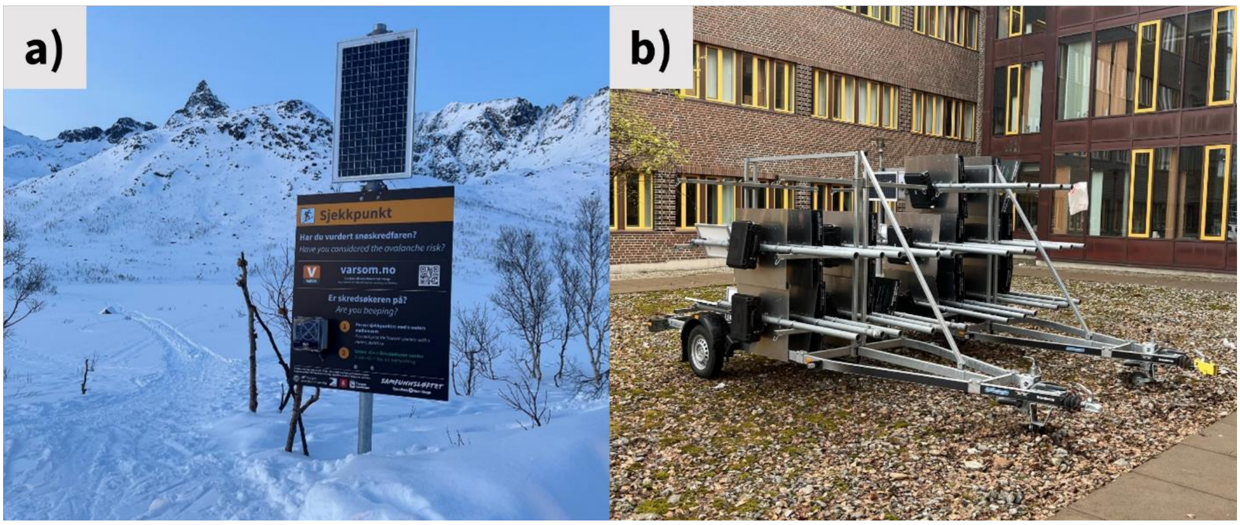

Figure 3: a) The CP mounted in the field in winter conditions. b) The two custom made trailers to transport the CPs between their operational location and the storage and service site.

3.3 Site selection

Using the Strava Heatmap (Strava, 2023), we identified locations that are the main trailheads being used for skiing within the study area of roughly 1-hour drive from downtown Tromsø, Norway (Figure 1). After identifying the most used routes, we shared the map with three local avalanche experts to check whether we had missed any relevant locations, and to confirm the relevance of the selected sites. The process led to 35 sites being identified, but only 30 got approval from the land owner, and one was discarded due to construction (Figure 1; Table 3).

The last step to confirm the final selection of our CP locations, was to obtain permission from the relevant landowner at each location. Fortunately, 86% (30/35) of the requested locations were approved by the respective landowners, and we could proceed with these locations (Table 3). One location was later dropped due to a highway being built at the intended location. We therefore deployed 29 CPs during the first season from 2021-2022 (Figure 1).

The beacon checkers do not search for unique individual frequencies or individual people when counting the number of people passing each CP (adjusted to a detection range of 2-3 m). The range is like many typical trail counters, but the CPs have the advantage that there is a benefit for the skier to go past the beacon checker. This means that if one person is curious and walks back and forth to the sign 10 times, that person would be counted 10 times. It also means that for some trailheads, where the path leading away from the parking lot is very defined, it’s hard to avoid being counted in both directions. We have illustrated this problem in Figure 4, using two scenarios. In the one-pass scenario, the CP is placed in such a way that there is no detour to pass it on their departure, but on their return, there is the potential for people to go around the CP (e.g. skiing an adjacent slope to another point along the road). Therefore, in the case of one-pass, it is up to the backcountry skier to elect if they chose to pass or avoid the CP on their return. In a two-pass scenario, there is some level of geographic confinement which makes it impossible to not go pass the CP on both their departure and return. Careful consideration was given to each site, and adjustments were made to the data to reflect these scenarios. We have included a column in Table 3 showing what category each CP is in terms of one-pass or a two-pass scenario.

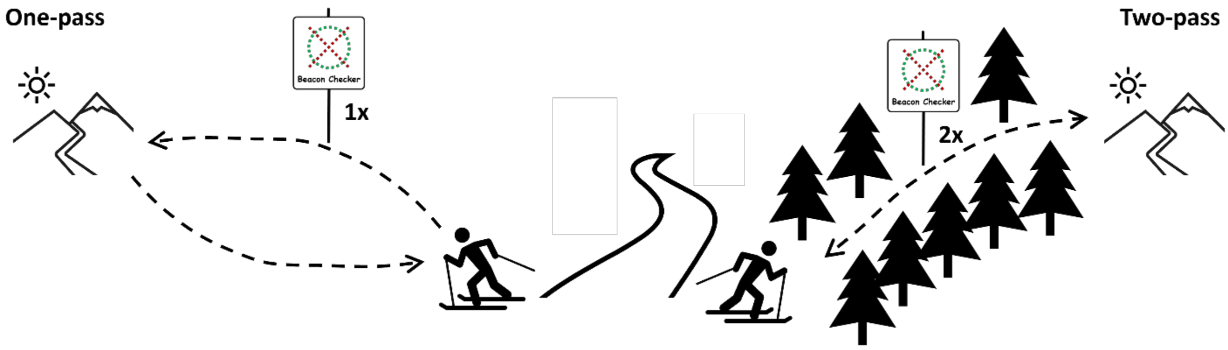

Figure 4: In most locations, the CP is placed so that it is logical to pass it on the ascent, while there is much room to avoid it on the descent (one-pass). However, in some locations, it is most convenient to pass it on both the ascent and the descent (two-pass).

Table 3: A list of all the locations grouped by region that were considered, and whether they had landowner permission and when they have been active during the last two seasons from 2021-2023. A qualitative assessment of whether each location is a one-time, or two-time, pass type is also presented as type.

ID	Location	Permission	Active	Type	Used in time-lapse validation
Kvaløya					
1	Tverrfjellet	Yes	21-23	one-pass	Yes
2	Durmålstinden	Yes	21-23	one-pass	Yes
3	Skittentinden 1	Yes	21-23	one-pass	Yes
4	Skittentinden 2	Yes	21-23	two-pass	Yes
5	Straumsaksla 1	Yes	21-23	one-pass	Yes
6	Straumsaksla 2	Yes	21-23	one-pass	Yes
7	Straumsaksla 3	Yes	21-23	one-pass	No
8	Storsteinnestinden 1	Yes	21-23	one-pass	No
9	Storsteinnestinden 2	Yes	21-23	one-pass	No
10	Steinskarfjellet	Yes	21-23	one-pass	No

Ringvassøya					
11	Bjørnskarstinden[2]	Yes			
12	Nordfjellet	Yes	21-23	two-pass	No
13	Skulgamtinden	Yes	21-23	one-pass	No
Rekvik					
14	Storstolpen	Yes	21-23	one-pass	No
15	Hollendaren	Yes	21-23	one-pass	No
16	Styrmannstinden[2]	Yes	21-22	one-pass	No
17	Buren	No			
Kvaløysletta					
18	Rødtinden	Yes	21-23	one-pass	No
19	Akselkollen	Yes	21-23	one-pass	No
20	Finnlandsfjellet[2]	Yes	21-22	one-pass	No
21	Botnfjellet	Yes	21-23	one-pass	No
22	Gråtinden	No			
Tromsø mainland					
23	Ullstinden	Yes	21-23	one-pass	No
24	Rundfjellet[1]	Yes	21-22	one-pass	No
25	Tromsdalstinden	Yes	21-23	two-pass	No
26	Middagsaksla	Yes	21-23	two-pass	No
27	Fagerfjellet	Yes	21-23	one-pass	No
28	Stormheimfjellet	Yes	21-23	two-pass	No
29	Gårdselvtind[1]	Yes	22-23	two-pass	No
30	Andersdalstinden	Yes	21-23	two-pass	No
31	Blåtinden	Yes	21-23	two-pass	No
32	Storkollen[4]	Yes			
33	Sollidalsaksla	No			
34	Bønntuva	No			
35	Gabrielfjellet	No			

[1] Malfunction during the first season. Not in use during the second season.

[2] Did not capture the traffic as expected during the first season. Not in use during the second season.

[3] Malfunction during the first season. New path established outside of beacon checker; counts are probably not accurate during second season.

[4] A new highway is being built at the intended location.

3.4 Validation using a time-lapse camera.

As it is not possible to count the number of unique people using the beacon checker method, we need to validated the number of counts received from the beacon checkers relative to the number of people entering backcountry terrain at each CP. To do this, we mounted a time-lapse camera on an adjacent mountain ridge taking frequent images (every 30 seconds).

According to Norwegian privacy law, a time-lapse camera taking images frequently is considered surveillance if it is possible to identify people on the images. It was therefore necessary to have a long distance between the camera and the CP to get the approval from the Norwegian Agency for Shared Services in Education and Research (SIKT). The data could only be used for validation of the time-lapse camera and had to be deleted immediately afterwards its intended use.

Due to limitations in terms of resources and location, we placed the camera on a single spot on Kvaløya with a direct line to three high-use trailheads with two CPs mounted at each location (some specific trailheads have access to backcountry terrain at both sides of the road, hence two CPs). This enabled us to get data from six different CPs including both one-pass and two-pass scenarios (as per Figure 4 and Table 3). Optimally, we would have moved the camera to other CPs, but due to landowner permissions and terrain characteristics that allowed images being taken from several hundred meters to kilometers away, the options were limited.

The time-lapse camera was built using a custom built hard-case box that could be pivoted in both vertical and horizontal planes. A digital single-lens reflex (DSLR) camera with an APS-C sensor was used in combination with a 140-560 mm zoom lens and an external digital time-lapse controller. The whole installation was powered by two LiFePo4 12V 24Ah batteries identical to the ones being used in the CPs. The camera was maintained every two weeks by replacing the memory card, batteries and resetting all camera settings from the 14th of February to June 1st during the 2023 season. Every two-week period, the camera was rotated between the three trailheads as the camera field of view could only cover one trailhead at the time. The time-lapse camera captured images every 30 seconds for a total of 108 days (194,400 images) between 08:00-09:00 and 23:00-24:00 (depending on daylight saving time).

To compare the number of skiers with the counts received from each CP, we manually went through all images. For every day, we noted the valid timeframe of the images (e.g. start, blurred periods, end) and the number of skiers entering backcountry terrain. We also noted how many that returned from backcountry terrain, but this data was not used for the analysis. Finally, we compared the number of skiers entering backcountry terrain with the counts from each CP during the day (e.g. if 24 skiers entered avalanche terrain and the CP logged 30 counts, the ratio would be 0.80).

3.5 Operational issues with the CPs.

During the period of deployment, various operational challenges impacted the data collection process at several CPs. These interruptions and malfunctions are crucial to acknowledge for accurate data interpretation and analysis.

3.5.1 The 2021-2022 season

During the first season from 2021-2022, we intended to set up 29 CPs. However, due to the limited availability of parts as a result of the Covid-19 pandemic and resulting supply-chain issues, only 22 CPs were placed out from 1st of December (Table 3; Appendix-1).

Unfortunately, *Straumsaksla 2* never commenced operation due to a technical error that went unnoticed, so we do not have data from this location during the first season. Furthermore, the CP at *Skittentinden 1* experienced a data logger malfunction, ceasing its operation from 1st of December through 8th of December 2021. Later in December, a widespread power outage occurred on Kvaløya (Table 3; Appendix 1) as these CPs were set up in early November. This happened due to lower solar input than expected. The problem leads to significant data gaps from the 18th of December 2021 to 4th of January 2022. The problem was rectified by adding a second battery to all CPs (Figure 1). Another short outage on the Tromsø mainland (Appendix-1) occurred from January 21st to 23rd, 2022.

Additional seven CPs were installed on March 25th, 2022, when the final parts had arrived. These were strategically selected for late installation due to their low expected traffic in the first half of the season, or low priority (Appendix-1). Due to failures with equipment, we quickly realized that we would have to reduce the number of locations to allocate spare parts. Bjørnskarstind and Rundfjellet was therefore decommissioned instantly due to the unavailability of replacement parts and low priority.

Some CPs faced individual challenges as well. *Gårdselvtind* malfunctioned and was eventually discontinued due to a shortage of essential spare parts and the placement of an erroneous data logger at the site. From the 13th of February until 7th of March 2022, the beacon checker at *Botnfjellet* malfunctioned. The error came from the gain module which adjusts the detection distance. The error made the CP count all beacons within range, and not the threshold distance of 2-3 m. Although the period was easy to identify due to the unusually large traffic data reported, the issue was discovered too late to prevent the recording of inaccurate data during that specific timeframe.

3.5.2 The 2022-2023 season

From the start of the season, 25 CPs were placed out (Table 3; Appendix-2). Two CP (*Ullstinden* and *Straumsaksla 3*) never commenced operation. The failure of these stations went unnoticed due to an oversight in the routine data monitoring and verification processes. For *Straumsaksla 3*, the detection of the issue was particularly challenging due to its typically low traffic in the early part of the season.

The same error that occurred during the 21-22 season at *Botnfjellet* was identified at *Stormheimfjellet* from the 10th of February 2023. The error was quickly identified, and the beacon checker was replaced by the 17th of February 2023.

In conclusion, the data collected during the two skiing seasons should be analyzed with consideration for these operational challenges. These outlined issues provide context for the data gaps and anomalies observed in the recorded backcountry skier data, ensuring a more accurate and informed interpretation and analysis.

4 Results

The intention was to set up 29 CPs for the first season from 2021-2022. Unfortunately, two CPs were never commissioned, and one CP never commenced operation. The remaining 26 CPs had an overall downtime of 4.7% (207 out of 4,424 days).

During the second season from 2022-2023, we intended to set up 25 CPs. Two CPs failed to collect data. The remaining 23 CPs had an overall downtime of 0.2% (8 out of 4 163 days), which is a large improvement from the previous season.

4.1 Validation using a time lapse camera.

When we reviewed the time lapse camera images, a substantial number of the images were unusable due to erroneous set-up, including focus and camera settings (i.e. ISO, shutter time and aperture). This left a total of 75 days from February 14th to April 30th (135 000 images) where skiers could be identified. Roughly 22% of these images were unusable due to darkness within the 15-hour period between 08:00-09:00 and 23:00-24:00. The polar nights are longer in early winter, meaning that a larger proportion of these unusable images occurred in the early season. Another 4% the images where unusable due to bad visibility such as fog, and dew on the lens. This left us with 101 470 images to analyze. After manually reviewing all the images, we found a total of 1 399 people passing the six CPs within the periods of the time-lapse camera being operational. This means that for one-pass CPs, 0.87 of people counted by the CP are observed to have passed the site on average, with values ranging from 0.41 to 1.14 (i.e., almost 1 count per person). For two-pass CPs, 1.92 of people counted by the CP are observed to have passed the site on average (i.e. almost 2 counts per person) (Table 4).

Table 4: A time-lapse camera was placed out taking images of six different beacon stations at three different locations. The number of days, images, skiers, and accuracy for each location is presented in each column.

	Station ID	No. of days	No. of images	No. of skiers	No. of counts	Ratio
One-pass	Straumsaksla 1	29	33 746	70	29	0.41
	Skittentinden 1			414	449	1.08
	Durmålstinden	15	17 488	384	232	0.60
	Tverrfjellet			395	363	0.92
	Straumsaksla 2	18	22 768	120	137	1.14
	Summary	**64**	**74 002**	**1 399**	**1211**	**0.87**
Two-pass	Skittentinden 2	18	22 768	115	221	1.92
	Summary	**18**	**22 768**	**115**	**221**	**1.92**

4.2 Adjust for validation metrics

Using the findings from the validation with time lapse camera, we can empirically adjust our data accordingly. For one-pass CPs, we have divided the counts from the beacon checker by 0.87 to get the number of unique trips. We do the same for two-pass CPs, where we divided the counts by 1.92 to get the number of unique trips (Table 5; Figure 5).

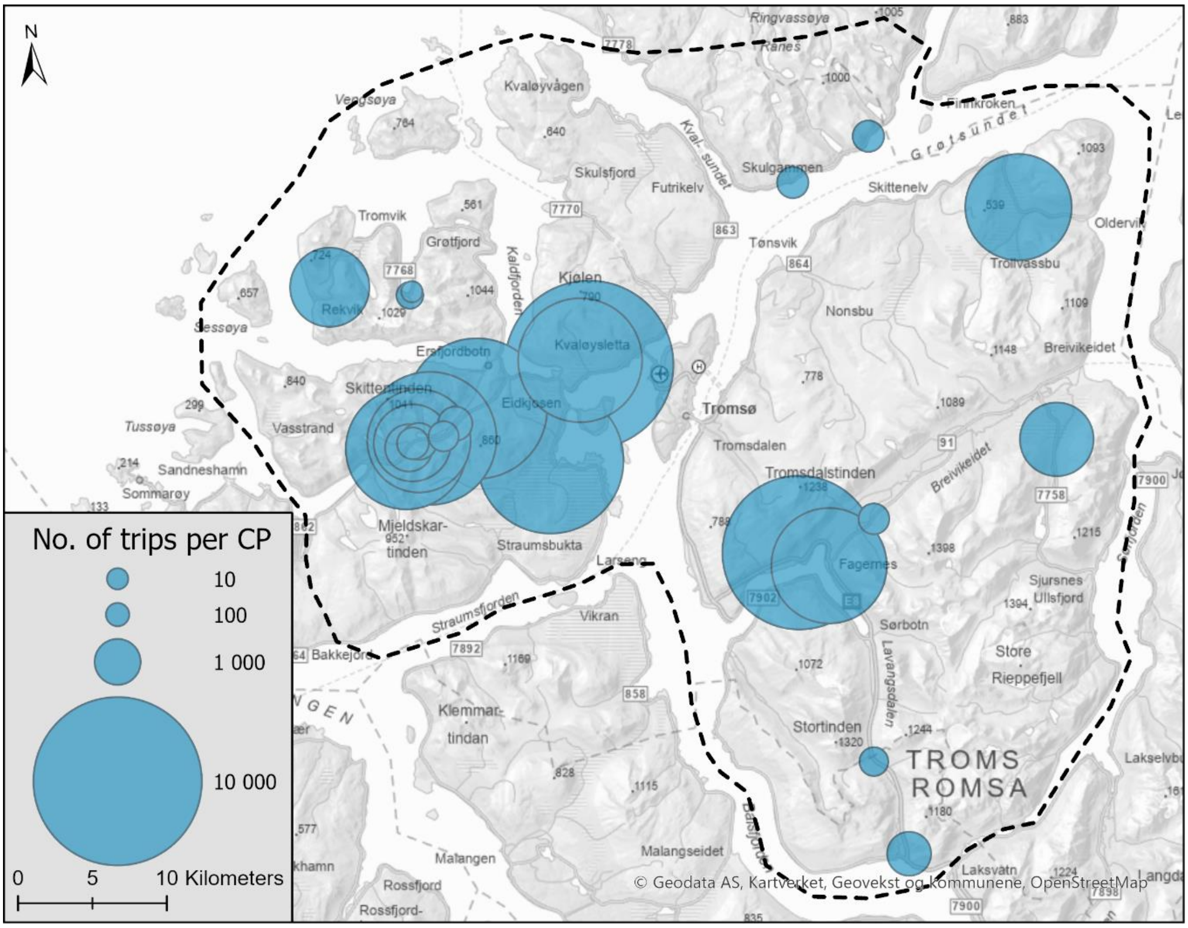

Figure 5: The number of unique trips from each CP illustrated. The larger the circle, the more trips is being made in the area (one circle per CP).

Table 5: A summary of counts from all stations is provided below (rounded to closest 10s). For more detailed information on each station throughout the season, see Appendices-1 and 2.

		No. of beacon checker counts		No. of unique trips	
ID	**Location**	**2021-2022**	**2022-2023**	**2021-2022**	**2022-2023**
1	Tverrfjellet	2 120	1 840	2420	2 100
2	Durmålstinden	260	790	300	900
3	Skittentinden 1	720	1 510	820	1 720
4	Skittentinden 2	1 830	1 440	950	750
5	Straumsaksla 1	290	150	330	170

6	Straumsaksla 2	0	640	N/A	730
7	Straumsaksla 3	360	N/A	420	N/A
8	Storsteinnestinden 1	2 540	1 900	2 900	2 170
9	Storsteinnestinden 2	410	110	470	130
10	Steinskarfjellet	3 060	1 700	3 490	1 940
12	Nordfjellet	190	220	100	120
13	Skulgamtinden	230	180	260	200
14	Storstolpen	240	2 060	280	2350
15	Hollendaren	160	60	190	70
16	Styrmannstinden	10	N/A	10	N/A
18	Rødtinden	2 390	1 700	2 730	1 940
19	Akselkollen	2 630	3 210	3 000	3 660
20	Finnlandsfjellet	110	N/A	130	0
21	Botnfjellet	3 200	1 770	3 650	2 020
23	Ullstinden	3 390	N/A	3 870	N/A
25	Tromsdalstinden	2 380	2 880	1240	1 500
26	Middagsaksla	250	150	130	80
27	Fagerfjellet	2 400	1 340	2 740	1 530
28	Stormheimfjellet	1 430	660	740	340
29	Gårdselvtind	810	230	420	120
30	Andersdalstinden	250	60	130	30
31	Blåtinden	630	280	330	140
	Sum	**32 290**	**24 880**	**32 050**	**24 710**

4.3 Skier traffic by hour

To better understand the distribution by time of day, we grouped our dataset from all CPs by hour. To do this, we only used one-pass CPs. Type 2 CPs would not be representative in this context as we expect each skier to pass the CP two times, making it impossible to know which registration accounted for heading out time. The data shows increasing traffic from 06:00 to about 09:00, with increasing traffic levels until around 09:00. From 09:00 to around 20:00, there is a gradual decrease in people starting their trips. There is also some traffic late in the evening and through the night (Figure 6).

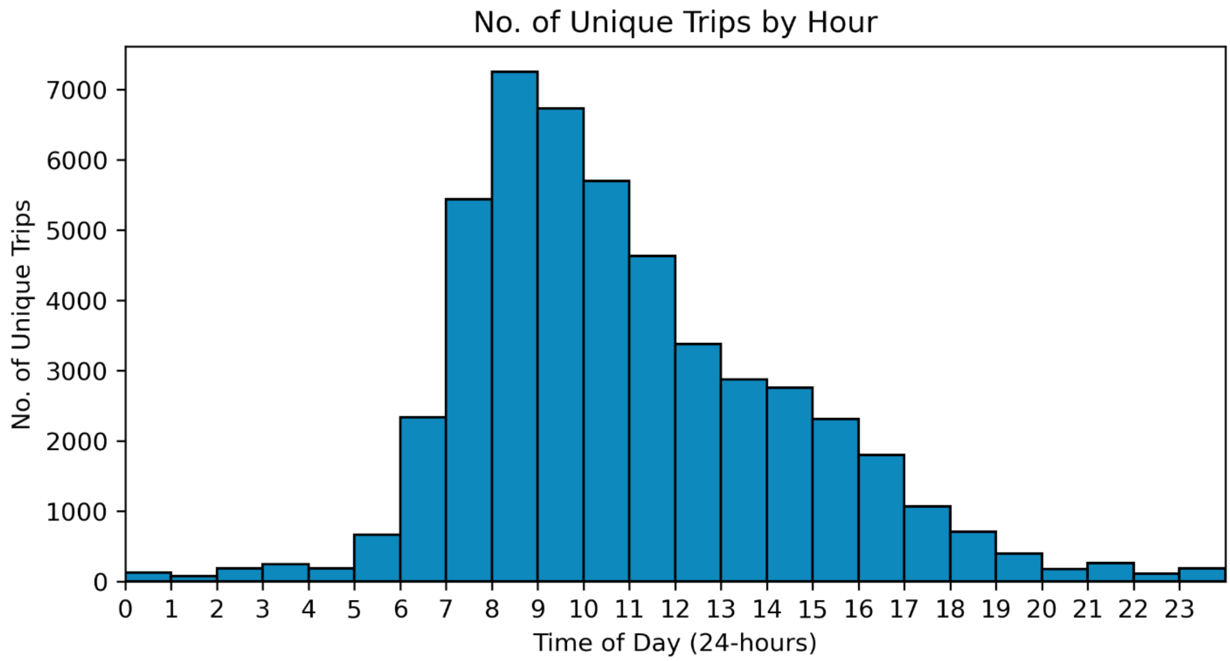

Figure 6: The distribution of skier traffic throughout the day is shown above. Most people are out between 06:00 and 18:00, with the peak between 08:00 and 09:00. Some skiers are out during the night which is not uncommon in this region with modern headlamps. Only one-pass CPs are used here, as two-pass CPs would not be representative in this context, as we expect each skier to pass the CP two times.

4.4 Skier traffic by day week

A distinct difference between weekdays and weekends characterizes the distribution of traffic throughout the week. The highest level of activity was observed on Saturdays and Sundays. In contrast, the weekdays, from Monday to Friday, show relatively lower and consistent counts of skiers per day. However, there is a slight increase in traffic from Monday (~6 200) to Friday (~7 500) (Figure 7).

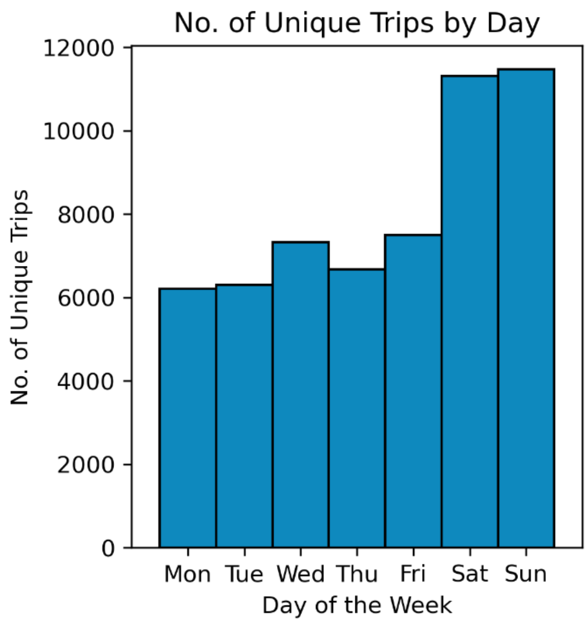

Figure 7: The distribution of traffic throughout the week. Most people are out during the weekend, but there is also a significant amount of traffic during the weekdays.

4.5 Skier traffic by month

To get a better understanding of the seasonal variations, we excluded any CPs that experienced failures for periods exceeding two weeks (specifically, CPs 7, 12, 13, 15, 16, 20, 23 and 29). Ideally, the analysis would consider only CPs that provided uninterrupted data across both seasons. However, the extensive power outage in the first season, particularly in December, necessitated the inclusion of CPs with partial data to maintain a viable sample size for comparison.

If we compare the distribution of skier traffic throughout the season by month (Figure 8), we can see that the trend in traffic is gradually increasing from December to April. There is approximately the same amount of traffic in January and February. March and April represent the most popular months, with April being the peak. In May, the traffic decreases to a level just below January and February, but significantly higher than December. The traffic for the 2021-2022 season was higher than the 2022-2023 season in all months except for December and March, where the 2022-2023 season saw more traffic. When comparing the two seasons using the Pearson correlation coefficient, we find a value of 0.89, indicating a strong positive linear relationship between the datasets. Additionally, the p-value of 0.016 suggests that this correlation is statistically significant.

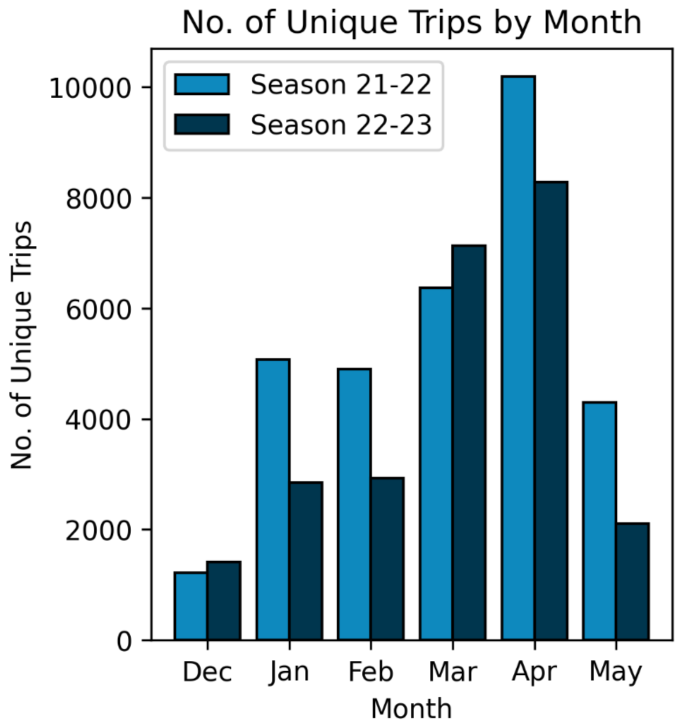

Figure 8: The data illustrates a monthly distribution of unique skiing trips, with the lowest number of trips occurring in December, and a notable spike observed in March and April.

4.6 Seasonal variations

To maintain consistency in our analysis, we again excluded CPs that experienced failures for periods exceeding two weeks, specifically CPs 7, 12, 13, 15, 16, 20, 23, and 29. A cumulative data visualization reveal that the traffic is fairly consistent for both seasons. Notably, the 21-22 season show a marginally more pronounced mid-season peak in February, although the 22-23 season bridges that gap over the next month and a half. In the final month of the 21-22 season, we found a relative increase compared to the 22-23 season, culminating in the highest number of unique trips for the entire season (Figure 9).

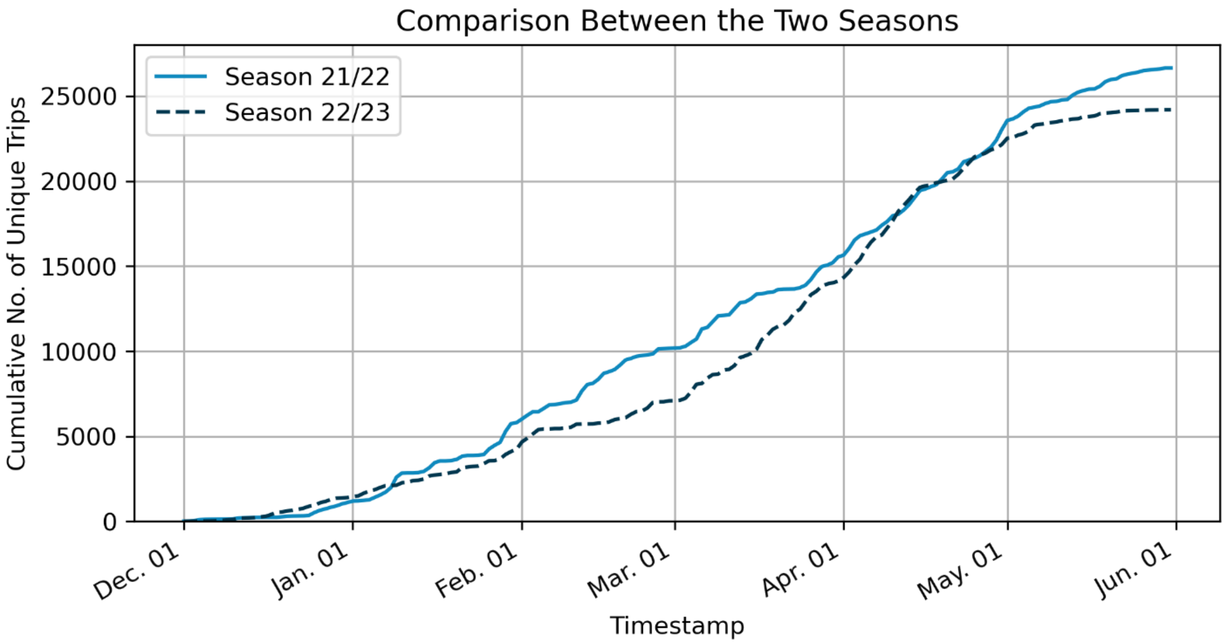

Figure 9: A cumulativ comparison of no. of unique trips from both seasons. CPs that experienced failures for periods exceeding two weeks (specifically, CPs 7, 12, 13, 15, 16, 20, 23 and 29 are excluded).

5 Discussion

5.1 Validation using time-lapse camera.

In our study, we needed to validate skier count data from CPs, as they do not represent unique skiers. We employed a time-lapse camera set to capture images every 30 seconds to achieve this. The 30-second interval was defined to have as few images to process while still being frequent enough to detect all skiers passing through the picture frame. Our impression from the manual validation is that this interval was suitable for our purposes, as skiers are not likely to pass through the camera field of view within the 30 second timeframe.

During February's shorter daylight hours, the camera operated from 09:00 to 22:00. After the switch to summertime on March 26th, the timing shifted to 08:00 to 21:00. Looking back, extending this operational period would have been beneficial as daylight hours increased towards the spring.

To reduce the processing time of manually going through all the images, we noted how many people passed each CP daily combined with timestamps defining the counted period. This allowed us to compare daily counts at each CP for the specific time frame. However, the accuracy varied daily, influenced by the number of people using the trailhead and their interactions with the CP. For example, a single individual passing the trailhead without using the CP results in a 0% validation rate for that day. Conversely, if one person passes multiple times, curious about the sign, it might result in a count of five for a single individual. During days with more counts, this effect decreases.

Through this method, we observed that the accuracy rates converged over several days to an average of 0.87 for one-pass CPs and 1.92 for two-pass CPs. One-pass CPs were validated at five different locations with ratios ranging from 0.41 to 1.14. We believe the ratio differences are primarily due to the placement of each CP. For example, at the Durmålstinden trailhead, the parking lot is situated on a plateau, with the CP positioned lower and not as visible, contributing to a lower rate. Similarly, the Straumsaksla 1 CP is located 20-30 m off the natural path to the mountain, with optimal placement hindered by a large swamp. Given the nature of these examples, it is more appropriate to evaluate the validity of the CPs based on these multi-day averages rather than making day-to-day comparisons.

5.2 Limitations

Although we find our results promising, we must acknowledge certain limitations in our methodology. The CPs are mounted in harsh and remote areas. Even though we made all precautions possible, it is inevitable to avoid technical errors such as low battery voltages, moisture in electronics and the CPs falling over due to strong winds (e.g. 30-50 m/s). To limit these issues, we always had a person available to do maintenance on short notice. In most cases, this allowed us to keep the CPs running with a low downtime.

Another limitation for the study itself is the dependence on a landowner permission to mount a CP at each trailhead. While we rarely faced this restriction in our desired locations, it could be a big issue if the study where to be recreated somewhere else. Additionally, we operate under the assumption that the ratios derived from our validation are applicable to all CPs. We would also like to emphasize that our sample size for two-pass counting points was smaller than ideal, making two-pass CPs more uncertain. We also rely on the assumption that our categorization into one-pass and two-pass CPs is accurate.

Not all locations are suitable for CPs. Examples where a CP is challenging is locations with no designated trailhead or parking lot. Many popular backcountry trips in Norway could begin at different locations, making it hard to cover all usage with a single CP. Furthermore, we believe the actual placement of each CP in relation to the parking lot could have a big impact on the ratio we are able to count. An example of this could be if the CP is mounted in a way that makes it a detour in contrast to something that is right in front of you when leaving the trailhead. In some cases, the material cost of multiple CPs, including the beacon checker, signage, batteries, datalogger and pole could make the study infeasible for many, making it a limitation.

5.3 Temporal distributions

Our results show the hourly, daily, and monthly distribution of backcountry trips across the Tromsø region. The results are in line with what we expected with most skiers starting their backcountry trip before noon (Figure 5). There is also some activity during the night, which is not uncommon in Tromsø with headlamps in the early winter and 24-hour daylight from the end of April.

Saturdays and Sundays have the highest daily rate of skiers, but only accounts for 40.1% of the overall traffic. Weekdays have a relatively lower daily rate, but accounts for 59.9% of the overall traffic (Figure 6). The fact that there is a high amount of backcountry skier usage during weekdays could be of high value to the Norwegian Avalanche Warning Service (NAWS) when they allocate their resources.

Our results indicate that nearly half (56.3%) of the backcountry touring days take place in March and April. This trend aligns closely with data on avalanche incidents (including fatalities, injuries, being caught in an avalanche or near misses) within the study area over 15 seasons from 2008 to 2023 (Varsom, 2023). Notably, 55.8% of the incidents (48 out of 86), also happened during these two months. While we could analyze fatalities, injuries, and avalanche incidents (caught but not buried or injured) individually, the relatively small sample size could lead to statistical issues. A small sample size can result in unreliable or skewed statistics that might not provide a valid representation of broader trends or risk factors. We considered comparing our data with regional bulletin website usage. However, we do not trust the analytics from the study period as NAWS transitioned from Universal Analytics to Google Analytics 4 during this same period.

5.4 Future work

Our methodology represents an initial step towards achieving a representative sample for an entire region. Future work could include the potential to approximate the overall seasonal background information in the study area by collecting a large dataset of GPS tracks through crowd sourcing. With a comprehensive set of GPS data, we could conduct a GIS analysis to determine the proportion of tracks that originate from each CP. This approach would enable us to estimate the percentage of total traffic captured by our CPs relative to the data collected through crowd sourced methods.

Expanding our methodology to regions with different characteristics from our current study area would also be beneficial. This expansion could provide insights into regional variations in backcountry usage patterns. Additionally, there might be room for technological advancements in beacon checker technology. Enhancements could include the ability to identify number of unique signals within a range or to detect other prevalent signals like WLAN (i.e. Wi-Fi) or Bluetooth, thereby offering a more accurate and nuanced understanding of skier counts and patterns.

5.4.1 Recommendations for future application

In this section, we would like to provide some advice for future application of this method. After two seasons of data collection, maintenance, and lots of *what ifs* that we were not able to anticipate:

- Make sure to always have enough spare parts on hand, as something will fail occasionally, or simply be lost. We have found it easier to swap all electronics (beacon checker, datalogger, batteries) with a new setup, and resolve the error in the lab.
- Use glue when mounting the foundation for the CPs, do not trust expansion bolts. The vibration from the wind will over time unscrew the bolts, making the CP fall over.
- Always have a person available to do maintenance when needed, and make sure that there is more than one person that can do maintenance. Furthermore, make everything modular and use wire connections with clear markings, (or connectors) making it less likely to connect something wrong. It only takes one wrong wire connection to burn a beacon checker or a datalogger. These precautions make it easier to have multiple people do maintenance.
- Use silica gel in the beacon checker housing. They are not 100% waterproof.
- Make sure that the datalogger and beacon checker is dried-out after each season, and make sure that everything is working properly before a new season. It is much easier to fix errors in the lab, compared to in the field.
- Always make sure to test the CP before leaving the site.

6 Conclusion

We believe our study is a proof-of-concept using beacon checker technology increasing our understanding of the backcountry usage at regional scales. We have managed to quantify a large proportion of the backcountry skiing population over a 2 589 km^2 area, offering valuable insights into various timescales, including hourly, weekly, and yearly distributions of backcountry usage.

Over two seasons, from December to May from 2021 to 2023, we recorded 56 760 individual trips from 26-29 trailheads. Saturdays and Sundays see the highest daily activity rates, comprising 40.1% of total weekly traffic, while weekdays, though less busy per day, account for the remaining 59.9%. The peak season for winter backcountry skiing is during March and April (when counts from December to May are considered), accounting for 56.3% of all traffic. This monthly usage aligns with avalanche incident data, where 55.8% of incidents occur during the same two months.

While our methods still have some limitations, we argue that a large scale spatially distributed system as presented here, provides the best method to currently estimate backcountry usage across a remote and dispersed region. However, our findings also highlight the need for further research to build upon the groundwork we have laid to be able to calculate the usage for an entire region.

Data availability

The data from this study are available from the corresponding author upon request.

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Competing interests

The authors declare that they have no conflict of interest.

Statement

During the preparation of this work the corresponding author used ChatGPT 4.0 from OpenAI in order to improve readability and language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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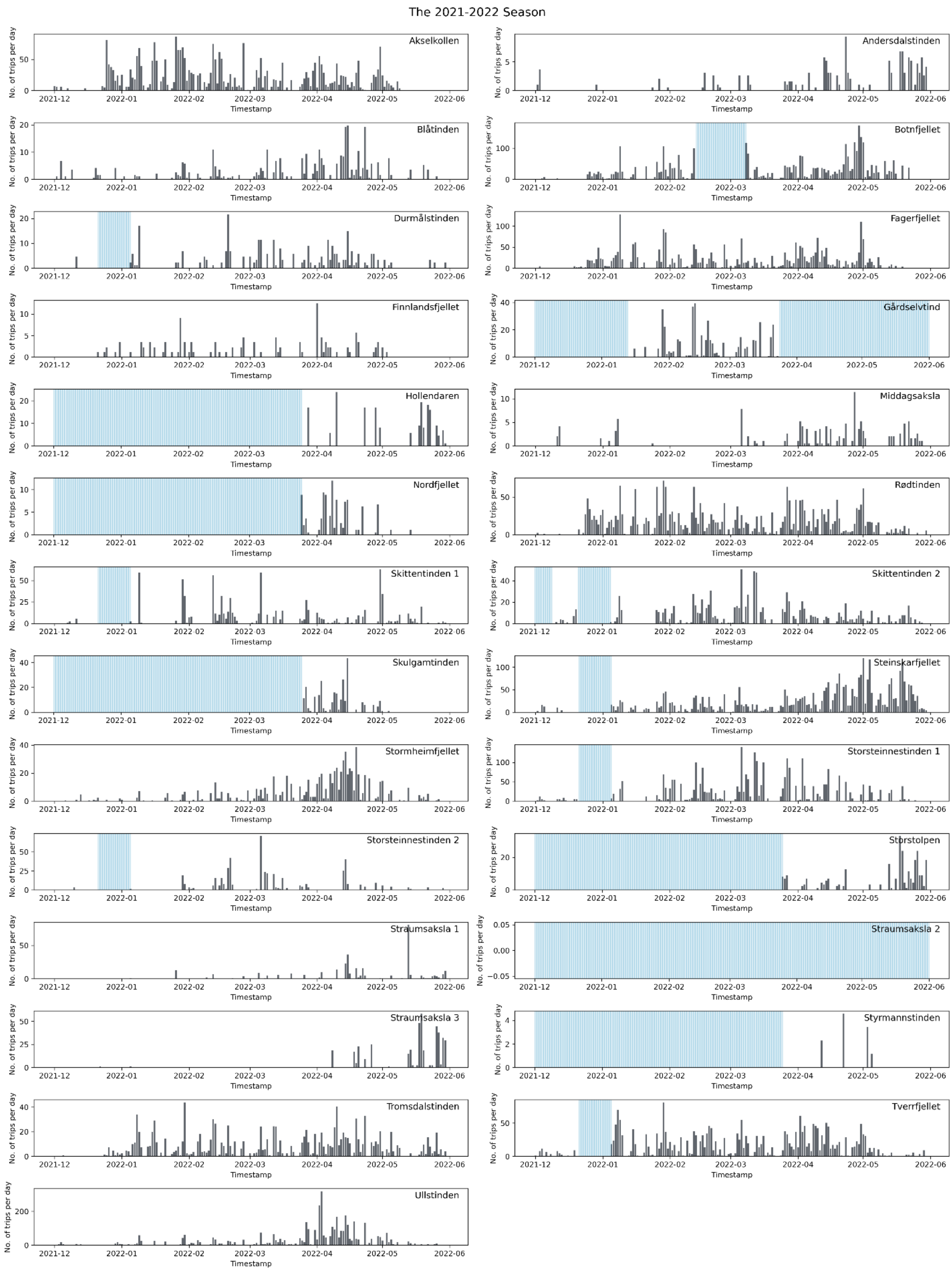
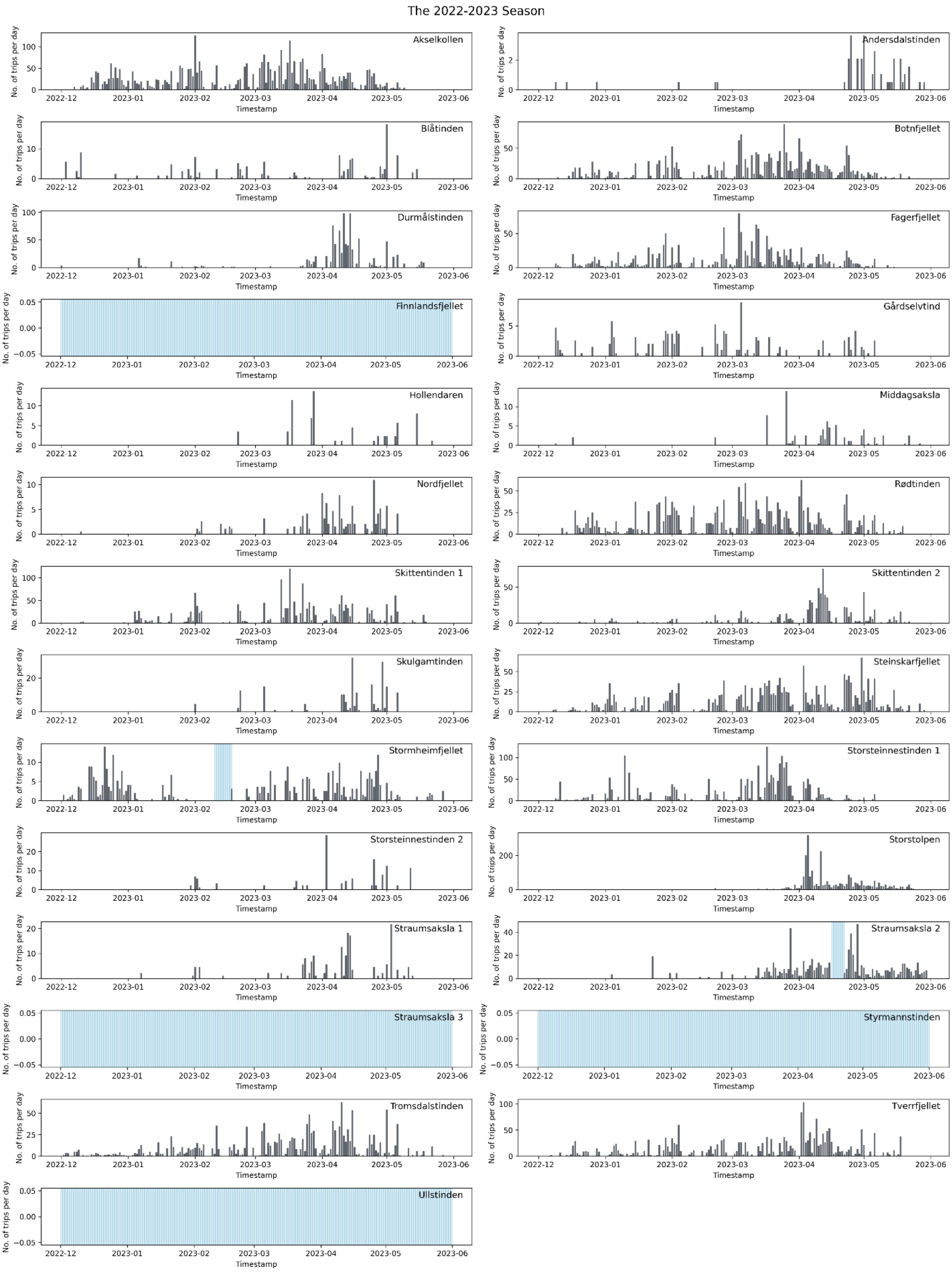
Appendix


The 2021-2022 Season
Akselkollen
Andersdalstinden
Blåtinden
Botnfjellet
Durmålstinden
Fagerfjellet
Finnlandsfjellet
Gårdselvtind
Hollendaren
Middagsaksla
Nordfjellet
Rødtinden
Skittentinden 1
Skittentinden 2
Skulgamtinden
Steinskarfjellet
Stormheimfjellet
Storsteinnestinden 1
Storsteinnestinden 2
Storstolpen
Straumsaksla 1
Straumsaksla 2
Straumsaksla 3
Styrmannstinden
Tromsdalstinden
Tverrfjellet
Ullstinden
No. of trips per day
Timestamp

Appendix-1: A plot for each station during the first season from 2021-2022. Timesteps with blue shading mark periods where the beacon checker has malfunctioned, or no data collecting was in progress.


The 2022-2023 Season
Akselkollen
Andersdalstinden
Blåtinden
Botnfjellet
Durmålstinden
Fagerfjellet
Finnlandsfjellet
Gårdselvtind
Hollendaren
Middagsaksla
Nordfjellet
Rødtinden
Skittentinden 1
Skittentinden 2
Skulgamtinden
Steinskarfjellet
Stormheimfjellet
Storsteinnestinden 1
Storsteinnestinden 2
Storstolpen
Straumsaksla 1
Straumsaksla 2
Straumsaksla 3
Styrmannstinden
Tromsdalstinden
Tverrfjellet
Ullstinden
No. of trips per day
Timestamp

Appendix-2: A plot for each station during the first season from 2022-2023. Timesteps with blue shading mark periods where the beacon checker has malfunctioned, or no data collecting was in progress.